

SHORT-TERM LOAD FORECASTING

A DISSERTATION

submitted in partial fulfilment of
the requirements for the award of the degree
of
MASTER OF ENGINEERING
in
ELECTRICAL ENGINEERING
(Power System Engineering)

By

SUSHIL CHAUHAN



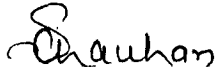
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February, 1988

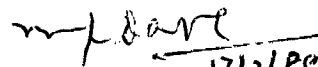
CANDIDATE'S DECLARATION

I hereby, certify that the work which is being presented in the dissertation entitled, 'SHORT-TERM LOAD FORECASTING' in partial fulfilment of the requirements for the award of the degree of MASTER OF ENGINEERING in ELECTRICAL ENGINEERING with specialization in POWER SYSTEM ENGINEERING, submitted in the Electrical Engineering Department, University of Roorkee, Roorkee [India], is an authentic record of my own work carried out for a period of about six months from September, 1987 to February 1988, under the supervision of Dr. M.P. Dave, Professor, Electrical Engineering Department, University of Roorkee, Roorkee, India.

The matter embodied in this dissertation has not been submitted by me for the award of any other degree.


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This is to certify that the above statement made by the candidate is correct to the best of my knowledge.


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ACKNOWLEDGEMENT

I wish to express my deep sense of gratitude to my guide, Dr. M.P.Dave, Professor, Electrical Engineering Department, University of Roorkee, Roorkee, without whose co-operation, inspiration and guidance it would have been impossible to complete the thesis.

Thanks are due to staff members of Ram Nagar Substation and Hydrology Department of University of Roorkee, Roorkee for helping me in providing the required data.

The computer centre staff, specially Dr. Jeeya Lal, who has played a role of prime importance in getting my thesis completed, also deserve a special word of thanks from me.

In the end, I am grateful to all whose name I have missed and who have played a part in seeing through the thesis to the final phase.

SUSHIL CHAUHAN

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ABSTRACT

Considerable work has been carried out in recent years on problem concerned with load flow analysis, economic generation scheduling and system-security checking in electrical power systems. An aspect of the overall problem which has not received much attention is that of short term forecasting of electrical load demand. It is, however, important from the practical point of view of economic generation scheduling and security checking to be able to predict accurately load demand several hours in advance. In this report various methods which are commonly used for short-term load prediction are discussed in Chapter-2 along with their relative merits. The method based on ref. [5] which has been adopted for probabilistic forecasting of hourly power-system loads with a lead time varying from 24-hours to one week, has been included in Chapter-3 along with necessary flow charts for developing computer programs. The forecasting is based on both historical load data and information from latest weather forecast. The developed program combines stochastic load model and adaptive weather load models optimally to yield an adaptive forecast especially suited for on line control of power systems. Adaptive capability in this context is taken to be ability of the model to update its own parameters according to its past performance, a feature that makes the forecasting procedure particularly suitable for on-line use.

The developed computer program has been run on actual load and weather variables (Temperature and humidity) records obtained from Ram Nagar Sub-station and Hydrology department of Roorkee University respectively. Results have been found satisfactory and are presented in Chapter-4 of this report. The conclusions of the study are drawn in Chapter -5.

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CHAPTER -1

INTRODUCTION

1.1 Definition of Load Forecasting [1]

Load is a general term meaning either demand or energy where demand is the time rate of change of energy. The term forecast refers to projected load requirement using systematic process of defining future loads in sufficient quantitative detail so that important powers-system expansion decisions can be made. For effective power system expansion, estimates of both powers and energy are crucial. An accurate forecast depends on the judgement of the forecaster and it is impossible to rely strictly on analytical procedures to obtain an accurate forecast. Also Good judgement alone can not be over emphasized in forecasting future requirements and analytical tools must be used.

In some cases a total forecast is obtained by combining forecast for various classes of customers such as residential, commercial, industrial, agricultural and other. For the better prediction of load it is imperative for the forecaster to be well versed with the characteristics of varieties of loads i.e. growth rate with time and effect of weather fluctuations. In many cases seasonal variations in residential component are responsible for the seasonal variations in system peak. The extent of residential influence will depend upon the percentage of total system load that is residential. Increase in per capita consumption due to wide spread use of weather sensitive devices, need to include weather effects in forecasting

future requirements become imperative.

Let it be emphasized that solar energy technology may have a tremendous impact on load patterns experienced by electric utilities. It is well-documented fact that uses of solar energy technology for heating and airconditioning is well with in the state of art. If wide spread acceptance of solar conditioning occurs, it will be incumbent on the forecaster to anticipate its impact on utility industry.

Forecasting methodology to be followed depends upon period of interest for load forecasting. Short and medium term forecasting can be done using conventional procedures i.e. by extrapolation of certain factors characterizing hourly modulation of load. For long term forecasting consumption is broken down in to homogeneous sectors. The preceding extrapolation technique applied to different consumption classes makes it possible to generate individual load curves thus giving a global level by summation. This approach also makes allowance for structural deformation of consumption.

1.2 Importance of Load Forecasting [1,2,3]

Load forecasting has always been an integral part of power system planning and operation. However, it did not receive as much attention in the past as it deserves because the fuel supplies, especially hydrocarbons, were cheap and abundant and utilities could find funds for erecting enough gas/oil generation plants at relatively short lead times. In the last few years, conditions have considerably changed

and the past practices have to be suitably modified. Thus load forecasting will assume greater importance in the years to come.

Long term demand forecast is used to determine the capacity of generation, transmission and distribution system additions and energy forecasts determine the type of facilities required i.e. whether peaking generating unit or base load unit should be installed as there is substantial difference in their cost. Whereas the importance of short-term forecasting is realised in service reliability and efficient operating performance of power supply system, particularly in case of thermal power plant which demands accuracy in the forecast of system load. This is necessary in order that generating capacity adequate to supply the system load, maintain system security and supply the necessary spinning reserve. The scheduling of spinning reserve as coverage for the loss of largest unit or the loss of that transmission capacity which renders unavailable the greatest amount of generating capacity, is an accepted principle of reliable system operation.

1.3 Classification of Load forecasting [1,4]

Depending on the time period of interest, a specific forecasting procedure may be classified as -

- (a) Short term load forecasting
- (b) Long term load forecasting.

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(a) Short term load forecasting - A technique for computing twenty four hour forecasts is essential for monitoring and controlling power system operation. Load forecasts are necessary for on-line solution of scheduling problems, such as unit commitment and economic dispatch and also for security analyses by line load flow solution.

The forecasts of these hourly loads which may correspond to a system load, an area load or a bus load are of direct value for the short term operation of the system. Total system load is needed in daily scheduling the most economic allocation between different plants. In addition for thermal plants load forecasts up to several hours in advance are needed to account for economics of starting up and shutting off various plants. Hourly bus-load forecasts are needed for number of off-line applications related to economic and system security problems. On line control requires forecasts of bus loads as input to different analysis programs that monitor and control the systems operation.

The forecast should be sufficiently accurate throughout the lead time period. Here load time period varies from hours to a week. In particular accuracy of the forecasted daily peak load and the daily minimum load is important because these forecasts are used for scheduling spinning reserve and interchanges. In addition to forecast accuracy the following consideration are also important.

- (i) The computer storage required
 - (ii) The computer time required
 - (iii) The load and/or weather data required.
- (b) Long term load forecasting

Forecasting techniques may be based on extrapolation or on correlation or on a combination of both. Correlation techniques of forecasting is advantageous in forcing the forecaster to understand clearly the inter relationship between growth patterns and other measurable factors. No one forecasting method, it must be emphasized, is effective in all situations. The accuracy of a forecast is crucial to any electric utility, since it dictates the timing and characteristics of major system additions. A forecast that is too low can easily result in lost revenue from sales to neighbouring utilities or even in load curtailment on the other hand, forecasts that are too high can result in severe financial problems due to excessive investment in an electric plant that is not fully utilized or, equivalently it is operated at low capacity factor. In long term forecasting lead time for forecast varies in years.

1.4 Method Adopted for short term load forecasting [5]

In present work computer program in FORTRAN IV for probabilistic forecasting of hourly power-system loads with lead times of 1 to 24 hours is developed. The forecasts produced are based on both historical hourly load data and information from the latest weather forecast. The methodology

combines stochastic load models and adaptive weather load models **optimally** to yield an adaptive forecasting procedure especially suited for real time control of power systems. Being an adaptive model it avoids the frequent tuning of its parameters from year to year. The details of the method are included in chapter -3.

1.5 Data Requirements and Source

To test the developed computer program hourly load data for 102 days i.e. from 1st August, 87 to 9 November, 87 has been collected from 132 KV Ramnagar grid substation. The above mentioned data has been observed on 33 KV feeder supplying power to Roorkee town.

Daily records of weather variables, average temperature and relative humidity has been collected from Hydrology department of Roorkee University for the same period.

The processing of the historical data is done only once for initialisation of the model parameters. Once the initialisation is completed and model parameters are updated, on the basis of current load values forecasts are made using the updated model parameters and latest weather forecast.

1.6 Forecasting Procedure [5]

A highly simplified flow chart of the forecasting procedure is given in Fig. 1.1. It combines two forecasting models, a stochastic model to relate the future loads to the past loads and a weather load model to represent the effects of

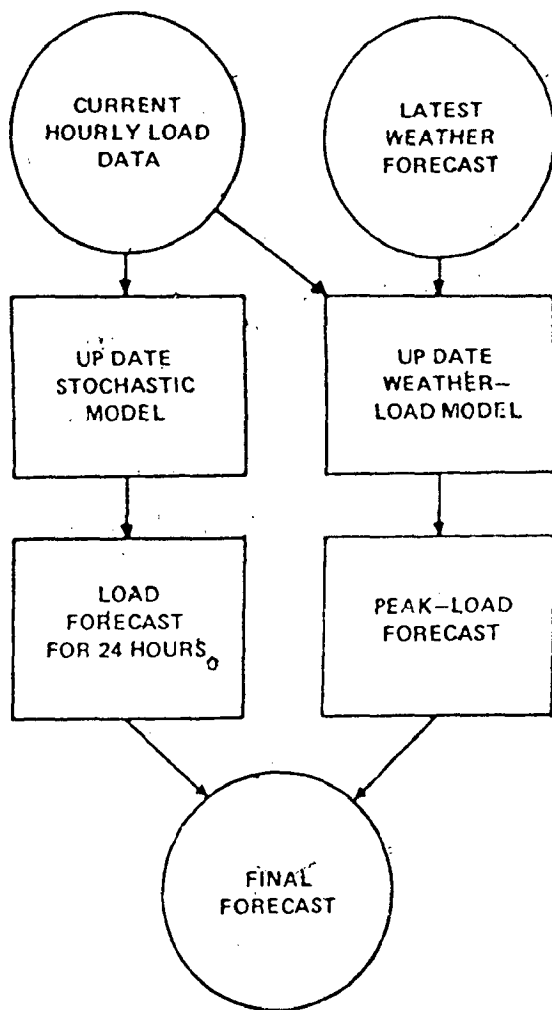


FIG. 1.1

Simplified Flow Chart For Forecasting Procedure

weather variables on future loads. The models themselves are updated as the forecast are produced.

1.7 Arrangement of the details

Chapter 2, includes the discription of different techniques used for short term load forecasting. Chapter-3 presents the details of the method adopted for forecasting. Programming details are also discussed in the same chapter. Forecasting results are given in Chapter-4. Conclusions drawn on the present work are included in Chapter-5.

CHAPTER - 2

REVIEW OF THE METHODS USED FOR SHORT-TERM LOAD FORECASTING

The problem of short-term load forecasting has been the subject of several recent publications. Earlier efforts by Matthewman and Nicholson [3] were mainly directed towards performing regression studies between the load data and a number of preselected weather variables. In these studies the model used was static in nature and there was no guarantee that it would perform as well in the prediction of future loads as it did in determining past ones. In the later studies by Toyoda et.al^[6] and Christianse [4] weather information has been ignored and an adaptive time series approach has been adopted. The limitation of these approaches is self evident, the weather, which plays an important role in future load swings, has no place in these models. In the later publication by Pradeep C.Gupta et al [5] a forecasting technique was adopted that avoided both the above mentioned limitations. The forecasting model contains an adaptive weather load model to utilize the weather forecast information and an adaptive stochastic model to utilize the historical load data in making the statistically optimum load forecasts. In reference [7] pattern-recognition technique was used for forecasting hourly loads. The only drawback of the scheme is large computer storage requirements for classifying n dimensional pattern space in to separate

regions or clusters. In recent publication by Martin T. Hagan and Suzanne M. Behr [8] it is shown that Box and Jenkins time series models are well suited to short term load forecasting where as in reference [9] two different adaptive and weather sensitive models are used based on the fact that different weather variables are found to be relevant in summer and winter. Adaptivity is attained through careful usage of Kalman filtering and Bayesian techniques.

The purpose of the present chapter is ~~to present~~ the brief description of the different techniques used for short term load forecasting and their limitations. The literature includes the description of the following methods.

2.1 Methods involving meteorological data [3]

If the demands for a particular half hour are plotted serially day by day, the points form a time series with a pronounced trough in summer months and a peak in winter months. Upon this seasonal trend is superimposed, a regular rhythmic variation between days of the week, together with an erratic variation which is attributable to weather fluctuations.

The meteorological factors found to affect the demand may be summarised as follows

- (a) Temperature
- (b) Cloud cover and visibility
- (c) Wind velocity
- (d) Relative humidity
- (e) Precipitation.

The erratic variation of load attributable to weather fluctuation is then some function of these factors, and much efforts of prediction has been directed to determine the nature and value of this function under the prevailing meteorological conditions.

Bearing these points in mind, the load demand x at any instant may be written as

$$x = a + d + G \quad \dots(2.1)$$

where a is the base load at a particular instant in question, d is the day-of-week correction and G is a function of the various meteorological factors influencing the load. This equation forms the common starting point of three different methods of prediction [2.1(a),2.1(b),2.2] two of which are based on meteorological data and one on past load data only.

(a) Method of Prediction Using Weather Weighting [3]

In the method of weighting proposed by Dryar [10], load is separated into two main components. a base load, and a variable quantity which reflects the effect of weather. The base load is determined from past records by weighting meteorological factors and applying combined weight as percentage reduction to the system load. Initially, the proper weighting of elements of the weather will only be attained after a period of trial and error.

Using a chart of base loads an accurate load estimate can be made using proper weighting of three of meteorological

factors (namely temperature, cloudiness and wind velocity) based on the best available weather forecast.

Re-estimates, and any necessary scheduling adjustments, are then periodically made as more up-to-date weather forecasts are obtained. The feasibility of this method lie in the consistency of the calculation of base load. Such consistency must be evidenced in the following manner.

- (i) The base load for the daily peak period must be uniform for the mid week days.
- (ii) The base load for each half-hour of these days must be uniform.
- (iii) Peak and hourly base loads for each Saturday and Sunday over a period of number of weeks must be consistent.

Any change in the base load from year to year on account of increased overall demand will soon become evident, and the necessary adjustment must be made.

(b) Multiple Regression Methods [3]

In an analysis by Davies, the meteorological information is reduced to a number of specific factors designated as follows

- (i) effective temperature T
- (ii) cooling power of the wind W
- (iii) illumination index L
- (iv) rate of precipitation P

In deriving the functional relationships between the variation of demand and the specific meteorological factors to which it is sensitive, the basic assumption is again made that the weather-sensitive component of the demand may be expressed as sum of functions of the respective meteorological factors.

Linear regression

The first approximation which can be made is to assume a linear functional relationship. If one year data are used to derive the functional relationships, it is necessary to eliminate the combined seasonal and long term trend and also the day-of-the week effect.

A regression equation of the form

$$x = a + b_1T + b_2W + b_3L + b_4P + F(t) + d \quad \dots(2.2)$$

is therefore fitted to the data, where x is the demand at fixed time each day, T, W, L, P are the corresponding specific meteorological factors, a, b_1, b_2, b_3, b_4 are constants, d is the day of-the -week correction, $F(t)$ is a polynomial function of the time of the year for a particular week and accounts for variations in the base load with the time of the year. Thus $a + F(t)$ is the base load at the week.

In this expression, the known quantities are the dependent variable x and the independent variables T, W, L, P, t and the object of the analysis is an estimation of the regression coefficients b_1, b_2, b_3, b_4 and the values of d . In equation 2.2 meteorological factors may be added or removed depending

upon the environment condition for the time under consideration. The quantities of immediate interest in the analysis are the meteorological regression coefficients b_1, b_2, b_3, b_4 , which effectively measure the change in demand per unit change of each meteorological variable, and the day-of-the-week correction d . Having calculated the values of b_1, b_2, b_3, b_4 and d , the run of basic demands may be determined by adjusting the actual demands to some standard set of weather conditions and eliminating the day-of-the-week variation. As relationship between demand and the specific meteorological factors to which it responds are nonlinear, the linear functions introduced into the regression analysis will yield only average effects over the range covered by the data.

2.2 Method Involving Past Load Data only [5]

Spectral Expansion- In order to develop a fully automatic power system, it is necessary and convenient to have a model of prediction utilising the most readily available data. On the basis of this consideration, Farmer [12] has developed a theory using past load data only.

Since the basic pattern of load demand tends to repeat it self after every 24 hours, it is possible to consider the time for each day, whether continuous or discrete, as being a member of an ensemble of time series. We thus have the problem of predicting a nonstationary process given an ensemble of same functions.

Considering the load curve divided into part-day periods of several hours duration. Fig. 2.3 shows a typical day divided into 8 hours periods overlapping by 2 hours. The daily load curves for a particular period form an ensemble, and it is reasonable for this period to define the load on the m th day at the n th instant of time as x_{mn} . An ensemble (with $m=5$) for the period 1200 to 2000 is shown in Fig. 2.4.

x_{nm} can be written as

$$x_{mn} = \alpha_{mn} + f_1(T_m) \beta_{mn} + f_2(L_m) \gamma_{mn} + f_3(W_m) \delta_{mn} + \dots (2.5)$$

where $f_1(T_m)$, $f_2(L_m)$, $f_3(W_m)$ etc are functions of temperature T_m , illumination L_m , and wind velocity W_m . The quantity α_{mn} represents the base load, and the factors β_{mn} , γ_{mn} , δ_{mn} ... allow for varying importance of the weather parameters with time of day.

The chief advantage of spectral expansion method undoubtedly lies in the fact that no meteorological data are required for its predictions, and consequently the need for expensive instrumentation or the use of possibly inaccurate weather forecasts is saved.

The chief disadvantage of spectral technique lies in its inability to take account of rapid changes which may be caused by the onset of storms or television programmes of national interest or a change in consumers pattern on account of holidays or strikes. These fairly infrequent events, which are normally known in advance, could be accounted for by putting a compensating program into the computer as and when required.

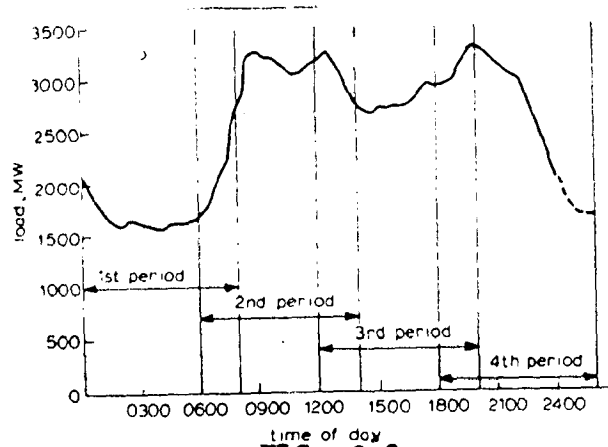


FIG. 2.3

Load Curve Divided into Part-day periods

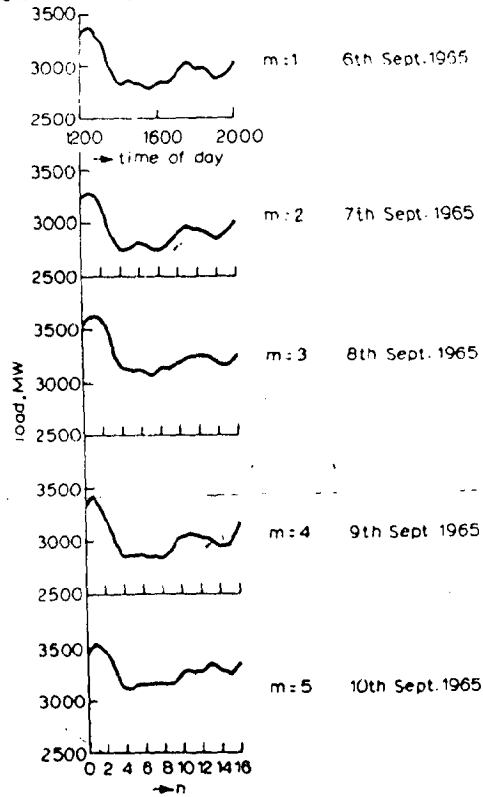


FIG. 2.4

Ensemble of five Functions for the period 1200 to 2000 H.

2.3 Method of Prediction Using Pattern-Recognition Techniques [3,7]

Pattern recognition techniques are generally applied in the study of variables whose total physical principles behind their variation is unknown, but certain kinds of measurements explain their behaviour. Approach to the problem of prediction is based on the fact that daily electrical load patterns in the same geographical area were assumed to have been repeated sometime in the past as a result of similar climatological conditions. This method of prediction utilizes recent load and weather information in addition to weather load relationships. The basic 24-hour load pattern is divided into slots each slot consisting of 2 to 4 hours. This division allows for various weather parameters to be considered for different times of the day. Within each time slot it is assumed that changes in weather pattern do not affect the load significantly. Fig.2.2 shows a standard system of pattern recognition which is adopted here.



Fig. 2.2

(i) Feature Processing -

The purpose of features processing is to extract, accumulate and evaluate the relative significance of all the

weather variables such as temperature, relative humidity wind velocity etc. in the vicinity of electrical power system. Auto-correlation analysis is performed since it is well-known fact that daily load patterns correlate closely with the previous days climatic condition. The choice for independent weather variables to be selected depends upon the season being analysed. For example humidity is significant in the summer time analysis, and in the same manner, windchill factor is significant in winter time analyses.

(ii) Feature Selection -

In this various means are used to find out the most efficient independent variables that explain similar load patterns on an electrical power system. Two types of studies were performed on weather variables from feature processing.

(a) All combination Regression

(b) Stepwise linear Regression analysis.

In study (a), the multiple correlation coefficient squared factors for all combination of weather variables were determined. Study (b) was performed to obtain total squared error.

(iii) Decision

It incorporates the following functions -

(a) Cluster Analysis - Variables selected through feature selection were used to perform cluster analysis to separate the different dates into classes with similar

climatic parameters. Variation within a class or cluster represent the unknown nature of load. The optimum number of classes could be one with different cluster as dense and as far as possible. The numbers of classes could also be dependent on available data. Weights can be given to different selected variables to enhance or reduce their relative importance and also to normalize different variables.

(b) Growth Elimination - In order to use load information dating several years back, load growth will be eliminated by the concept of percent spread. Load values will be converted to percent spread values while preserving the shape.

$$\text{Percent spread} = S_t = \frac{L_t - L_{\min}}{L_{\max} - L_{\min}} \times 100 \quad \dots(2.6)$$

where,

L_t = load at time t (MW)

L_{\min} = Minimum load for that year (MW)

L_{\max} = Maximum load for that year (MW)

In performing the conversion each load value will be converted to a value between zero and 100. Zero corresponds to the minimum load for the period of study and 100 corresponds to the maximum load for the same period.

(c) Interpolation - Cluster analysis will identify the best dates for load forecasting of particular day. Depending on the lead time either current weather information (lead time 1-3 hours), or forecasted weather information (lead time up to 24 hours) will be used in the cluster analysis to identify

the above dates. It can be proved that if the ratios of minimum to maximum load for two particular days are equal, the corresponding piecewise shapes will only be different by scalar. Percent spread factor will convert all the load to a common base by perserving the shape which will satisfy the above condition.

Interpolation can be repeated 8 times for the three-hour intervals to obtain a base load curve. We will have

$$\frac{F'(t)}{F(t)} = K \pm E$$

where,

$F'(t)$ = Actual load curve at time t

$F(t)$ = Base load curve at time t

K = Constant (Scalar)

E = Error

So, the forecast for time $(t+1)$ will be

$$F''(t+1) = K \cdot F(t+1) \pm E \quad \dots (2.7)$$

where constant K will be changed adaptively (1-3 hours) as new load information is received.

Maximum error of 4 percent was computed by comparing forecasted and actual load curves. This method is suitable for small area power systems due to limitation of geographical area and applicability of weather parameters. In a large power system diversity of loads distort the weather sensitive pattern of load.

2.4 State Estimation Technique [6]

Present day power system engineers have achieved schemes for on-line real time control of complex power systems. A precise short-term forecasting method for estimating the status of systems is required for this purpose.

Before one makes a forecasting model it is necessary to decide the structure of load. It is essential to find a proper modeling of load and some methods of identifying noise characteristics for practical application of state estimation to load forecasting.

The state variables in the load forecasting models are

- (1) The system load it-self
- (2) The increment of system load
- (3) The short term and long term load patterns.

In load forecasting, it is very important to decide how far in future prediction are to be made. The method of forecasting depends upon the forecasting period. **If it is** desired to predict the system load 1 or 2 hours in advance, then the effect of weather fluctuations is not predominant and can be neglected.

State equation can be written as

$$\begin{bmatrix} X_{n+1} \\ \Delta_{n+1} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X_n \\ \Delta_n \end{bmatrix} + \begin{bmatrix} \epsilon_n^1 \\ \epsilon_n^2 \end{bmatrix} \quad \dots(2.8)$$

where X_n is the system load at n th instant, Δ_n is load increment at n th interval. Observation equation

$$Y_n = [1 \ 0] \begin{bmatrix} X_n \\ \Delta_n \end{bmatrix} + n_n \quad \dots(2.9)$$

where Y_n is an observation value of load at n , n_n , ε_n^1 , ε_n^2 are the intrinsic system noises. All noises are assumed to occur independently. The most optimal forecast values of states are sequentially given by

$$\begin{bmatrix} X_{n+1} \\ \Delta_{n+1} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X_n \\ \Delta_n \end{bmatrix} + \begin{bmatrix} K_{n+1}^1 \\ K_{n+1}^2 \end{bmatrix} \left[Y_{n+1} - [1 \ 0] \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X_n \\ \Delta_n \end{bmatrix} \right] \quad \dots(2.10)$$

Equation (2.10) can be written as

$$X_{n+1} = (1 - K_{n+1}^1) (X_n + \Delta_n) + K_{n+1}^1 Y_{n+1} \quad \dots(2.11)$$

$$\Delta_{n+1} = (1 - K_{n+1}^2) \Delta_n + K_{n+1}^2 (Y_{n+1} - X_n) \quad \dots(2.12)$$

The above formulation is the same as the exponential smoothing technique for fluctuation with increment. However this forecasting model has excellent properties that of optimal correcting gains, K_{n+1}^1 and K_{n+1}^2 , sequentially determined by prior information about variances of noise, and that of obtaining the least mean square error of forecasting.

If it is desired to predict the system load 24 hours in advance then in addition to load increment, effect of weather variables such as temperature and humidity is taken

in to account while modeling the forecasting system. So the structure of system load and observation is written as

$$\begin{bmatrix} X_{n+1} \\ \Delta_{n+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \alpha_n \end{bmatrix} \begin{bmatrix} X_n \\ \Delta_n \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ \beta_n & \gamma_n \end{bmatrix} \begin{bmatrix} T_n \\ H_n \end{bmatrix} + \begin{bmatrix} \epsilon_n^1 \\ \epsilon_n^2 \end{bmatrix} \quad \dots(2.13)$$

$$Y_{n+1} = [S_{n+1} \quad 1] \begin{bmatrix} X_{n+1} \\ \Delta_{n+1} \end{bmatrix} + n_{n+1} \quad \dots(2.14)$$

where X_n is the load at n , Δ_n is the load fluctuation because of weather conditions - temperature T_n and humidity H_n . S_{n+1} is the coefficient of daily standard load pattern ($S_n \approx S_{n+T}$, $T = 24$ hours). $\alpha_n, \beta_n, \gamma_n$ and S_n can be calculated from data series ($Y_0, Y_1, Y_2 \dots Y_n$). So the optimal forecasting values of states using the new observed values are sequentially given by

$$X_{n+1} = X_n + K_{n+1}^1 [Y_{n+1} - (S_{n+1} X_n + \alpha_n \Delta_n + \beta_n T_n + \gamma_n H_n)] \quad \dots(2.15)$$

$$\Delta_{n+1} = \Delta_n + K_{n+1}^2 [Y_{n+1} - (S_{n+1} X_n + \alpha_n \Delta_n + \beta_n T_n + \gamma_n H_n)] \quad \dots(2.16)$$

where correcting gains K_{n+1}^1 and K_{n+1}^2 are determined using the prior information about noise $\epsilon_n^1, \epsilon_n^2, n_{n+1}$. Utilising the results of (2.15) and (2.16) the forecasting load Y_{n+T} at $n+T$ is given by

$$Y_{n+T} = S_{n+T} X_n + \Delta_{n+T} \quad \dots(2.17)$$

In a practical application of load modeling such as the introduced above, there is often no prior information about noise variance. Therefore some identification algorithms

- L an $n \times n$ matrix of constant, called the transition matrix, with the property, $\bar{f}(t) = Lf(t-1)$.
- \bar{R} a column vector of 'n' constants called the smoothing vector.

General Model - The observed load $X(t)$ is represented as a linear combination of known functions of time and a noise component, as shown below

$$X(t) = \bar{a}' f(t) + \epsilon(t) \quad \dots(2.18)$$

The coefficients \bar{a} are assumed to be locally constant. The coefficients are gradually changing, but slowly enough so that they can be considered constant over a time span equal to or greater than the maximum lead time. Under this assumption, forecasts can be computed by extrapolating the expression in (2.18). Using the known fitting functions $f(t)$ and estimates $\bar{a}(T)$ of the current values of the coefficients i.e. from

$$X_{\tau}(T+\tau) = \bar{a}'(T) \bar{f}(t+\tau) \quad \dots(2.19)$$

To employ this method, we need (a) an appropriate set of fitting functions and (b) a method for estimating the coefficients from observed values of load. Estimates of the coefficients are revised hourly where as the fitting functions are stationary.

The estimates of the coefficients are computed using weighted least square criterion. A constant β ($0 < \beta < 1$) is selected and the estimates $\bar{a}(T)$ are computed by minimizing the equation given below

$$\sum_{j=0}^{\alpha} \beta^j [X(T-j) - \bar{a}'(T) \bar{f}(T-j)]^2 \quad \dots(2.20)$$

The constant β controls the rate at which the past errors are discounted.

After selecting the fitting functions and the smoothing constant, the vector \bar{h} and the transition matrix L are calculated. L and \bar{h} are stored as program constants and forecasts are computed according to the following algorithm.

(A) The estimates of the coefficients are revised according to

$$\bar{a}(T) = L' \bar{a}(T-1) + \bar{h} [X(T) - X_1(T)] \quad \dots(2.21)$$

(B) New forecasts are then computed from (2.19)

Calculation of L and \bar{h} - It is found that r.m.s value of forecast error is minimum when the smoothing constant is taken as 0.994.

On analysing hourly load data of two years it was found that ~~weekly variations are quite consistent through out the year.~~ So it was decided that the best approach would be to develop a model for the hourly loads over an interval of one week rather than separate 'week day' and 'week end' models. The weekly variations in hourly load are described as a cyclic function of time with a period of one week. It was decided that a Fourier series would be the most appropriate model which meets the requirements for the fitting functions.

The model selected is of the form

$$X(t) = C + \sum_{i=1}^m (a_i \sin W_i t + b_i \cos W_i t) \quad \dots(2.22)$$

$$\sum_{j=0}^{\infty} \beta^j [X(T-j) - \bar{a}'(T) \bar{f}(T-j)]^2 \quad \dots(2.20)$$

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that is, a constant C and Fourier series with 'm' frequencies. Since a period of week is assumed, all w's are of the form

$$W = \frac{2\pi}{168} K_i$$

where K_i is a positive integer less than 84.

The fitting functions are expressed by

$$\bar{f}(t) = \begin{bmatrix} \sin \omega_1 t \\ \cos \omega_1 t \\ \sin \omega_2 t \\ \cos \omega_2 t \\ \vdots \\ \sin \omega_m t \\ \cos \omega_m t \end{bmatrix} \dots(2.23)$$

The coefficients c, a_i 's and b_i 's constitute the vector \bar{a} .

It was found nine frequencies should be introduced for

$K = 1, 2, 3, 4, 5, 6, 14, \text{ and } 28$.

The transition matrix L has the property

$$f(t) = L f(t-1) \dots(2.24)$$

The value of the smoothing vector \bar{h} is given by

$$\bar{h} = \left[\sum_{j=0}^{\infty} \beta^j f(-j) \bar{F}'(-j) \right]^{-1} f(0) \dots(2.25)$$

Estimates of variance of the forecast errors for various lead

times are updated according to

$$S_{\tau}^2(T) = \gamma S_{\tau}^2(T) + (1-\gamma)[X(T) - X_{\tau}(T)]^2 \dots(2.26)$$

The forecast model adapts automatically to seasonal changes and changes in daily fluctuations. The method is also operationally simple. An hourly matrix multiplication and a vector addition are required to update the model. Computer storage requirements are reasonable.

As the weather data has not been taken into account separately, it is reflected by the past data only so whenever there is abrupt change in weather the accuracy of the forecast gets jeopardised.

2.6 Adaptive Short-term forecasting of hourly loads using weather information

In this methods hourly load forecasts with a lead time of 24-hours are produced based on both historical load data and information from the latest weather forecast. This method combines stochastic load models and adaptive weather load models optimally to yield an adaptive forecasting procedure especially suited for on-line control of power systems. This method is discussed in detail in Chapter -3.

CHAPTER -3

COMPUTER PROGRAMMING

OF

ADAPTIVE SHORT TERM FORECASTING

3.1 Basics of Method

The forecasting model in the method used contains an adaptive weather load model to utilize the weather forecast information and an adaptive stochastic model to utilize the historical load data in making the statistically optimum load forecasts. This adaptive features enables the model to update its own parameters according to its past performance. So the forecasting model is suitable for on-line usage. Simplified flow chart of forecasting procedure is already shown in Fig. 1.1. The procedure is explained under the following sections.

3.1.1 Stochastic load model

The hourly system load is divided in to three components.

$$Z(i, j) = T(i, j) + WC(i, j) + X(i, j) \quad \dots(3.1)$$

where,

$Z(i, j)$ = system load measured in hourly MWH at hour j and day i

$T(i, j)$ = Basic component of load at hour j and day i

$WC(i, j)$ = Weekly cycle component (day-of-the-week effect) at hour j and day i

$X(i, j)$ = Residual component containing the effect of weather variation at hour j and day i.

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The nature of these three components is very different. $T(i,j)$ can be considered more or less constant from day to day, $WC(i,j)$ is a slowly changing component signifying the weekly pattern of the hourly loads and $X(i,j)$ is rapidly changing component containing fast hour to hour variations in the load due to numerous random factors such as weather conditions experienced by the load area served by the substation. An autoregressive type of model is chosen for the random component.

$$\underline{X}(i) = A \underline{X}(i-1) + \underline{W}(i-1) \quad \dots(3.2)$$

where,

$$\underline{X}(i) = \begin{bmatrix} X(i,1) \\ X(i,2) \\ \vdots \\ X(i,24) \end{bmatrix}$$

$\underline{X}(i)$ is a (24 X 1) column vector of residual components for the i th day.

A = (24 X 24) matrix of coefficients.

$\underline{W}(i-1)$ = (24 X 1) column vector of model error terms.

In this model each element of $\underline{X}(i)$ is linear function of all the elements of $\underline{X}(i-1)$. An unknown (24X24) covariance matrix Q is defined such that

$$E [\underline{W}(i) \underline{W}(i)^T] = Q \quad \dots(3.3)$$

where $\underline{W}(i)^T$ denotes the transpose of $\underline{W}(i)$. An equivalent form of equation (3.3) can be written for the (j,k) th element of Q as

$$Q(j,k) = E[W(i,j) W(i,k)] \quad \dots(3.4)$$

where $W(i,j)$ is the model error term for hour j of the i th day.

3.1.2 Weather load model

The forecasting procedure required a ~~weather~~ load model in which daily peak load is represented in terms of weather-variables. The model also contains terms corresponding to the basic load and the weekly pattern similar to those used in the stochastic model. The model is of the form.

$$Y(i) = B(i) + S(i) + W(i) + \epsilon(i) \quad \dots(3.5)$$

where,

$Y(i)$ = Peak load on the i th day

$B(i)$ = Basic load component of peak load on i th day

$S(i)$ = Weekly pattern component of the peak load on the i th day

$W(i)$ = Weather-sensitive component of the peak load on the i th day

$\epsilon(i)$ = Random component of the peak load on the i th day.

Strictly speaking, $B(i)$ and $S(i)$ should be defined as elements of $T(i,j)$ and $WC(i,j)$. However, better estimates can be expected to result if $B(i)$ and $S(i)$ are estimated independently of $T(i,j)$ and $WC(i,j)$ respectively.

The weather-sensitive component $W(i)$ is assumed to be a linear function of suitably transformed values of weather variables such as temperature and humidity observed at the load centre. A general form of the model is given by

$$W(i) = \sum_{j=1}^k C_j W_j(i) \quad \dots(3.6)$$

where,

k = number of weather variables in the model.

$W_j(i)$ = j th weather variable (or a transformed value of the variable) on the i th day

C_j = unknown j th coefficient of the model.

There will be seven values in the weekly pattern corresponding to each day of the week. Thus

$$S(i) = \sum_{j=1}^7 S_j P_j(i) \quad \dots(3.7)$$

where,

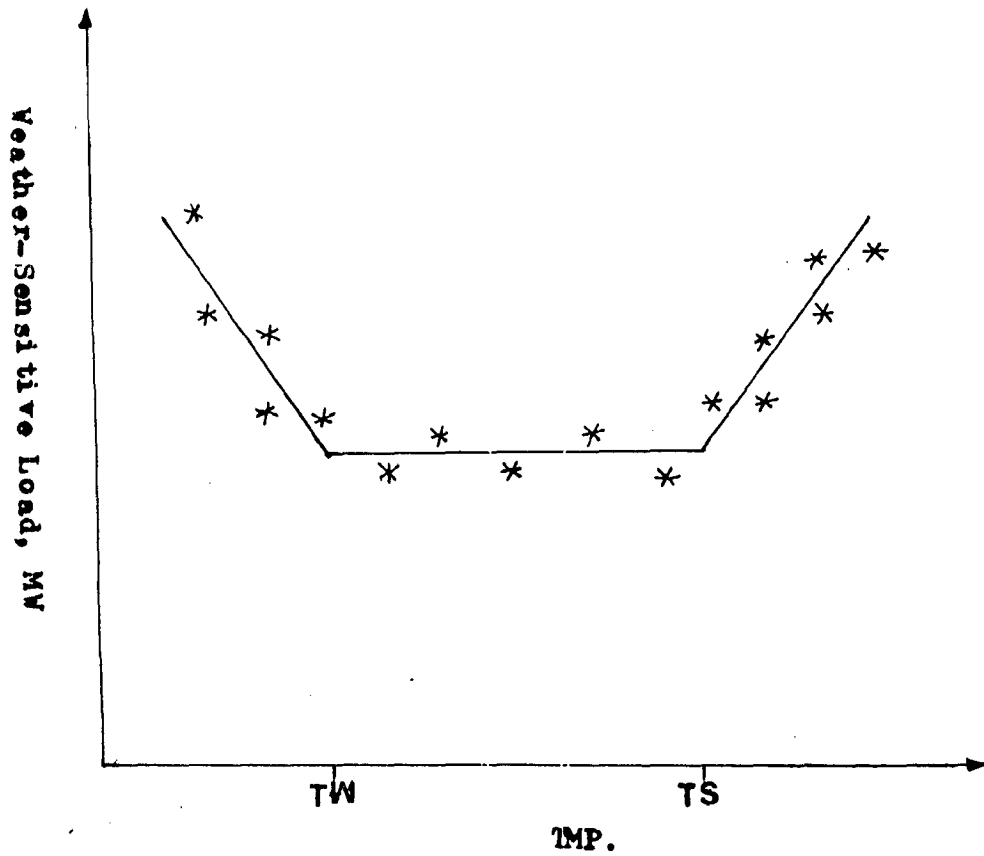
S_j = j th value of weekly pattern ($j=1$ corresponds to Sunday)

$P_j(i)$ = 1 if the i th day corresponds to the j th day of the week
0 otherwise

The weather variables selected are the average daily temperature and the relative humidity. As shown in Reference [11], it is necessary to make a nonlinear transformation of the temperature variable in order to formulate a linear weather load model of the type shown in equation (3.6). In order to transform the weather variable it is necessary to study the effect of weather variables on the load.

(a) Effect of Temperature

To determine the effect of temperature on the load it is common to plot a scatter diagram of daily peaks versus daily average temperature. The scatter diagram



Daily average temperature

FIG.NO. 3.1

is shown in Fig. 3.1. Using curve fitting techniques, weather variable can be transformed as under.

$$\begin{aligned} WV_1(i) &= TMP(i) - TS && \text{if } TMP(i) > TS \\ &= 0 && \text{if } TW < TMP(i) < TS \\ &= TW - TMP(i) && \text{if } TMP(i) < TW \end{aligned} \quad \dots(3.8)$$

where TW and TS are the fixed parameters of the transformation and TMP(i) is the average temperature on the ith day.

(b) Effect of Humidity

For agricultural load it is observed that load requirement is negligible when the relative humidity approaches 100 percent. But as the relative humidity decreases the agricultural load starts increasing. So the relative humidity can be transformed by the following relation.

$$WV_2(i) = 100 - \text{Relative humidity} \quad \dots(3.8(b))$$

3.1.3 Initialization Procedures

Initialization procedures involve identification of the unknown parameters of the weather-load model and of the matrices A and Q of the stochastic model. In addition the current values of T(i,j), WC(i,j), X(i,j) of equation (3.1) and B(i) and Si of equations (3.5) and (3.7) are also required.

Identification of A and Q - The identification of A and Q is based on the residual component $X(\cdot)$ of the historical load data. Since the residual component is not directly available, it is necessary to first estimate T(i,j) and WC(i,j) from the given

load data. Each element is obtained by filtering the weekly pattern and the residual component from the load data.

$$T(i,j) = 1/7 \sum_{k=i-6}^i Z(k,j) \quad \begin{matrix} j=1,2,\dots,24 \\ i=7,8,\dots,N \end{matrix} \quad \dots(3.9)$$

where N is the number of days for which load data is available.

The weekly pattern component $WC(i,j)$ is obtained by an exponential smoothing filter.

$$WC(i,j) = WC(i-7,j) + \alpha [Z(i,j) - T(i,j) - WC(i-7,j)]$$

$$\begin{matrix} j = 1,2,\dots,24 \\ i = 8,9,\dots,N \end{matrix} \quad \dots(3.10)$$

where α is a filter constant (0.2 to 0.5) and

$$WC(k,j) = Z(k,j) - T(7,j) \quad k=1,2,\dots,7 \quad \dots(3.11)$$

Here using equations (3.9), (3.10) and (3.11), the residual components $\underline{X}(\cdot)$ can be estimated from the given load data.

Let these be denoted by $\underline{X}(1), \underline{X}(2), \dots$, etc.

Post-multiplying equation (3.2) with $\underline{X}^T(i)$ and taking the expected values gives the following

$$Q = \begin{bmatrix} 0 & -A \\ 0 & 0 \end{bmatrix} A^T \quad \dots(3.12)$$

$$\text{where } \begin{bmatrix} 0 & \\ 0 & \end{bmatrix} = E[\underline{X}(i) \underline{X}^T(i)] \quad \dots(3.12)$$

Similarly post-multiplying equation (3.2) by $\underline{X}^T(i-1)$ and taking the expected values gives

$$A = \begin{bmatrix} 1 & \\ 0 & \end{bmatrix} \begin{bmatrix} -1 \\ 0 \end{bmatrix} \quad \dots(3.14)$$

where

$$\begin{bmatrix} 1 & \\ 0 & \end{bmatrix} = E[\underline{X}(i) \underline{X}^T(i-1)] \quad \dots(3.15)$$

Equation (3.12) and (3.14) constitute the identification equations for identifying A and Q. Matrices Γ_0 and Γ_1 are estimated from the residual components $\underline{X}(\cdot)$ of the historical data as follows

$$\Gamma_0 = \frac{1}{N} \sum_{i=1}^N \underline{X}^T(i) \underline{X}^T(i) \quad \dots(3.16)$$

$$\Gamma_1 = \frac{1}{N-1} \sum_{i=2}^N \underline{X}(i) \underline{X}^T(i-1) \quad \dots(3.17)$$

Identification of weather load Model - The unknown parameters of weather-load model are identified by minimizing the exponentially weighted sum of squares of prediction error. So we minimize.

$$E = \sum_{n=1}^N [Y(n) - B(n) - \sum_{i=1}^7 S_i P_i(n) - \sum_{i=1}^k C_i W_i(n)]^2 \beta^{N-n} \quad \dots(3.18)$$

$B(n)$ in the above expression is estimated by exponential smoothing scheme,

$$B(n) = B(n-1) + \alpha [Y(n-1) - \sum_{i=1}^7 S_i P_i(n-1) - \sum_{i=1}^k C_i W_i(n-1) - B(n-1)] \quad \dots(3.19)$$

where β is a constant between 0 and 1. Constant α is also assumed known. The normal values for α and β are respectively 0.2 and 0.985.

Equation (3.19) can be written as

$$B(n) = Y(n-1) - \sum_{i=1}^k C_i \bar{W}_i(n-1) - \sum_{i=1}^7 S_i \bar{P}_i(n-1) \quad \dots(3.20)$$

where,

$$\begin{aligned}\bar{Y}(n-1) &= \alpha Y(n-1) + (1-\alpha) \alpha Y(n-2) + \dots \\ &= \alpha Y(n-1) + (1-\alpha) \bar{Y}(n-2) \quad \dots (3.21)\end{aligned}$$

$$\begin{aligned}\bar{W}_i(n-1) &= \alpha W_i(n-1) + (1-\alpha) \alpha W_i(n-2) + \dots \\ &= \alpha W_i(n-1) + (1-\alpha) \bar{W}_i(n-2) \quad \dots (3.22)\end{aligned}$$

$$\begin{aligned}\bar{P}_i(n-1) &= \alpha P_i(n-1) + (1-\alpha) \alpha P_i(n-2) + \dots \\ &= \alpha P_i(n-1) + (1-\alpha) \bar{P}_i(n-2) \quad \dots (3.23)\end{aligned}$$

Hence equation (3.18) becomes

$$\begin{aligned}E &= \sum_{n=1}^N [Y(n) - \bar{Y}(n-1) - \sum_{i=1}^7 S_i (P_i(n) - \bar{P}_i(n-1)) \\ &\quad - \sum_{i=1}^k C_i (W_i(n) - \bar{W}_i(n-1))]^2 \beta^{N-n} \quad \dots (3.24)\end{aligned}$$

If the initial values of $\bar{Y}(n)$, $\bar{W}_i(n)$ ($i=1, 2, \dots, k$), $\bar{P}_i(n)$ ($i=1, 2, \dots, 7$) are known, the subsequent values can be estimated using equations (3.21), (3.22) and (3.23) and the unknown parameters S_i and C_i can be determined by a least squares method. For computational economy, a recursive estimator is used. Let

$$\Delta Y(n) = Y(n) - \bar{Y}(n-1) \quad \dots (3.25)$$

$$a^T = (S_1, S_2, \dots, S_7, C_1, C_2, \dots, C_k)$$

$$\begin{aligned}\phi^T(n) &= [P_1(n) - \bar{P}_1(n-1), P_2(n) - \bar{P}_2(n-1), \dots, W_1(n) - \bar{W}_1(n-1), \\ &\quad W_2(n) - \bar{W}_2(n-1), \dots] \quad \dots (3.27)\end{aligned}$$

$\hat{a}(N)$ = optimum estimate of the coefficient vector a at the N th iteration. Then $\hat{a}(N)$ can be written as

$$\hat{a}(N) = \hat{a}(N-1) + P(N) \phi(N) [\Delta Y(N) - \phi^T(N) \hat{a}(N-1)] \quad \dots (3.28)$$

where $P(N)$ is a newly defined variable.

$$P(N) = 1/\beta(N-1) - \frac{1}{\beta^2} P(N-1) \phi(N) [1 + \phi^T(N) \frac{1}{\beta} P(N-1) \phi(N)^{-1}] \phi^T(N) P(N-1) \dots (3.29)$$

To perform the identification process by using equations (3.28) and (3.29), we require initial value of $\bar{Y}(\cdot)$, $\bar{W}_i(\cdot)$, $\bar{P}_i(\cdot)$, $a(\cdot)$ and $P(\cdot)$. In order to obtain these, the data base is divided into three parts as shown in Fig. 3.2

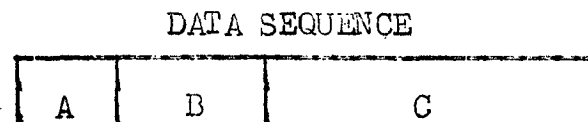


Fig. 3.2 Division of the historical data base in three parts for identification of weather-load model.

Part A is used for determining \bar{Y}_0 , \bar{W}_i0 , \bar{P}_i0 , the initial values of $\bar{Y}(n)$, $\bar{W}_i(n)$ and $\bar{P}_i(n)$. The initial values are determined by taking the simple averages

$$\bar{Y}_0 = \frac{1}{m} \sum_{n=1}^m Y(n) \dots (3.30)$$

$$\bar{W}_i0 = \frac{1}{m} \sum_{n=1}^m W_i(n) \quad i=1,2,\dots,K \dots (3.31)$$

$$\bar{P}_i0 = \frac{1}{m} \sum_{n=1}^m P_i(n) \quad i=1,2,\dots,7 \dots (3.32)$$

where m is the total number of days included in part A. Part B is used for the determination of initial values $\hat{a}(0)$ and $P(0)$. Using equations (3.21), (3.22), (3.23) and (3.27), the values of $\bar{Y}(n)$, $\bar{W}_i(n)$, $\bar{P}_i(n)$ and $\phi(n)$ are obtained. Then, $\hat{a}(0)$ and $P(0)$ are estimated from the following equations.

$$P(0) = \left[\sum_{j \in \text{PartB}} \phi(j) \phi(j)^T \right]^{-1} \quad \dots (3.33)$$

$$a(0) = P(0) \left[\sum_{j \in \text{PartB}} \phi(j) \Delta Y(j) \right] \quad \dots (3.24)$$

Part C of the data is used for updating $P(\cdot)$ and $a(\cdot)$ recursively and the values are stored for producing peak load forecasts with the current weather load data.

3.1.4 Adaptive Forecasting Procedure

The load forecast for the $(i+1)$ st day, $Z(i+1, j)$, $j=1, 2, \dots, 24$, is made on the basis of measurements of $Z(i, j)$, $j=1, 2, \dots, 24$ and the weather forecast $WV_j(i+1)$, $j=1, 2, \dots, k$ in the following steps.

Update $T(i, j)$ and $WC(i, j)$ - The basic component $T(i, j)$, $j=1, 2, \dots, 24$ is updated according to equation (3.9) and the weekly pattern component $WC(i, j)$ is updated according to equation (3.10). The residual component $X(i)$ is then determined as follows

$$X(i, j) = Z(i, j) - T(i, j) - WC(i, j) \quad j=1, 2, \dots, 24 \quad \dots (3.35)$$

Update A and Q : - Matrices A and Q are updated by reestimating the covariance matrices $[\cdot]_0$ and $[\cdot]_1$ by the following equations.

$$[\cdot]_0^i = [\cdot]_0^{i-1} + \frac{1}{i} [\underline{X}(i) \underline{X}(i)^T - [\cdot]_0^{i-1}] \quad \dots (3.36)$$

$$[\cdot]_1^i = [\cdot]_1^{i-1} + \frac{1}{i-1} [\underline{X}(i) \underline{X}(i-1)^T - [\cdot]_1^{i-1}] \quad \dots (3.37)$$

where Γ_0^i and Γ_1^i are the estimates of the covariance matrices Γ_0 and Γ_1 obtained by processing the data of the i th day. Equations (3.36) and (3.37) can be easily derived from equation (3.16) and (3.17). The algorithm given above is very efficient since the updating of covariance matrices is based on only the previous estimates and the new product terms $\underline{X}(i) \underline{X}^T(i)$ and $\underline{X}(i) \underline{X}^T(i-1)$.

The new estimates of A and Q are computed using updated estimates of Γ_0 and Γ_1 in equation (3.12) and (3.14).

Forecast Based on stochastic Model

The forecast of the next 24 values of residual component $\underline{X}(i+1)$ is produced by using equation (3.2) and assuming the forecast of model errors $\underline{W}(i+1)$ to be the expected value of $\underline{W}(i+1)$ i.e. zero.

$$\underline{X}(i+1) = A \underline{X}(i) \quad \dots(3.38)$$

The load forecast based on the stochastic model, $Z_s(i+1, j)$, is then given by

$$Z_s(i+1, j) = T(i, j) + WC(i+1, j) + X(i+1, j) \\ j = 1, 2, \dots, 24 \quad \dots(3.39)$$

In the forecasting equation (3.39), the basic component is assumed to be unchanged from the i th to the $(i+1)$ st day. The variance of the forecast $Z_s(i+1, j)$ is given by the variance of the J th model error term, i.e. $Q(j, j)$

$$\sigma_s^2(j) = Q(j, j) \quad \dots(3.40)$$

Update weather-load Model

The actual peak load for the i th day, $Y(i)$ is determined from the load data

$$Y(i) = \text{Max}_j [Z(i,j)] \quad \dots(3.41)$$

By using equations (3.21), (3.22), (3.23), (3.25), (3.28) and (3.29), the parameters of the weather load model $a(i)$ are updated.

Peak load forecast Based on Weather forecast -

The peak load forecast for the $(i+1)$ st day is calculated as follows

$$Y(i+1) = B(i+1) + S(i+1) + \sum_{j=1}^k C_j \tilde{W}_j(i+1) \quad \dots(3.42)$$

where $\tilde{W}_j(i+1)$ is the forecast of the j th variable for the $(i+1)$ st day.

The variance of $Y(i+1)$, σ_y^2 is computed by updating the variance estimate based on the observed peak-load forecast error of the i th day i.e.

$$\sigma_y^2 = \sigma_y^2 + \frac{1}{i} [\{ Y(i) - \hat{Y}(i) \}^2 - \sigma_y^2] \quad \dots(3.43)$$

Composite Load Forecast

The composite load forecast is the optimum combination of the forecast based on stochastic model and the peak load forecast based on weather load model. If the maximum value of $Z_S(i+1, j)$, $j=1, 2, \dots, 24$ is the same as $Y(i+1)$, then composite forecast is same as given by stochastic model namely, $Z_S(i+1, j)$, $j=1, 2, \dots, 24$. However, the weather forecast brings extra information about the future loads and hence, in most cases, $Y(i+1)$ and the maximum of $Z_S(i+1, j)$ are different. Two

stochastic estimates are combined to obtain a suitable weighted average of the two estimates. The equations for computing a composite load forecast $Z(i+1)$ from $Z_s(i+1, j)$ and $Y(i+1)$ are the following.

$$Z(i+1, j) = Z_s(i+1, j) + \frac{[Y(i+1) Z_{sp}]Q(j, p)}{Q(p, p) + \sigma_y^2} \quad \dots(3.44)$$

where,

$$Z_{sp} = \max_j \{ Z_s(i+1, j) \} \quad \dots(3.45)$$

and p is the hour of the day associated with Z_{sp} . The forecast variance, σ_j^2 , is reduced from its original value since extra information in the form of the peak load forecast has been used in the composite forecast.

$$\sigma_j^2 = Q(j, j) - \frac{Q^2(j, p)}{Q(p, p) + \sigma_y^2} \quad \dots(3.46)$$

$$j = 1, 2, \dots, 24$$

Special holidays modify the daily load pattern in a way that is generally different from the regular pattern of weekends. Special holidays are observed to differ from one holiday to another, although the load pattern of each holiday remains approximately the same from year to year. Where enough data are available, it is possible to determine an average load pattern for each special holiday from historical load data. These average estimates can then be used in the load forecasts for special holidays.

3.2 Flow-Chart

The flow-chart for the developed program has been presented in two sub-sections. Flow chart given in subsection 3.2.1 stands for initialising and identifying the parameters of stochastic load model and weather load model. The values of parameters calculated in this section are passed to adaptive forecasting program.

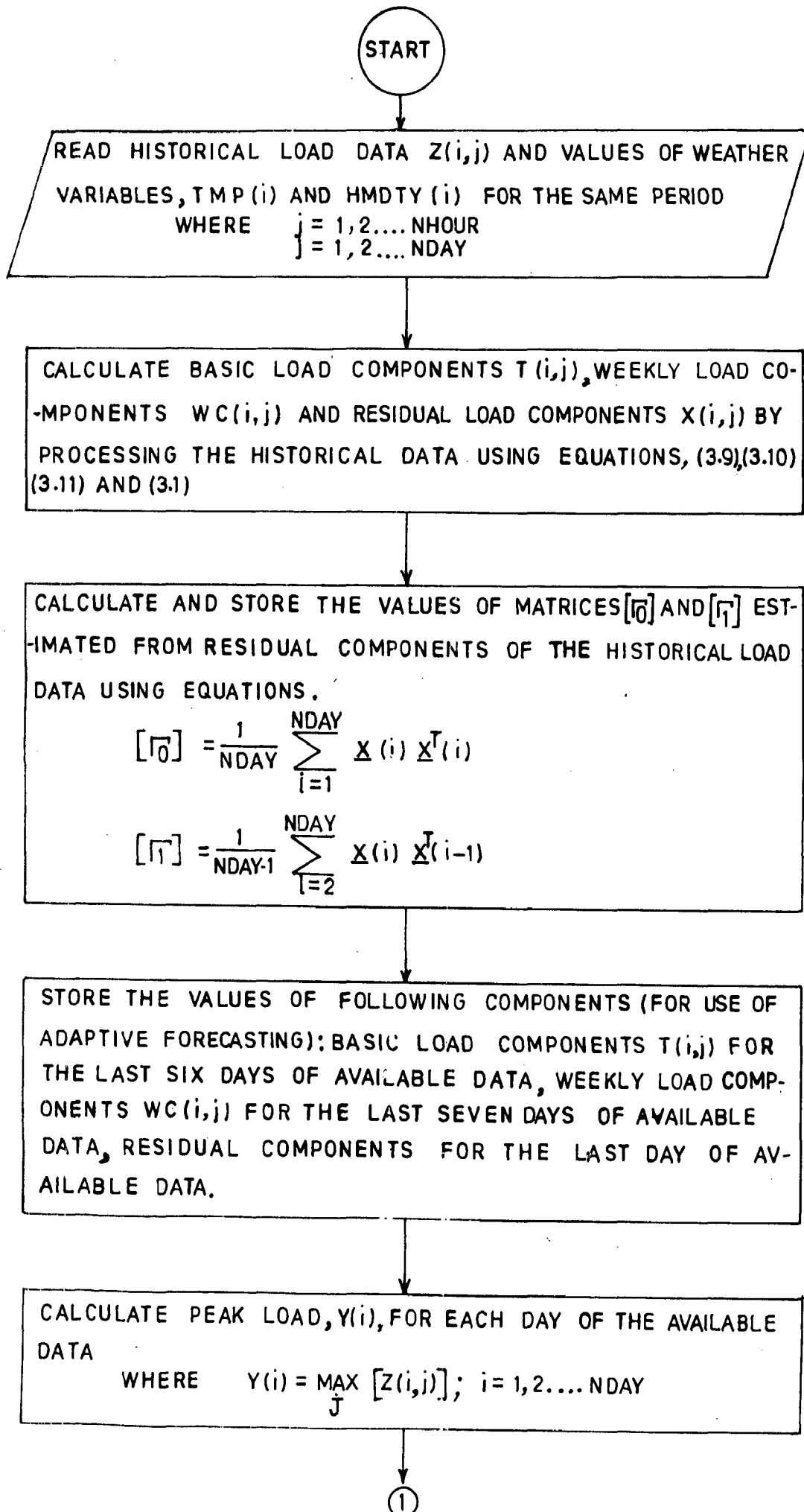
Flow-chart presented in section 3.2.2 stands for adaptive forecasting program. In this flow-chart, parameters already stored in the previous flowchart are taken out, processed along with current hourly load data, current values of weather variables and forecasted values of weather variables to make hourly -load forecast for the next 24 hours.

3.3 Details of Programming

The flow-charts given in the previous section have been implemented in FORTRAN IV on DEC-2050 computer of R.U.C.C. The software package for short-term load forecasting with lead time of 24 hours consists of two sections.

Section -1 This section is titled, 'Forecasting Incorporating Effect of Temperature' and is given in Appendix-1. It includes the effect of only one weather variable i.e. daily average temperature while making load forecast for the next 24-hours. Two programs have been developed in this section. First program is used to identify and initialise parameters of stochastic model and weather load model as per flow chart.

FLOW CHART FOR INITIALISATION OF STOCHASTIC LOAD MODEL AND WEATHER LOAD MODEL



1

TRANSFORM WEATHER VARIABLES, TEMPERATURE & HUMIDITY USING FOLLOWING EQUATIONS:

$$\begin{aligned} WV_1(i) &= TMP - TS & \text{IT } TMP(i) > TS \\ &= 0 & \text{IT } TW < TMP(i) > TS \\ &= TW - TMP(i) & \text{IT } TMP(i) < TW \end{aligned}$$

$$\begin{aligned} WV_2(i) &= 100 - HMDTY(i) \\ i &= 1, 2, \dots, NDAY \end{aligned}$$

CALCULATE INITIAL VALUES OF $Y(n)$ $WV_i(n)$ AND $P_i(n)$ USING FIRST PART OF AVAILABLE DATA AND UPDATE THEIR VALUES USING SECOND AND THIERD PART OF AVAILABLE DATA USING EQUATIONS: (3.21) TO (3.23) AND (3.30) TO (3.32)

INITIALISE MATRICES $[P]$ AND $[\hat{a}]$ USING SECOND PART OF THE AVAILA BLE DATA USING EQUATIONS

$$[P(0)] = \left[\sum_{J \in \text{PART B}} \theta(j) \theta^T(j) \right]$$

$$[\hat{a}(0)] = [P(0)] \left[\sum_{J \in \text{PART B}} \theta(j) \Delta Y(j) \right]$$

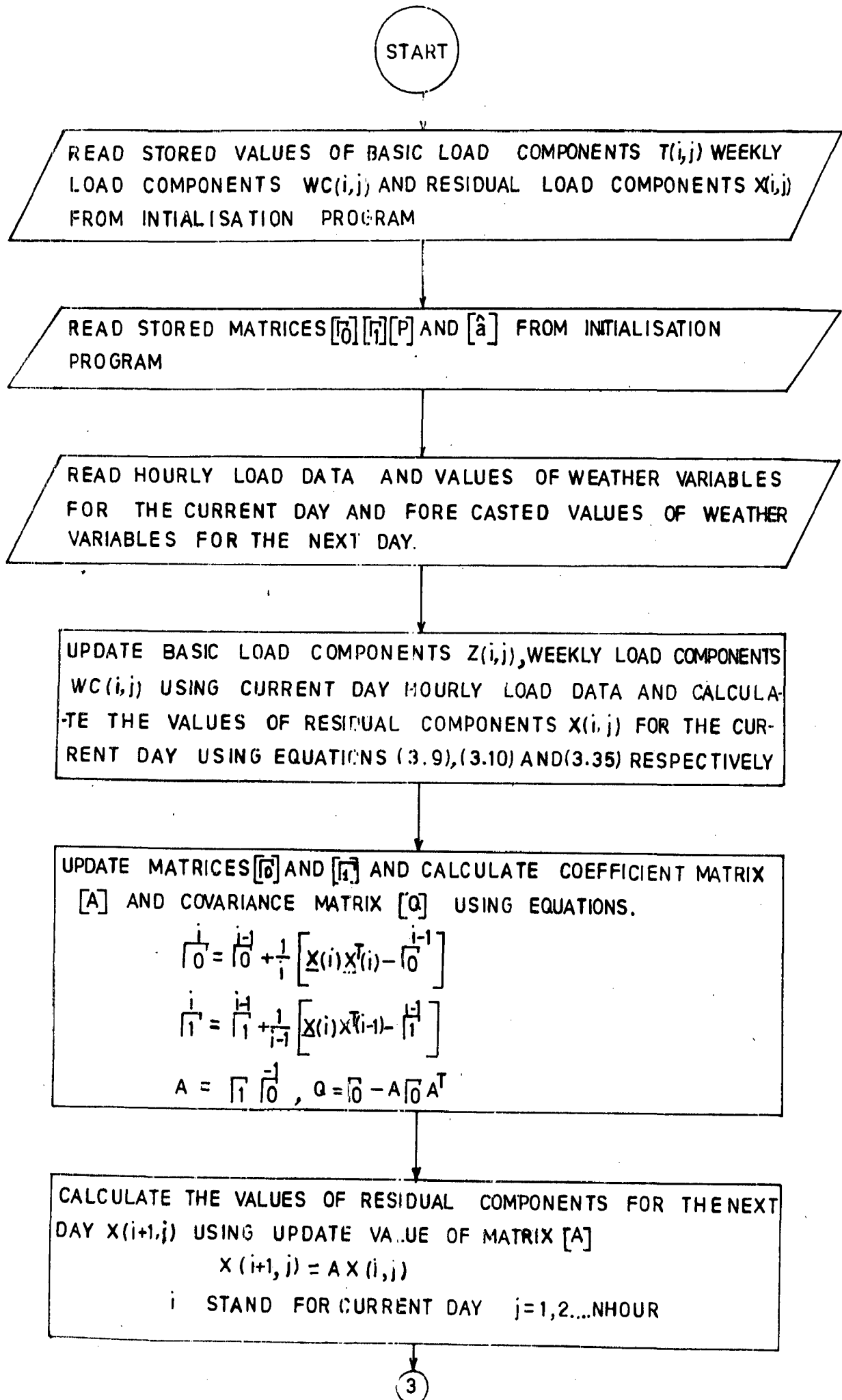
WHERE $J=1, 2, \dots, 8$ IF NO. OF WEATHER VARIABLES = 1
 $J=1, 2, \dots, 9$ IF NO. OF WEATHER VARIABLES = 2

UPDATE MATRICES $[P]$ AND $[\hat{a}]$ SUCCESSIVELY USING THIRD PART OF AVAILABLES LOAD DATA. EQUATIONS INVOLVED ARE (3.28), AND (3.29)

STORE MATRICES $[P]$ AND $[\hat{a}]$ FOR THE LAST DAY OF AVAILABLE LOAD DATA (TO BE USED FOR ADAPTIVE LOAD FORECASTING)

STOP

3.2.2 FLOW CHART FOR ADAPTIVE FORECASTING:



3

FORE CAST HOURLY LOAD AND VARIANCE FOR THE NEXT 24 HOURS ON THE BASIS OF STOCHASTIC LOAD MODEL USING EQUATIONS:

$$\hat{Z}_S(i+1, j) = T(i, j) + WC(i+1, j) + X(i+1, j)$$

$$\sigma_S^2(j) = Q(j, j); \quad j = 1, 2, \dots, \text{NHOUR}$$

i = CORRESPONDS TO CURRENT DAY

UPDATE MATRICES [P] AND [Q] USING CURRENT HOURLY LOAD DATA AND VALUES OF WEATHER VARIABLES FROM EQUATIONS (3.28) AND (3.29)

CALCULATE BASIC LOAD COMPONENTS FOR THE NEXT DAY USING EQUATIONS:

$$B(i+1, j) = \bar{Y}(i) - \sum_{i=1}^k c_i \bar{WV}_i(i) - \sum_{i=1}^7 s_i \bar{P}_i(i)$$

$$j = 1, 2, \dots, \text{NHOUR}$$

k = NO. OF WEATHER VARIABLES CONSIDERED

FORE CAST PEAK LOAD FOR THE NEXT 24 HOURS USING FORECASTED VALUES OF WEATHER VARIABLES FROM EQUATION (3.42)

FORE CAST HOURLY LOAD DATA AND VARIANCE FOR NEXT 24 HOURS BY OPTIMALLY COMBINING THE FORECAST BASED ON STOCHASTIC LOAD MODEL AND WEATHER LOAD MODEL FROM EQUATIONS: (3.44) TO (3.46)

STOP

Second program is used to update the values of parameters provided by the first program, utilising current load data and observed value of weather variable and simultaneously makes forecast for the next 24 hours (as per flow chart).

Section -2 This section bears heading, 'Forecasting incorporating Effect of Temperature and Humidity and is also given in Appendix-1. It includes the effect of two weather variables i.e. daily average temperature and daily relative humidity. Like Section-1 it also consists of two programs. One for initialisation and identification of stochastic and weather load parameters where as the second program updates these parameters and makes forecast for the next 24 hours taking into account the effect of temperature and humidity.

The above mentioned programs use the following sub-routines.

MATINV(X,A,L): The function of this subroutine is to calculate the inverse of the matrix [X]. Matrix [A] is the out put of the sub-routine, i.e. $[A] = [X]^{-1}$. L specifies the order of matrix [X]. The distinguishing feature of this subroutine is that the original matrix [X] does not get destroyed.

MATMUL(A,B,C,L1,L2,L3) - The function of this subroutine is to calculate the product of two matrices A and B as and when required by the main program. C is the output matrix. L1 denotes the number of rows in matrix [A]. L2 is equal to the number of columns in matrix [A] or number of rows in matrix B. L3 represents the number of columns in matrix [B].

ARRAY(MODE, I, J, N, M, S, D) - If MODE=1, it converts single dimension matrix into double dimension matrix. In this case [S] is input matrix and D is output matrix. N implies no. of rows and M implies no. of columns in the output matrix. I and J implies dimensions of input matrix [S].

If MODE=2, it converts double dimension matrix in to single dimension matrix. In this case D is the input matrix and S is the output matrix. This subroutine is used in conjunction with MINV subroutine.

MINV (A, N, D, L, M) - [A] is the matrix whose inverse is required D is the determinant of the matrix. In this subroutine original matrix [A] gets destroyed.

CPU time required by the initialisation program varies from 7 to 8 seconds for processing the data of 92 days. Whereas the CPU time required by the adaptive program varies from 3 to 4 seconds.

CHAPTER - 4

COMPUTATIONS AND RESULTS

The developed programs have been run on actual load data and weather variables records obtained from Ramnagar Substation, Roorkee and Hydrology department of Roorkee University respectively. For this purpose, following data were obtained.

1. Hourly load data for a period of 102 days from 1 Aug. 1987 to 10 Nov. 1987, out of this 92 days data were used for initialising and updating parameters of load models and the rest of data **were used** for the comparison of results. Hourly load data is given in Appendix - 2.
2. Daily average temperature and relative humidity records are also given in Appendix-2. For the execution of programs, constant α and β were fixed at the following values.

$$\alpha = 0.2, \quad \beta = 0.985$$

Overall results are divided in the following parts.

Part A In this part results are obtained by incorporating the effect of average temperature only. Results are further subdivided in to two sections. In the first section, load forecasts are made with a lead time of 24 hours and after every 24 hours, the parameters of models have been updated. The above forecasts have also been compared with the actual values of hourly loads observed on the same days.

In second section load projects are made with a lead time of one week, assuming weather forecasts were available.

Part B - In this part results have been obtained by taking into account the effect of average temperature and relative humidity. Here also results have been subdivided into two sections. In the first section, hourly load forecasts are made with a lead time of 24 hours and after every 24 hours the parameters of models have been updated. In the second section load projections are made with a lead time of one week. The above forecasts have also been compared with the actual values of hourly loads observed on the same days.

The computed values of hourly-load forecasts followed by their graphical comparison with the actual hourly loads observed on the same data are presented in a sequence as per the following table.

Thus it will be observed that there is a good agreement in the forecasted and actual values occurring especially in view of the fact that the least count of the observation is 5 units. Sample results are included in Appendix - 3.

Forecasting incorporating effect of	Lead time of forecasts	Forecasted day	Maximum S.D estimated		Maximum S.D actually observed		Comparison graph sheet (Fig.No.)
			S.D.	Hours	S.D.	Hours	
Temperature	24 hours	Nov.2,87	5.44	21	6.52	07	4.1
	24 hours	Nov.3,87	5.76	09	5.52	09	4.2
	24 hours	Nov.7,87	5.45	21	6.05	21	4.3
	24 hours	Nov.8,87	5.47	17	6.28	17	4.4
	4 days	Nov.5,87	5.83	20	6.89	07	4.5
	1 week	Nov8,87	5.89	17	6.65	17	4.6
Temperature and Humidity.	24 hours	Nov.2,87	5.45	21	6.52	07	4.7
	24 hours	Nov.3,87	5.72	18	6.32	19	4.8
	24 hours	Nov.7,87	5.46	16	6.29	10	4.9
	24 hours	Nov.8,87	5.48	13	6.12	17	4.10
	4 days	Nov.5,87	5.81	21	6.81	07	4.11
	1 week	Nov.8,87	5.87	21	6.63	09	4.12

FORECAST FOR NOV. 2, 1987.
INCORPORATING EFFECT OF TEMPERATURE
LEAD TIME = 24 HOURS

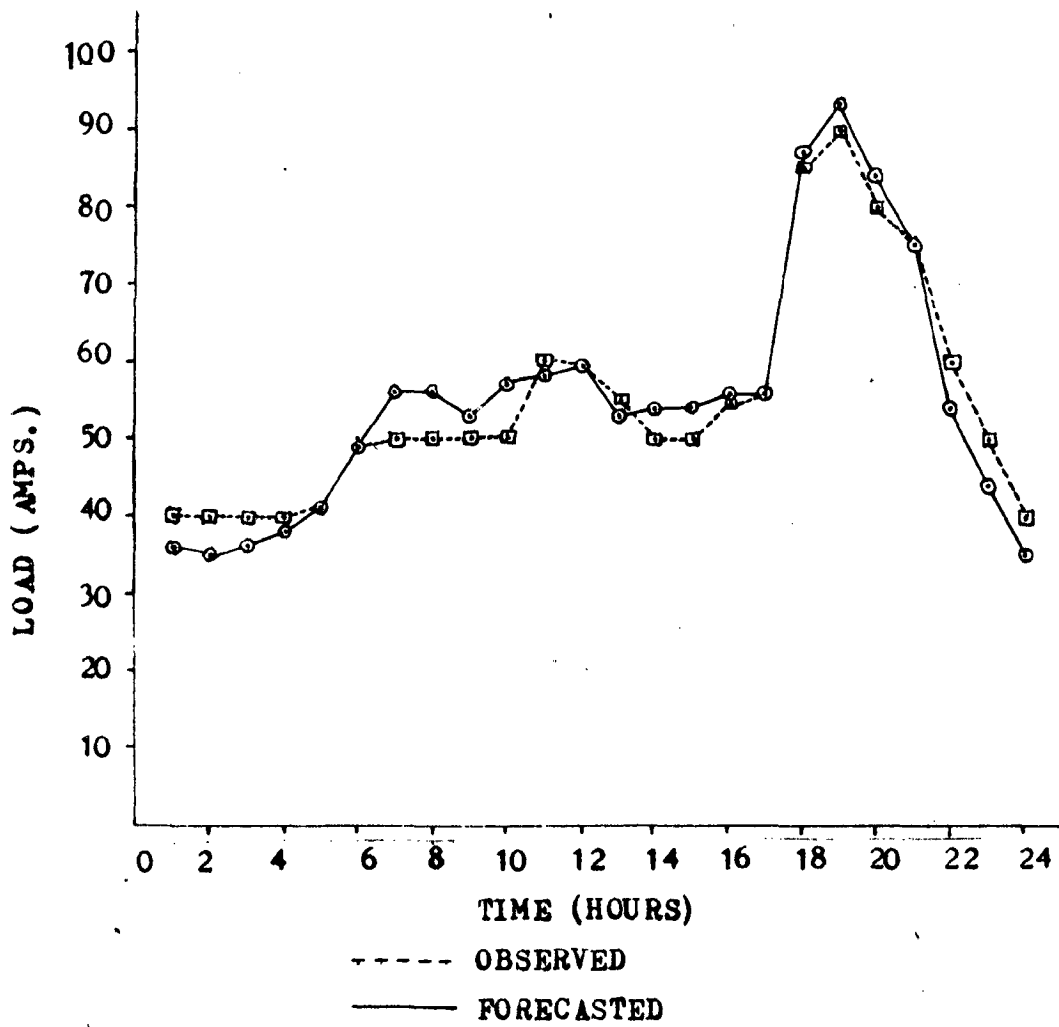


FIG. NO. 4.1

FORECAST FOR NOV. 3, 1987
INCORPORATING EFFECT OF TEMPERATURE
LEAD TIME = 24 HOURS

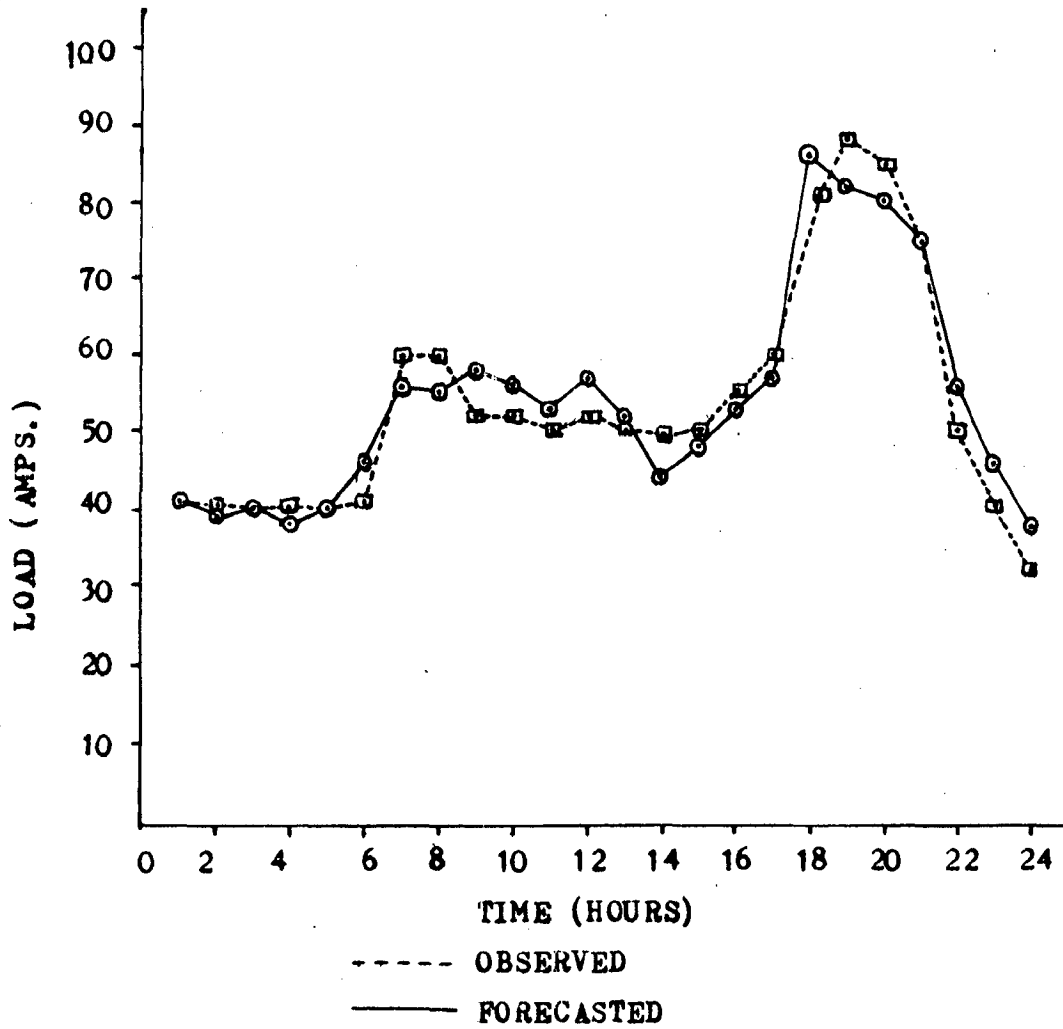


FIG. NO. 4. 2

FORECAST FOR NOV. 7, 1987
INCORPORATING EFFECT OF TEMPERATURE
LEAD TIME = 24 HOURS

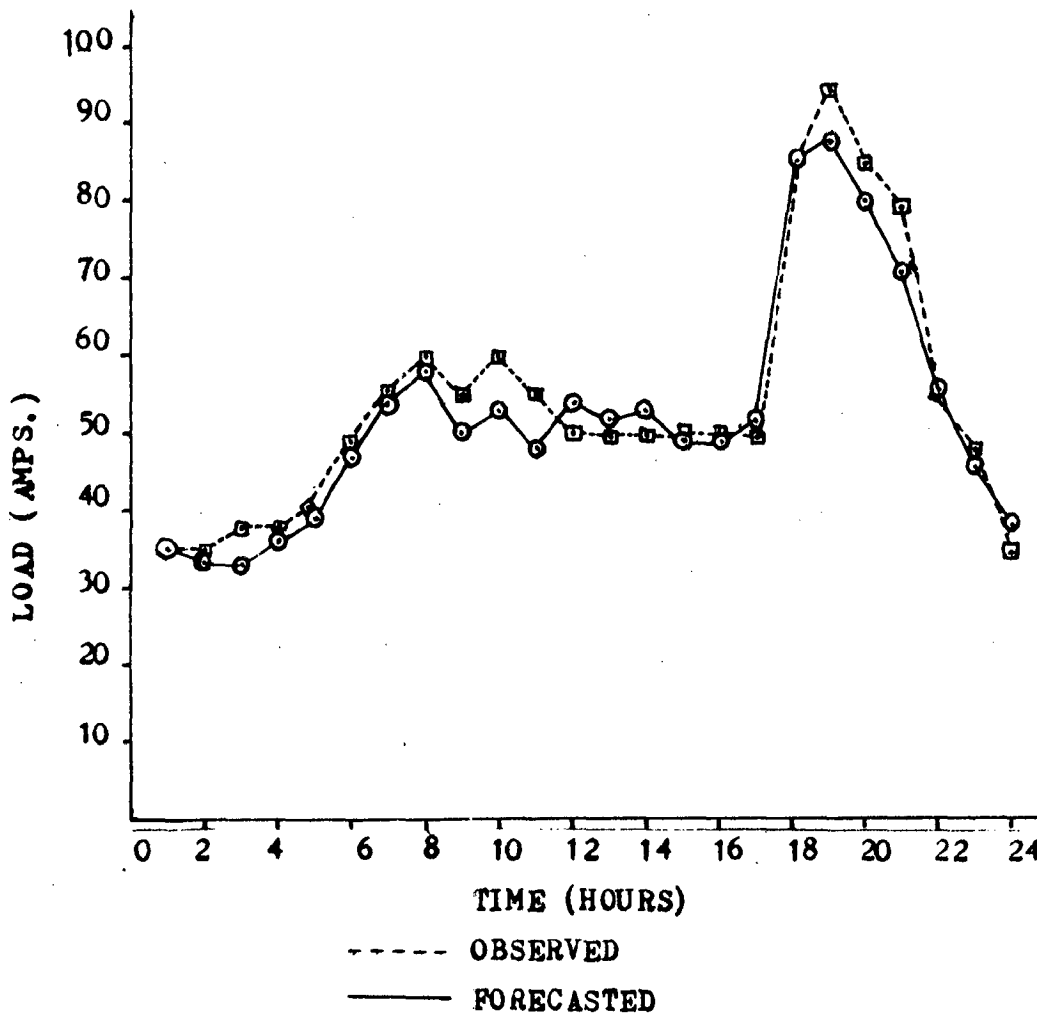


FIG. NO. 4.3

FORECAST FOR NOV. 8, 1987
INCORPORATING EFFECT OF TEMPERATURE

LEAD TIME = 24 HOURS

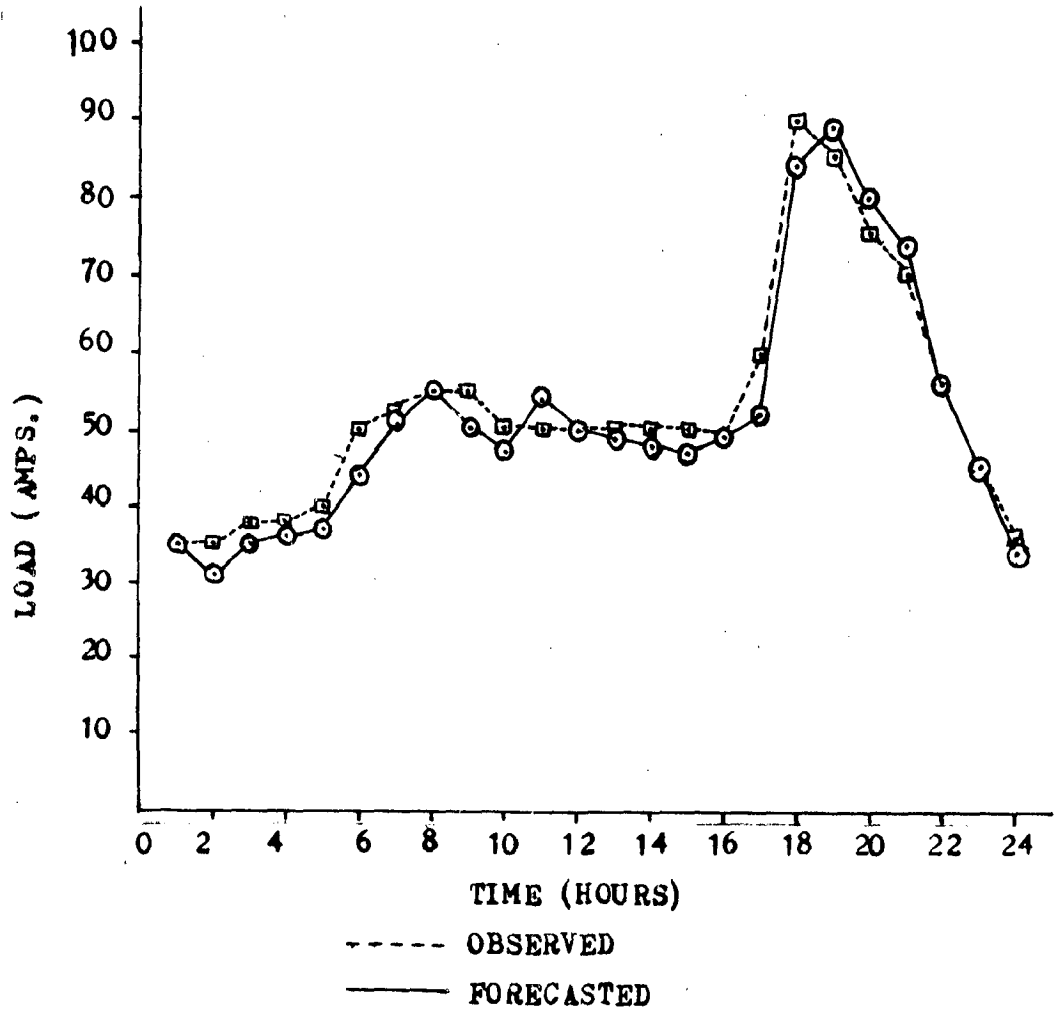


FIG. NO. 4.4

FORECAST FOR NOV. 5, 1987.
INCORPORATING EFFECT OF TEMPERATURE
LEAD TIME = 4 DAYS

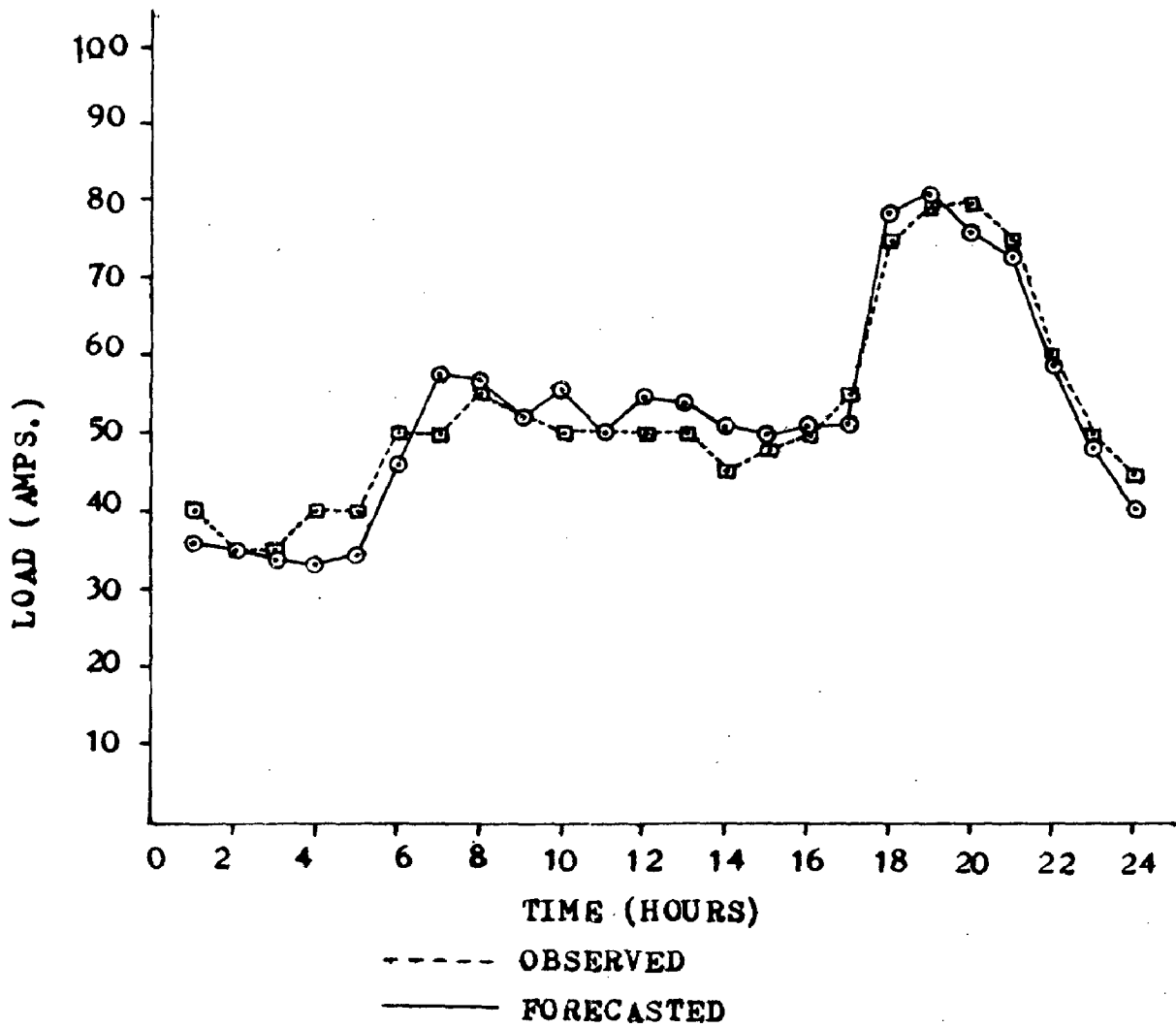


FIG. NO. 4.5

FORECAST FOR NOV. 8, 1987

INCORPORATING EFFECT OF TEMPERATURE

LEAD TIME = 1 WEEK

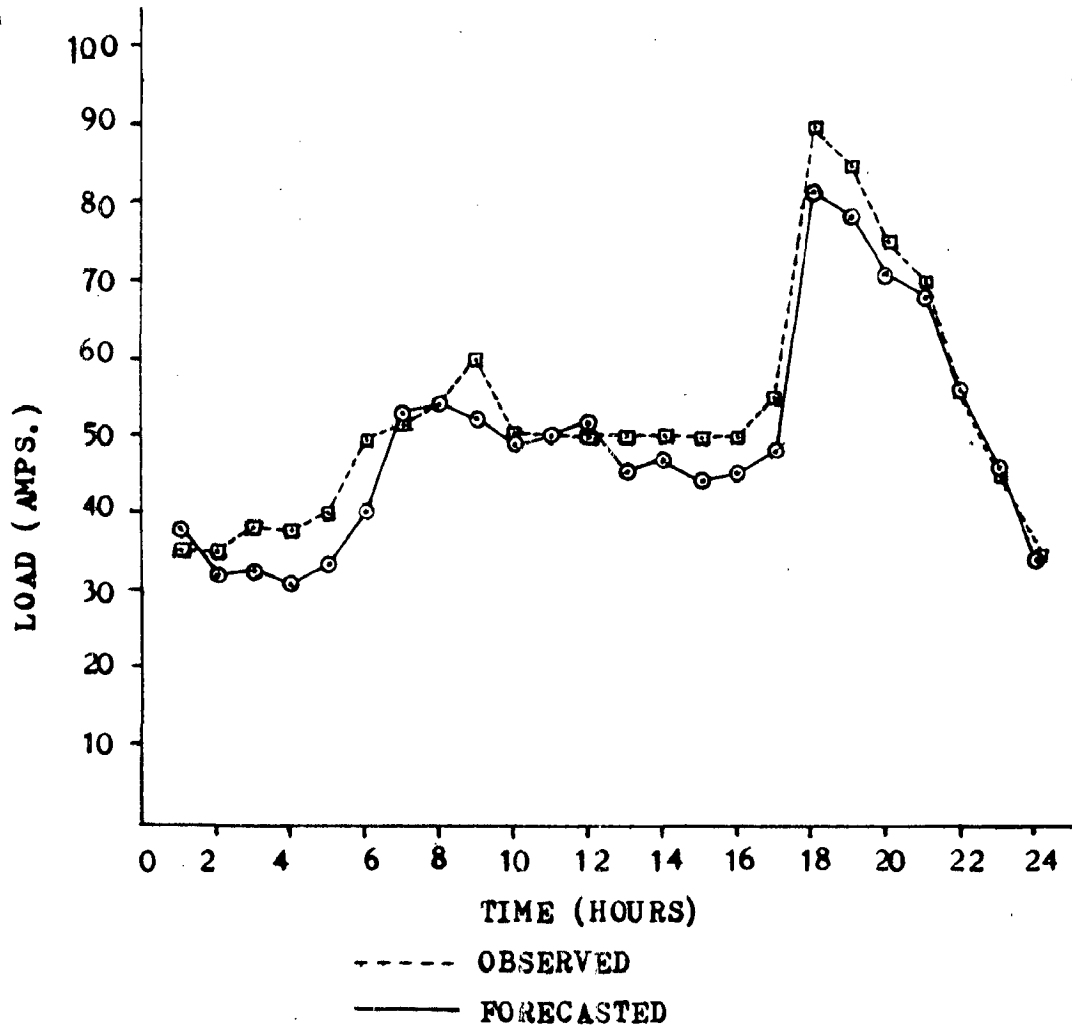


FIG. NO. 4.6

FORECAST FOR NOV. 2, 1987.

INCORPORATING EFFECT OF TEMPERATURE AND HUMIDITY

LEAD TIME = 24 HOURS

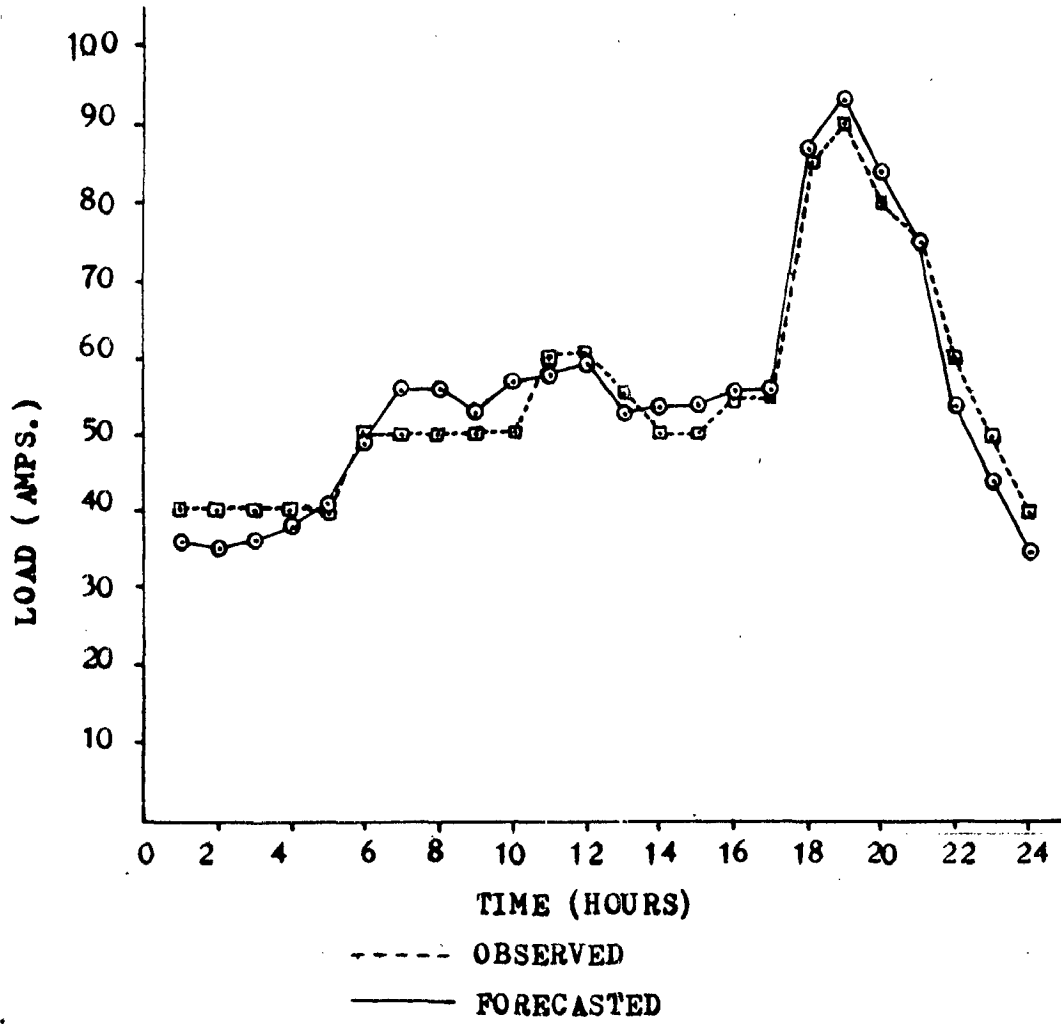


FIG. NO. 4.7

FORECAST FOR NOV. 3, 1987.

INCORPORATING EFFECT OF TEMPERATURE AND HUMIDITY

LEAD TIME = 24 HOURS

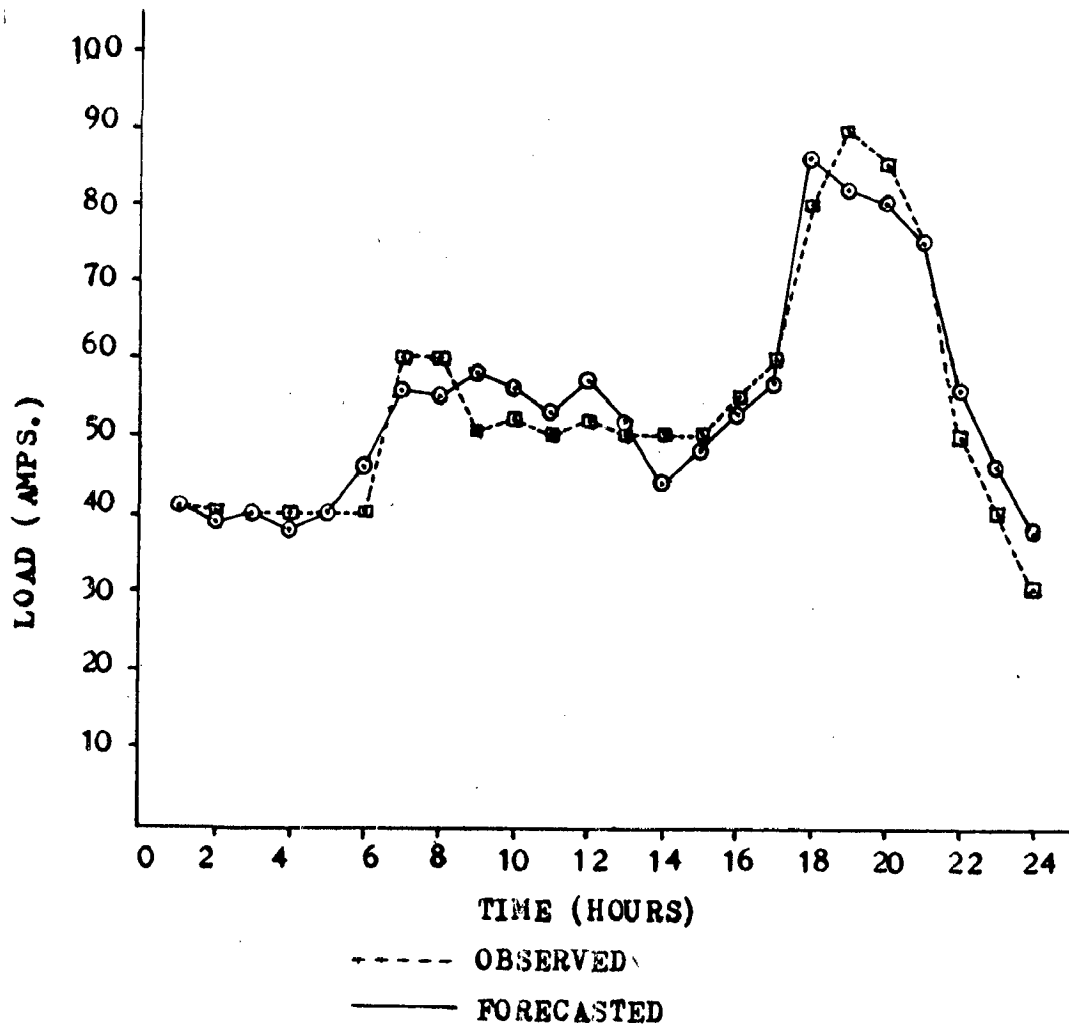


FIG. NO. 4.8

FORECAST FOR NOV. 7, 1987
INCORPORATING EFFECT OF TEMPERATURE AND HUMIDITY
LEAD TIME = 24 HOURS

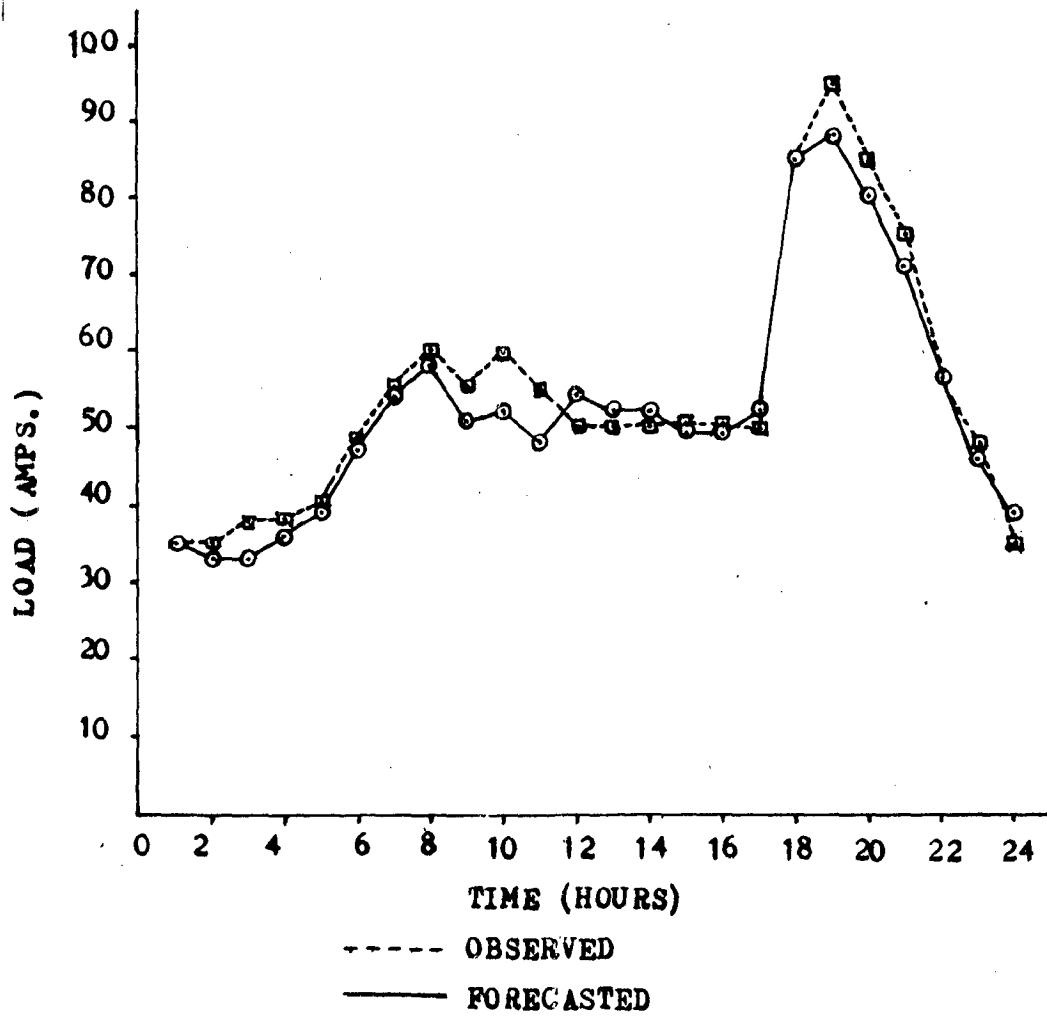


FIG.NO. 4.9

FORECAST FOR NOV. 8, 1987

INCORPORATING EFFECT OF TEMPERATURE AND HUMIDITY

LEAD TIME = 24 HOURS

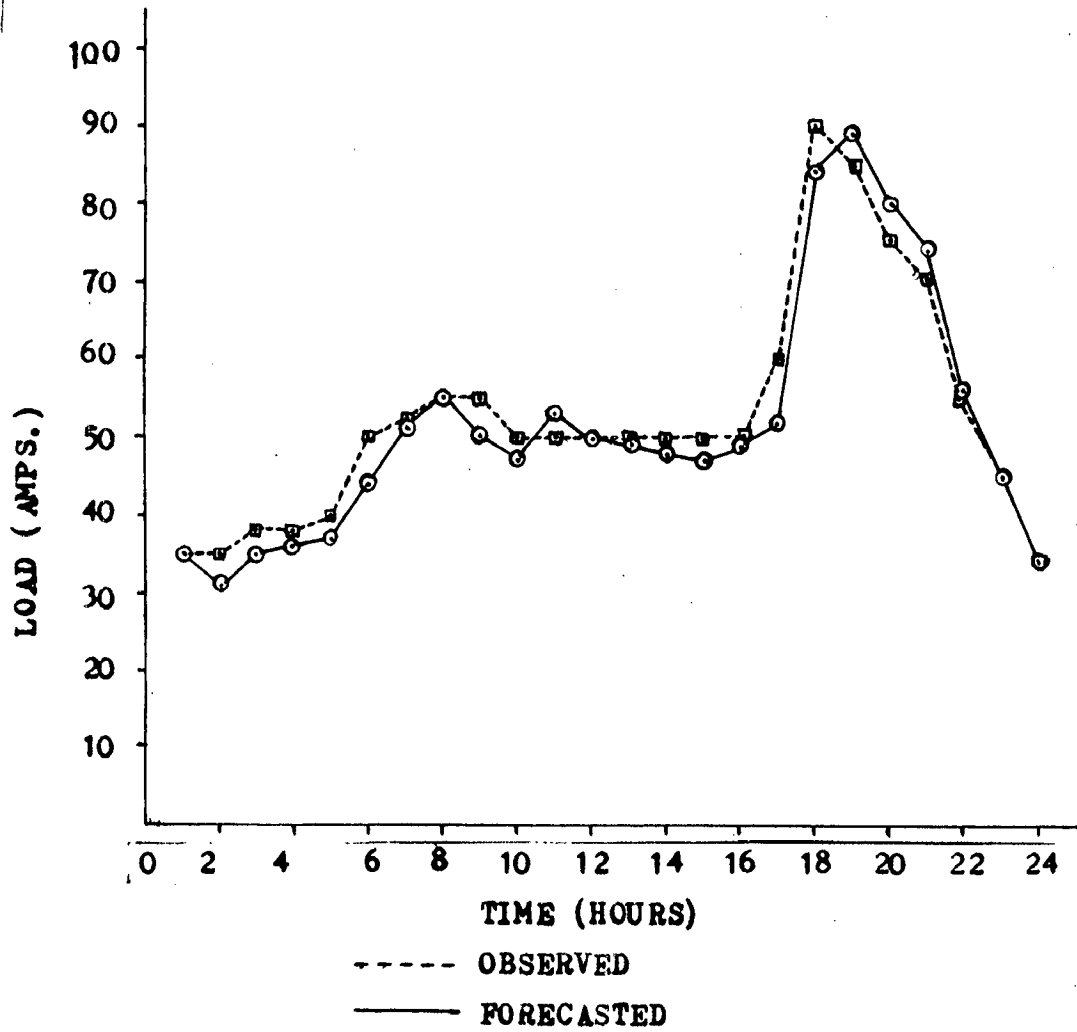


FIG. NO. 4.10

FORECAST FOR NOV. 5, 1987
INCORPORATING EFFECT OF TEMPERATURE AND HUMIDITY
LEAD TIME = 4 DAYS

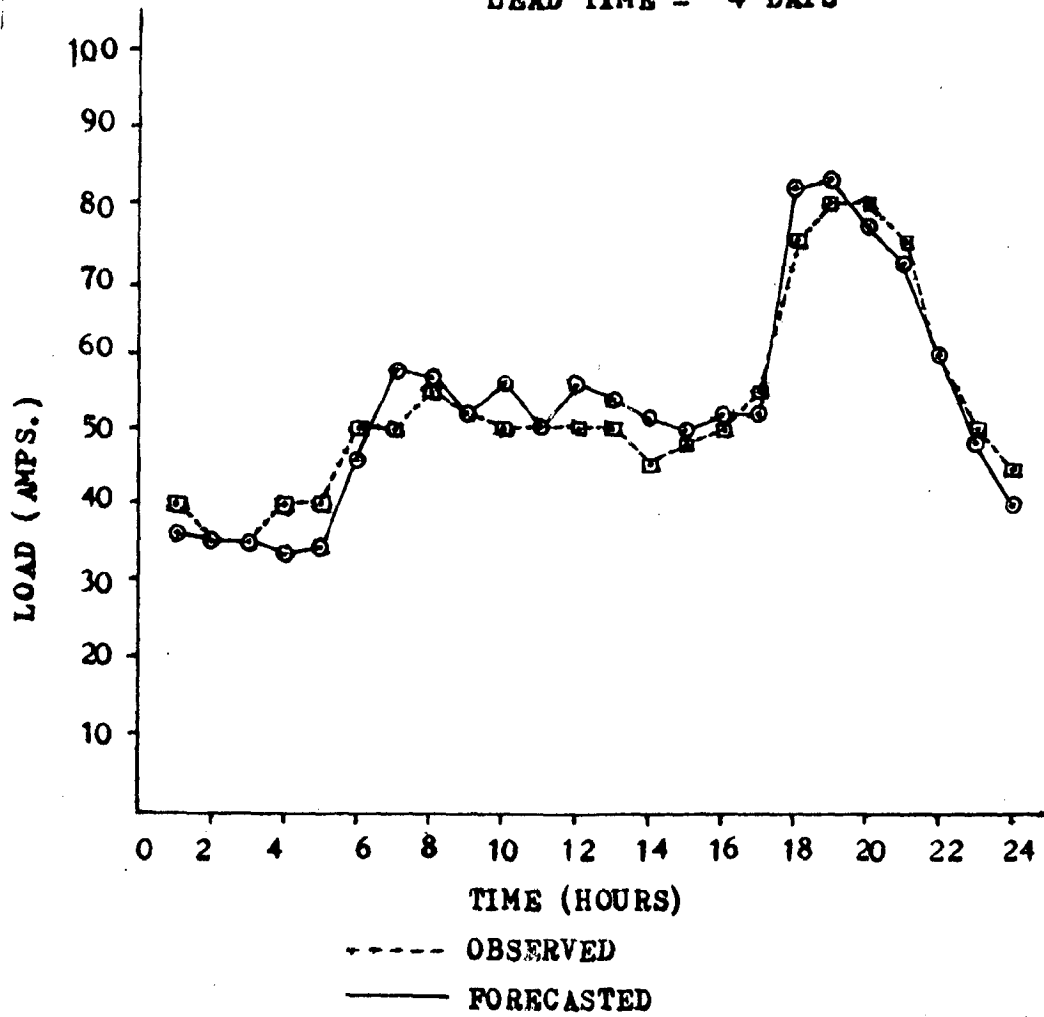


FIG.NO. 4.11

FORECAST FOR NOV. 8, 1987
INCORPORATING EFFECT OF TEMPERATURE AND HUMIDITY
LEAD TIME = 1 WEEK

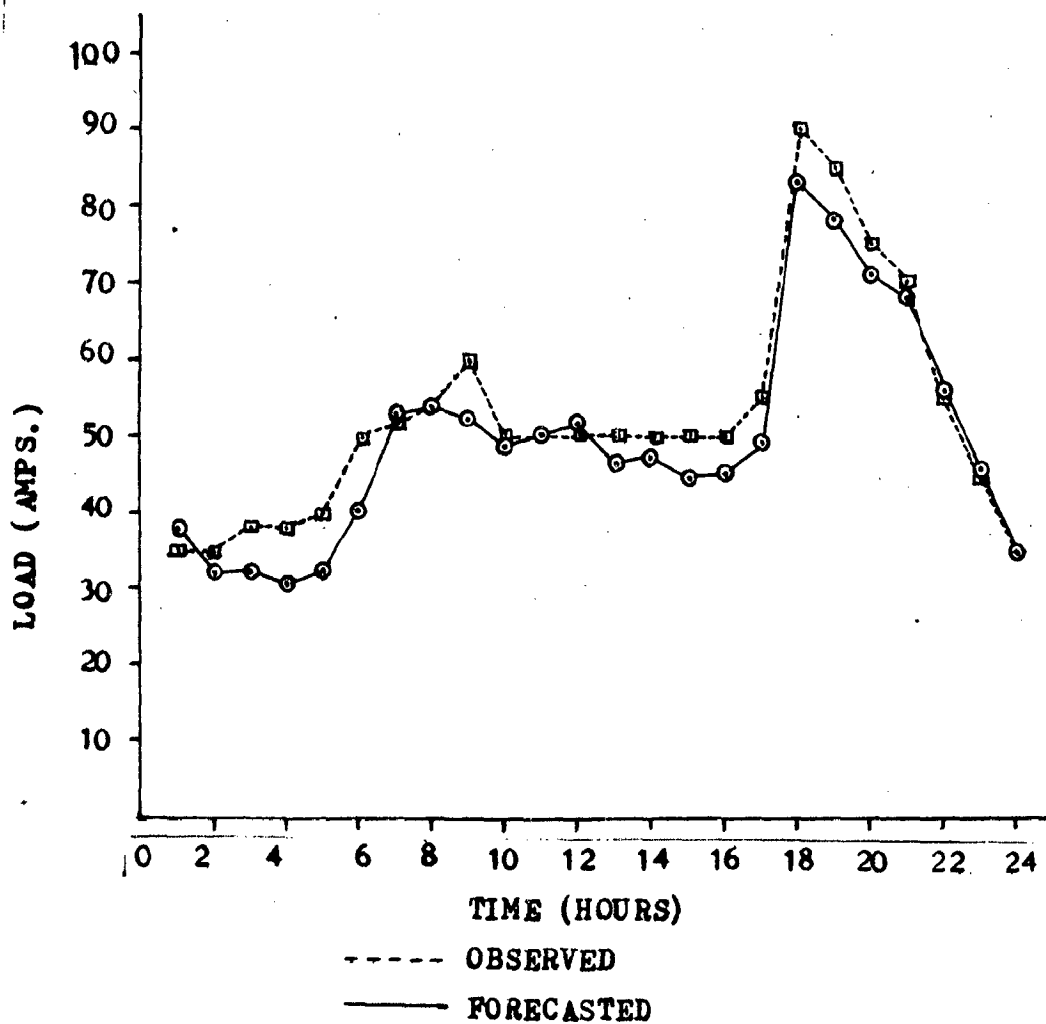


FIG. NO. 4.12

CHAPTER - 5

CONCLUSIONS

The short-term load forecasting program developed here offers following advantages.

1. The methodology takes both historical load data and weather information in to account in forecasting hourly loads.
2. The forecasting models are adaptive in the sense that the model parameters are automatically corrected to keep track of the changing load conditions.
3. The methodology can be used effectively as an on-line software package in the utilities control computer system.
4. The methodology produces not only load forecasts but also probable error in each forecast.
5. The methodology has been developed in such a manner that it allows ready adoption to different power systems.

Forecasts made by this method have been found quite satisfactory even with a lead time of one week when compared with actual values. The maximum standard deviation observed with forecasts in one week advance is 6.89 however when forecasts are made by daily updating the model parameters it has been found that maximum standard-deviation was 6.52. The probable cause for the higher magnitude of standard deviation are -

- (1) From the very first observation of load data it appears that the most of values are given as multiple of five (i.e. average step \approx 5.6 percent of peak load) rather than in decimal points. So it is one of most crucial factors in deciding the magnitude of standard deviation.
- (2) As in the methodology used it is required to take the inverse of 8X8 or 9X9 matrix in initialisation operation which is not diagonally dominant with the result large truncation errors are introduced.

The accuracy of adopted methodology can be further improved if instead of daily average values, hourly weather forecasts were used. At the same time α can be assigned different values in different reasons to improve the forecasting accuracy.

In this part of program dealing with historical data could be worked out off-line and only the adaptive part need to be done ~~on~~-line. Thus this method is well suited for on-line load forecasting.

The present program doesnot have a provision for bad data rejection and special holiday forecasting.

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* * * * *
* APPENDIX - 1 *
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00100 *****
00200 C      PROGRAM FOR IDENTIFICATION AND INITIALISATION
00225 C      OF PARAMETERS OF STOCHASTIC LOAD MODEL AND
00237 C      WEATHER LOAD MODEL
00250 *****
00260 C      IF INTERMEDIATE RESULTS ARE DESIRED THEN REMOVE
00270 C      '*' FROM THE FIRST COULMN OF RESPECTIVE
00280 C      PRINT-STATEMENTS IN THE PROGRAM
00300 C=====
00400      DIMENSION Z(365,24),T(365,24),WC(365,24),TOWO(24,24),
00500      1 TOW1(24,24),X(365,24),A(24,24),AT(24,24),
00600      2 ATO(24,24),TOINV(24,24),Q(24,24),ATOAT(24,24),
00700      3 TMP(365),WV(365),P(7,365),Y(365),POBAR(7),
00800      4 YMIN(365),WVMIN(365),PMIN(7,365),DELY(365),
00900      5 PHAIT(365,8),A0(8),AE(365,8),
01000      6 AZERO(8),PEE(365,8,8),TAM1(8,8),
01100      7 PO(8,8),POINV(64),JL(64),JM(64)
01150 C=====
01152 C      Z(N,J)          LOAD IN AMPERS ON N TH DAY
01154 C      AND JTH HOUR
01158 C      TMP(N)         TEMPERATURE ON N TH DAY
01160 C      Y(N)           PEAK LOAD ON N TH DAY
01162 C      NDAY          NUMBER OF DAYS FOR WHICH LOAD
01164 C                      DATA IS AVAILABLE
01166 C      NHOOR          HOURS PER DAY,24
01168 C      N1            LOAD DATA FOR FIRST TO N1 DAY
01170 C                      CONSTITUTE THE FIRST PART OF LOAD DATA
01172 C      N2            LOAD DATA FOR N1+1 TO N2 DAY
01174 C                      CONSTITUTE THE SECOND PART OF LOAD DATA
01176 C                      THIRD PART OF LOAD DATA IS FROM N2+1
01178 C                      TO NDAY
01180 C      LDAY          DAY ON THE LAST DATE OF AVAILABLE DATA
01190 C=====
01200      OPEN(UNIT=1,FILE='LOD1.DAT')
01300      OPEN(UNIT=4,DEVICE='DSK',FILE='RES1.DAT')
01400      OPEN(UNIT=7,DEVICE='DSK',FILE='RES2.DAT')
01500      OPEN(UNIT=9,DEVICE='DSK',FILE='RES3.DAT')

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FORECASTING INCORPORATING EFFECT OF TEMPERATURE

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01600      OPEN(UNIT=10,DEVICE='DSK',FILE='RES4.DAT')
01700      READ(1,*) NHOOR,NDAY,N1,N2,ALPHA,BEETA,TS,TW,LDAY
01800      READ(1,*)((Z(I,J),J=1,NHOOR),I=1,NDAY),(TMP(I),I=1,NDAY)
01825 *****
01837 C      SECTION 1: STOCHASTIC LOAD MODEL
01843 C      IDENTIFICATION OF PARAMETERS
01846 *****
01900 C      CALCULATION OF BASIC LOAD COMPONENTS
01950 C=====
02000      DO10 I=7,NDAY
02100      DO 10 J=1,NHOOR
02200      SUM=0.0
02300      DO5 K=(I-6),I
02400      SUM=SUM+Z(K,J)
02500 5      CONTINUE
02600      T(I,J)=SUM/7.
02700 10     CONTINUE
02750 C=====
02800 C      CALCULATION OF BASIC LOAD COMPONENTS FOR THE
02850 C      FIRST SIX DAYS OF AVAILABLE DATA
02875 C=====
02900      DO 20 I=1,6
03000      DO20 J=1,NHOOR
03100      T(I,J)=T(7,J)
03200 20     CONTINUE
03300 *      PRINT49
03400 49     FORMAT(T10,'BASIC LOAD COMPONENT')
03500 *      PRINT31,( (T(I,J),J=1,NHOOR),I=1,NDAY)
03600 31     FORMAT(5X,3(5X,8E13.5/)/)
03650 C=====
03700 C      CALCULATION OF WEEKLY LOAD COMPONENTS
03750 C=====
03800      DO30 K=1,7
03900      DO 30 J=1,NHOOR
04000      WC(K,J)=Z(K,J)-T(7,J)
04100 30     CONTINUE
04200      DO 35 I=8,NDAY

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FORECASTING INCORPORATING EFFECT OF TEMPERATURE

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04300      DO 35 J=1,NHOUR
04400      WC(I,J)=WC((I-7),J)+ALPHA*(Z(I,J)-T(I,J)-WC((I-7),J))
04500  35    CONTINUE
04600 *    PRINT51
04700  51    FORMAT(T10,'WEEKLY COMPONENT')
04800 *    PRINT31,((WC(I,J),J=1,NHOUR),I=1,NDAY)
04850 C=====
04900 C      CALCULATION OF RESIDUAL COMPONENTS
04950 C=====
05000      DO40 I=1,NDAY
05100      DO40 J=1,NHOUR
05200      X(I,J)=Z(I,J)-T(I,J)-WC(I,J)
05300  40    CONTINUE
05400 *    PRINT71
05500  71    FORMAT(T10,'RESIDUAL COMPONENT')
05600 *    PRINT31,((X(I,J),J=1,NHOUR),I=1,NDAY)
05700      WRITE(4,*) ((Z(I,J),J=1,NHOUR),I=(NDAY-5),NDAY)
05800      WRITE(4,*) ((WC(I,J),J=1,NHOUR),I=(NDAY-6),NDAY)
05900      WRITE(4,*) (X(NDAY,J),J=1,NHOUR)
06000      F=FLOAT(NDAY)
06100      DO50 J=1,NHOUR
06200      DO50 K=1,NHOUR
06300      TOW0(J,K)=0.0
06400      DO60 I=1,NDAY
06500      TOW0(J,K)=TOW0(J,K)+X(I,J)*X(I,K)
06600  60    CONTINUE
06700      TOW0(J,K)=TOW0(J,K)/F
06800  50    CONTINUE
06900 *    PRINT33
07000  33    FORMAT(20X,'TOW0')
07100 *    PRINT31,((TOW0(J,K),K=1,NHOUR),J=1,NHOUR)
07200      DO70 J=1,NHOUR
07300      DO 70 K=1,NHOUR
07400      TOW1(J,K)=0.0
07500      DO 65 I=2,NDAY
07600      TOW1(J,K)=TOW1(J,K)+X(I,J)*X((I-1),K)
07700  65    CONTINUE

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07800      TOW1(J,K)=TOW1(J,K)/(F-1.0)
07900  70    CONTINUE
08000  *     PRINT69
08100  69    FORMAT(T15,'TOW1')
08200  *     PRINT31,((TOW1(J,K),K=1,NHOUR),J=1,NHOUR)
08300      WRITE(7,*) ((TOW0(I,J),J=1,NHOUR),I=1,NHOUR)
08400      WRITE(7,*) ((TOW1(I,J),J=1,NHOUR),I=1,NHOUR)
08500      NH=NHOUR
08600      CALL MATINV(TOW0,TOINV,NH)
08700      CALL MATMUL(TOW1,TOINV,A,NH,NH,NH)
08800  *     PRINT6
08900  6     FORMAT(/T10,'A'/)
09000  *     PRINT300,((A(I,J),J=1,NHOUR),I=1,NHOUR)
09100  300   FORMAT(5X,4(5X,6E15.7/))
09200      DO80 I=1,NHOUR
09300      DO80 J=1,NHOUR
09400      AT(I,J)=A(J,I)
09500  80    CONTINUE
09600      CALL MATMUL(A,TOW0,ATO,NH,NH,NH)
09700      CALL MATMUL(ATO,AT,ATOAT,NH,NH,NH)
09800      DO90 J=1,NHOUR
09900      DO90 K=1,NHOUR
10000      Q(J,K)=TOW0(J,K)-ATOAT(J,K)
10100  90    CONTINUE
10200  *     PRINT 7
10300  7     FORMAT(/T10,'Q'/)
10400  *     PRINT300,((Q(J,K),K=1,NHOUR),J=1,NHOUR)
10450 *****
10500  CC     SECTION 2: WEATHER LOAD MODEL
10600  CC     INITIALISATION OF PARAMETERS
10650 *****
10700  C      CALCULATION OF DAILY PEAK LOAD
10750  C=====
10800      DO 4 I=1,NDAY
10900      Y(I)=0.0
11000      DO4 J=1,NHOUR
11100      IF(Z(I,J).GT.Y(I)) Y(I)=Z(I,J)

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11200 4      CONTINUE
11250 C=====
11300 C      NON-LINEAR TRANSFORMATION OF THE WEATHER VARIABLE
11350 C=====
11400      DO 8 I=1,NDAY
11500      IF(TMP(I).GE.TS) WV(I)=TMP(I)-TS
11600      IF(TMP(I).GT.TW.AND.TMP(I).LT.TS) WV(I)=0.0
11700      IF(TMP(I).LE.TW) WV(I)=TW-TMP(I)
11800 8      CONTINUE
11900 *      PRINT296
12000 296    FORMAT(38X,'WV(I)'/)
12100 *      PRINT308,(WV(I),I=1,NDAY)
12200 308    FORMAT(30X,2E13.5/)
12250 C=====
12300 C      CALCULATION OF P(J,I)
12350 C=====
12400      MDAY=NDAY/7
12500      KDAY=NDAY-(MDAY*7)
12600      IF(LDAY.GT.KDAY) GO TO 12
12700      LDAY=LDAY+7
12800 12     IDAY=LDAY-KDAY
12900      IDD=IDAY+1
13000      DO16 K=1,NDAY
13100      IDAY=IDAY+1
13200      IF(IDAY.GT.7) IDAY=IDAY-7
13300      DO16 J=1,7
13400      IF(J.EQ.IDAY) GO TO 24
13500      P(J,K)=0.0
13600      GO TO 16
13700 24     P(J,K)=1.0
13800 16     CONTINUE
13900 *      PRINT 184
14000 184    FORMAT(/T20,'P(J,K)'/)
14100 *      PRINT 188,((P(J,K),J=1,7),K=1,NDAY)
14200 188    FORMAT(T5,7F5.1)
14250 C=====
14300 C      CALCULATOIN OF INITIAL VALUES,YOBAR,WVOBAR,POBAR(K)

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17800      DO52 I=1,7
17900      PMIN(I,(N-1))=ALPHA*P(I,(N-1))+(1.0-ALPHA)*PMIN(I,(N-2))
18000  52      CONTINUE
18100  48      CONTINUE
18200  *      PRINT248,(YMIN(N),N=N1,NDAY)
18300  248     FORMAT(/15X,'YMIN',5X,E15.7)
18400  *      PRINT249,(WVMIN(N),N=N1,NDAY)
18500  249     FORMAT(/15X,'WVMIN',5X,E15.7)
18600  *      PRINT270
18700  270     FORMAT(/30X,'PMIN(I,J)'/)
18800  *      PRINT274,((PMIN(I,J),I=1,7),J=N1,NDAY)
18900  274     FORMAT(5X,7E12.5)
19000      WRITE(9,*) YMIN(NDAY),WVMIN(NDAY),(PMIN(J,NDAY),J=1,7)
19100      WRITE(9,*) (P(J,NDAY),J=1,7)
19150  C=====
19200  C      CALCULATION OF DELTA Y(N)
19250  C=====
19300      DO56 N=N11DAY,NDAY
19400      DELY(N)=Y(N)-YMIN(N-1)
19500  56      CONTINUE
19600  *      PRINT280
19700  280     FORMAT(30X,'DELY(N)'/)
19800  *      PRINT284,(DELY(N),N=N11DAY,NDAY)
19900  284     FORMAT(25X,2E13.5/)
19950  C=====
20000  CC      MATRIX PHAI AND ITS TRANSPOSE
20050  C=====
20075      NC=8
20100      DO72 N=N11DAY,NDAY
20200      DO72 I=1,NC
20300      IF(I.GT.7) GO TO 76
20400      PHAIT(N,I)=P(I,N)-PMIN(I,(N-1))
20500      GO TO 72
20600  76      PHAIT(N,I)=WV(N)-WVMIN(N-1)
20700  72      CONTINUE
20800  *      PRINT212
20900  212     FORMAT(25X,'PHAIT(N,I)'/)

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11200 4      CONTINUE
11250 C=====
11300 C      NON-LINEAR TRANSFORMATION OF THE WEATHER VARIABLE
11350 C=====
11400      DO 8 I=1,NDAY
11500      IF(TMP(I).GE.TS) WV(I)=TMP(I)-TS
11600      IF(TMP(I).GT.TW.AND.TMP(I).LT.TS) WV(I)=0.0
11700      IF(TMP(I).LE.TW) WV(I)=TW-TMP(I)
11800 8      CONTINUE
11900 *      PRINT296
12000 296    FORMAT(38X,'WV(I)'/)
12100 *      PRINT308,(WV(I),I=1,NDAY)
12200 308    FORMAT(30X,2E13.5/)
12250 C=====
12300 C      CALCULATION OF P(J,I)
12350 C=====
12400      MDAY=NDAY/7
12500      KDAY=NDAY-(MDAY*7)
12600      IF(LDAY.GT.KDAY) GO TO 12
12700      LDAY=LDAY+7
12800 12     IDAY=LDAY-KDAY
12900      IDD=IDAY+1
13000      DO16 K=1,NDAY
13100      IDAY=IDAY+1
13200      IF(IDAY.GT.7) IDAY=IDAY-7
13300      DO16 J=1,7
13400      IF(J.EQ.IDAY) GO TO 24
13500      P(J,K)=0.0
13600      GO TO 16
13700 24     P(J,K)=1.0
13800 16     CONTINUE
13900 *      PRINT 184
14000 184    FORMAT(/T20,'P(J,K)'/)
14100 *      PRINT 188,((P(J,K),J=1,7),K=1,NDAY)
14200 188    FORMAT(T5,7F5.1)
14250 C=====
14300 C      CALCULATON OF INITIAL VALUES,YOBAR,WVOBAR,POBAR(K)

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14350 C=====
14400      YOBAR=0.0
14500      WVOBAR=0.0
14600      DO28 N=1,N1
14700      YOBAR=YOBAR+Y(N)
14800      WVOBAR=WVOBAR+WV(N)
14900 28    CONTINUE
15000      G=FLOAT(N1)
15100      YOBAR=YOBAR/G
15200      WVOBAR=WVOBAR/G
15300      DO32 K=1,7
15400      POBAR(K)=0.0
15500      DO36 N=1,N1
15600      POBAR(K)=POBAR(K)+P(K,N)
15700 36    CONTINUE
15800      POBAR(K)=POBAR(K)/G
15900 32    CONTINUE
16000 *    PRINT228,WVOBAR,YOBAR
16100 228   FORMAT(/15X,2F12.6)
16200 *    PRINT252
16300 252   FORMAT(30X,'POBAR(K)'/)
16400 *    PRINT256,(POBAR(K),K=1,7)
16500 256   FORMAT(27X,E15.7)
16550 C=====
16600 C      CALCULATION OF MEAN VALUES
16700 C      FOR THE SUCCESSIVE DAYS
16750 C=====
16800      YMIN(N1)=YOBAR
16900      WVMIN(N1)=WVOBAR
17000      DO44 I=1,7
17100      PMIN(I,N1)=POBAR(I)
17200 44    CONTINUE
17300      N1DAY=NDAY+1
17400      N11DAY=N1+1
17500      DO48 N=(N1+2),N1DAY
17600      YMIN(N-1)=ALPHA*Y(N-1)+(1.0-ALPHA)*YMIN(N-2)
17700      WVMIN(N-1)=ALPHA*WV(N-1)+(1.0-ALPHA)*WVMIN(N-2)

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17800      DO52 I=1,7
17900      PMIN(I,(N-1))=ALPHA*P(I,(N-1))+(1.0-ALPHA)*PMIN(I,(N-2))
18000  52      CONTINUE
18100  48      CONTINUE
18200  *      PRINT248,(YMIN(N),N=N1,NDAY)
18300  248     FORMAT(/15X,'YMIN',5X,E15.7)
18400  *      PRINT249,(WVMIN(N),N=N1,NDAY)
18500  249     FORMAT(/15X,'WVMIN',5X,E15.7)
18600  *      PRINT270
18700  270     FORMAT(/30X,'PMIN(I,J)'/)
18800  *      PRINT274,((PMIN(I,J),I=1,7),J=N1,NDAY)
18900  274     FORMAT(5X,7E12.5)
19000      WRITE(9,*) YMIN(NDAY),WVMIN(NDAY),(PMIN(J,NDAY),J=1,7)
19100      WRITE(9,*) (P(J,NDAY),J=1,7)
19150  C=====
19200  C      CALCULATION OF DELTA Y(N)
19250  C=====
19300      DO56 N=N11DAY,NDAY
19400      DELY(N)=Y(N)-YMIN(N-1)
19500  56      CONTINUE
19600  *      PRINT280
19700  280     FORMAT(30X,'DELY(N)'/)
19800  *      PRINT284,(DELY(N),N=N11DAY,NDAY)
19900  284     FORMAT(25X,2E13.5/)
19950  C=====
20000  CC      MATRIX PHAI AND ITS TRANSPOSE
20050  C=====
20075      NC=8
20100      DO72 N=N11DAY,NDAY
20200      DO72 I=1,NC
20300      IF(I.GT.7) GO TO 76
20400      PHAIT(N,I)=P(I,N)-PMIN(I,(N-1))
20500      GO TO 72
20600  76      PHAIT(N,I)=WV(N)-WVMIN(N-1)
20700  72      CONTINUE
20800  *      PRINT212
20900  212     FORMAT(25X,'PHAIT(N,I)'/)

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21000 *      PRINT216,((PHAIT(N,I),I=1,NC),N=N11DAY,NDAY)
21100 216    FORMAT(5X,8F12.6/)
21150 C=====
21200 CC      CALCULATION OF P0
21225 C=====
21300          DO82 J=1,NC
21400          DO82 K=1,NC
21500          P0(J,K)=0.0
21600          DO84 N=N11DAY,N2
21700          P0(J,K)=P0(J,K)+PHAIT(N,J)*PHAIT(N,K)
21800 84     CONTINUE
21900 82     CONTINUE
22600          CALL ARRAY(2,NC,NC,NC,NC,P0INV,P0)
22700          CALL MINV(P0INV,NC,C,JL,JM)
22800 *      PRINT288
22900 288    FORMAT(25X,'DETERMINANT'/)
23000 *      PRINT292,C
23100 292    FORMAT(35X,E13.5/)
23200          CALL ARRAY(1,NC,NC,NC,NC,P0INV,P0)
23300 *      PRINT240
23400 240    FORMAT(30X,'P0(I,J)'/)
23700 *      PRINT244,((P0(I,J),J=1,NC),I=1,NC)
23800 244    FORMAT(5X,8(E15.7))
23850 C=====
23900 CC      CALCULATION OF A(0)
23950 C=====
24000          DO89 J=1,NC
24100          A0(J)=0.0
24200          DO88 N=N11DAY,N2
24300          A0(J)=A0(J)+PHAIT(N,J)*DELY(N)
24400 88     CONTINUE
24500 89     CONTINUE
24600 *      PRINT264
24700 264    FORMAT(/30X,'A0(J)'/)
24800 *      PRINT260,(A0(J),J=1,NC)
24900 260    FORMAT(25X,E14.6)
25000 151    CONTINUE

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25100      DO91 I=1,NC
25200      AZERO(I)=0.0
25300      DO91 J=1,NC
25400      AZERO(I)=AZERO(I)+P0(I,J)*A0(J)
25500  91   CONTINUE
25600 *    PRINT232
25700  232  FORMAT(30X,'AZERO(J)'/)
25800 *    PRINT236,(AZERO(J),J=1,NC)
25900  236  FORMAT(25X,E15.7)
25950 C=====
26000 CC    CALCULATION OF PEE FOR SUCCESSIVE DAYS
26050 C=====
26100      DO92 I=1,NC
26200      DO92 J=1,NC
26300      PEE(N2,I,J)=P0(I,J)
26400  92   CONTINUE
26500      N21DAY=N2+1
26600      DO152 N=N21DAY,NDAY
26700      SUM4=0.0
26800      DO124 I=1,NC
26900      SUM3=0.0
27000      DO128 J=1,NC
27100      SUM3=SUM3+PHAIT(N,J)*PEE((N-1),J,I)
27200  128  CONTINUE
27300      SUM4=SUM4+SUM3*PHAIT(N,I)
27400  124  CONTINUE
27500      SUM4=1.0+SUM4/BEETA
27600      SUM4=1.0/SUM4
27700      DO132 I=1,NC
27800      SUM5=0.0
27900      DO136 J=1,NC
28000      SUM5=SUM5+PEE((N-1),I,J)*PHAIT(N,J)
28100  136  CONTINUE
28200      DO140 J=1,NC
28300      TAM1(I,J)=SUM5*PHAIT(N,J)
28400  140  CONTINUE
28500  132  CONTINUE

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28600      DO148 I=1,NC
28700      DO148 K=1,NC
28800      PEE(N,I,K)=0.0
28900      DO144 J=1,NC
29000      PEE(N,I,K)=PEE(N,I,K)+TAM1(I,J)*PEE((N-1),J,K)
29100  144  CONTINUE
29200      PEE(N,I,K)=PEE(N,I,K)/(BEETA**2)
29300      PEE(N,I,K)=PEE((N-1),I,K)/BEETA-PEE(N,I,K)*SUM4
29400  148  CONTINUE
29500  152  CONTINUE
29600  *    PRINT204
29700  204  FORMAT(T20,'PEE(N,I,K)'/)
29800  *    PRINT208,(((PEE(N,I,K),K=1,NC),I=1,NC),N=N2,NDAY)
29900  208  FORMAT(5X,8(5X,8E14.5)/)//)
29950  C=====
30000  CC    CALCULATION OF AE FOR SUCCESSIVE DAYS
30050  C=====
30100      DO156 J=1,NC
30200      AE(N2,J)=AZERO(J)
30300  156  CONTINUE
30400      DO176 N=N21DAY,NDAY
30500      SUM7=0.0
30600      DO164 J=1,NC
30700      SUM7=SUM7+PHAIT(N,J)*AE((N-1),J)
30800  164  CONTINUE
30900      SUM7=DELY(N)-SUM7
31000      DO168 I=1,NC
31100      AE(N,I)=0.0
31200      DO172 J=1,NC
31300      AE(N,I)=AE(N,I)+PEE(N,I,J)*PHAIT(N,J)
31400  172  CONTINUE
31500      AE(N,I)=AE(N,I)*SUM7+AE((N-1),I)
31600  168  CONTINUE
31700  176  CONTINUE
31800      WRITE(10,*) ((PEE(NDAY,I,J),J=1,NC),I=1,NC)
31900      WRITE(10,*) (AE(NDAY,J),J=1,NC)
32000  *    PRINT180

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32100 180 FORMAT(15X/T15,'AE'/)

32200 * PRINT185,((AE(I,J),J=1,NC),I=N2,NDAY)

32300 185 FORMAT(5X,8F13.5/)

32400 STOP

32500 END

32550 C*****

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00100 *****
00200 CC      PROGRAM FOR ADAPTIVE FORECASTING
00300 *****
00400      DIMENSION Z(8,24),WC(8,24),TMP(3),WV(3),Y(2),
00500      1  X(3,24),TOW0(24,24),TOW1(24,24),T(24),P(7,2),
00600      2  A(24,24),AT(24,24),TOINV(24,24),ATO(24,24),
00700      3  DELY(2),TAM1(8,8),PEE(2,8,8),AE(2,8),B(3),
00800      4  ATOAT(24,24),Q(24,24),ZS(24),SVAR(24),YMIN(2),
00900      5  WVMIN(2),PMIN(7,2),PHAIT(2,8),CVAR(24),ZC(24)
00950 C::::::::::::::::::::::::::::::::::::::::::::::::::
01000      OPEN(UNIT=3,DEVICE='DSK',FILE='INP1.DAT')
01100      OPEN(UNIT=4,DEVICE='DSK',FILE='RES1.DAT')
01200      OPEN(UNIT=5,DEVICE='DSK',FILE='INP2.DAT')
01300      OPEN(UNIT=6,DEVICE='DSK',FILE='INTL.DAT')
01400      OPEN(UNIT=7,DEVICE='DSK',FILE='RES2.DAT')
01500      OPEN(UNIT=9,DEVICE='DSK',FILE='RES3.DAT')
01600      OPEN(UNIT=10,DEVICE='DSK',FILE='RES4.DAT')
01650 C::::::::::::::::::::::::::::::::::::::::::::::::::
01700      READ(3,*) NH,ALPHA,BEETA,TS,TW
01800      READ(4,*)((Z(I,J),J=1,NH),I=2,7)
01900      READ(4,*)((WC(I,J),J=1,NH),I=1,7)
02000      READ(4,*) (X(1,J),J=1,NH)
02100      READ(5,*) (Z(8,J),J=1,NH),TMP(2),TMP(3)
02200      READ(6,*) NCOUNT,MCOUNT,YOLD,WVAR
02300      READ(7,*)((TOW0(I,J),J=1,NH),I=1,NH),
02400      1 ((TOW1(I,J),J=1,NH),I=1,NH)
02500      READ(9,*) YMIN(1),WVMIN(1),(PMIN(J,1),J=1,7)
02600      READ(9,*) (P(J,1),J=1,7)
02700      READ(10,*)((PEE(1,I,J),J=1,8),I=1,8),(AE(1,J),J=1,8)
02750 C::::::::::::::::::::::::::::::::::::::::::::::::::
02775 C      UPDATE BASIC ,WEEKLY PATTERN COMPONENT AND
02787 C      CALCULATE RESIDUAL COMPONENT
02793 C::::::::::::::::::::::::::::::::::::::::::::::::::
02800      DO13 J=1,NH
02900      T(J)=0.0
03000      DO15 I=2,8
03100      T(J)=T(J)+Z(I,J)

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03200 15      CONTINUE
03300      T(J)=T(J)/7.0
03400      WC(8,J)=WC(1,J)+ALPHA*(Z(8,J)-T(J)-WC(1,J))
03500      X(2,J)=Z(8,J)-T(J)-WC(8,J)
03600 13      CONTINUE
03700 *      PRINT 14
03800 14      FORMAT(10X,'BASIC LOAD COMPONENT'/)
03900 *      PRINT16,(T(J),J=1,NH)
04000 16      FORMAT(5X,8F12.6)
04050 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04075 C      CALCULATION OF PEAK LOAD
04087 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04100      Y(2)=0.0
04200      DO49 J=1,NH
04300      IF(Z(8,J).GT.Y(2)) Y(2)=Z(8,J)
04400 49      CONTINUE
04450 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04475 C      WEATHER VARIABLE TRANSFORMATION
04487 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04500      DO46 I=2,3
04600      IF(TMP(I).GE.TS) WV(I)=TMP(I)-TS
04700      IF(TMP(I).LT.TS.AND.TMP(I).GT.TW) WV(I)=0.0
04800      IF(TMP(I).LE.TW) WV(I)=TW-TMP(I)
04900 46      CONTINUE
04950 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04975 C      CALCULATION OF P(J,K)
04987 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
05000      DO53 J=1,7
05100      M=J+1
05200      IF(J.EQ.7) M=1
05300      P(M,2)=P(J,1)
05400 53      CONTINUE
05500 *      PRINT 211,(P(M,2),M=1,7)
05600 211     FORMAT(5X,'P(M,2)',5X,7F3.1)
05700      COUNT=FLOAT(MCOUNT)
05750 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
05775 C      UPDATE 'A' AND 'Q' MATRICES

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05787 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
05800      DO17 J=1,NH
05900      DO17 K=1,NH
06000      TOW0(J,K)=TOW0(J,K)+(X(2,J)*X(2,K)-TOW0(J,K))/COUNT
06100      TOW1(J,K)=TOW1(J,K)+(X(2,J)*X(1,K)-TOW1(J,K))/
06200      2 (COUNT-1.0)
06300  17  CONTINUE
06400      CALL MATINV(TOW0,TOINV,NH)
06500      CALL MATMUL(TOW1,TOINV,A,NH,NH,NH)
06600      DO21 I=1,NH
06700      DO21 J=1,NH
06800      AT(I,J)=A(J,I)
06900  21  CONTINUE
07000      CALL MATMUL(A,TOW0,ATO,NH,NH,NH)
07100      CALL MATMUL(ATO,AT,ATOAT,NH,NH,NH)
07200      DO23 J=1,NH
07300      DO23 K=1,NH
07400      Q(J,K)=TOW0(J,K)-ATOAT(J,K)
07500  23  CONTINUE
07550 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
07600 CC      FORECAST BASED ON STOCHASTIC MODEL
07650 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
07700      DO27 I=1,NH
07800      X(3,I)=0.0
07900      DO29 J=1,NH
08000      X(3,I)=X(3,I)+A(I,J)*X(2,J)
08100  29  CONTINUE
08200      ZS(I)=T(I)+WC(2,I)+X(3,I)
08300  27  CONTINUE
08350 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
08375 C      HOUR CORRESPONDING TO PEAK LOAD
08387 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
08400      ZSP=0.0
08500      DO35 J=1,NH
08600      IF(ZS(J).GT.ZSP) ZSP=ZS(J)
08700  35  CONTINUE
08800      DO36 J=1,NH

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08900      IF(ZS(J).EQ.ZSP) KP=J
09000  36    CONTINUE
09050 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
09075 C      STOCHASTIC VARIANCE
09087 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
09100      DO37 J=1,NH
09200      SVAR(J)=Q(J,J)
09300  37    CONTINUE
09400      REWIND 4
09500      WRITE(4,*) ((Z(I,J),J=1,NH),I=3,8)
09600      WRITE(4,*) ((WC(I,J),J=1,NH),I=2,8)
09700      WRITE(4,*) (X(2,J),J=1,NH)
09800      REWIND 7
09900      WRITE(7,*) ((TOW0(I,J),J=1,NH),I=1,NH),
10000  4    ((TOW1(I,J),J=1,NH),I=1,NH)
10050 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
10075 C      UPDATE WEATHER LOAD MODEL
10087 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
10100      YMIN(2)=ALPHA*Y(2)+(1.0-ALPHA)*YMIN(1)
10200      WVMIN(2)=ALPHA*WV(2)+(1.0-ALPHA)*WVMIN(1)
10300      DO51 J=1,7
10400      PMIN(J,2)=ALPHA*P(J,2)+(1.0-ALPHA)*PMIN(J,1)
10500  51    CONTINUE
10600 *      PRINT212,YMIN(1),YMIN(2),WVMIN(1),WVMIN(2)
10700 *      PRINT212,((PMIN(J,I),J=1,7),I=1,2)
10800  212   FORMAT(5X,4F12.4/)
10900      REWIND 9
11000      WRITE(9,*) YMIN(2),WVMIN(2),(PMIN(J,2),J=1,7)
11100      WRITE(9,*) (P(J,2),J=1,7)
11200      DO57 J=1,8
11300      IF(J.GT.7) GO TO 59
11400      PHAIT(2,J)=P(J,2)-PMIN(J,1)
11500      GO TO 57
11600  59    PHAIT(2,J)=WV(2)-WVMIN(1)
11700  57    CONTINUE
11800 *      PRINT213,(PHAIT(2,J),J=1,8)
11900  213   FORMAT(5X,'PHAIT',8E12.5/)

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12000      DELY(2)=Y(2)-YMIN(1)
12100      SUM4=0.0
12200      DO61 I=1,8
12300      SUM3=0.0
12400      DO63 J=1,8
12500      SUM3=SUM3+PHAIT(2,J)*PEE(1,J,I)
12600  63   CONTINUE
12800      SUM4=SUM4+SUM3*PHAIT(2,I)
13000  61   CONTINUE
13100      SUM4=1.0+SUM4/BEETA
13200      SUM4=1.0/SUM4
13400      DO65 I=1,8
13500      SUM5=0.0
13600      DO67 J=1,8
13700      SUM5=SUM5+PEE(1,I,J)*PHAIT(2,J)
13800  67   CONTINUE
14000      DO69 K=1,8
14100      TAM1(I,K)=SUM5*PHAIT(2,K)
14200  69   CONTINUE
14300  65   CONTINUE
14400  *    PRINT217,((TAM1(I,J),J=1,8),I=1,8)
14500  217  FORMAT(5X,'TAM1',3X,8E13.5)
14600      DO71 I=1,8
14700      DO71 K=1,8
14800      PEE(2,I,K)=0.0
14900      DO73 J=1,8
15000      PEE(2,I,K)=PEE(2,I,K)+TAM1(I,J)*PEE(1,J,K)
15100  73   CONTINUE
15200  *    PRINT218,PEE(2,I,K)
15300  218  FORMAT(5X,'PEE',3X,E13.5)
15400      PEE(2,I,K)=PEE(2,I,K)/(BEETA**2)
15500      PEE(2,I,K)=PEE(1,I,K)/BEETA-PEE(2,I,K)*SUM4
15600  71   CONTINUE
15700      SUM7=0.0
15800      DO75 J=1,8
15900      SUM7=SUM7+PHAIT(2,J)*AE(1,J)
16000  75   CONTINUE

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```

16100      SUM7=DELY(2)-SUM7
16200      DO77 I=1,8
16300      AE(2,I)=0.0
16400      DO79 J=1,8
16500      AE(2,I)=AE(2,I)+PEE(2,I,J)*PHAIT(2,J)
16600  79   CONTINUE
16700      AE(2,I)=AE(2,I)*SUM7+AE(1,I)
16800  77   CONTINUE
16900  *    PRINT72,(AE(2,I),I=1,8)
17000  72   FORMAT(5X,'AE',3X,8F12.6/)
17100  *    PRINT74,((PEE(2,I,J),J=1,8),I=1,8)
17200  74   FORMAT(5X,'PEE',3X,8E13.5/)
17300      REWIND 10
17400      WRITE(10,*) ((PEE(2,I,J),J=1,8),I=1,8),(AE(2,J),J=1,8)
17500      SUM2=0.0
17600      DO70 J=1,7
17700      SUM2=SUM2+AE(2,J)*PMIN(J,2)
17800  70   CONTINUE
17900      B(3)=YMIN(2)-AE(2,8)*WVMIN(2)-SUM2
18000      SUM=0.0
18100      DO83 J=1,7
18200      SUM=SUM+AE(2,J)*P(J,2)
18300  83   CONTINUE
18350 C::::::::::
18375 C      PEAK LOAD FORECAST BASED ON WEATHER MODEL
18387 C::::::::::
18400      YW=B(3)+SUM+AE(2,8)*WV(3)
18500      IF(MCOUNT.EQ.0) GO TO 89
18600      SQ=Y(2)-YOLD
18700      WVAR=WVAR+(SQ**2-WVAR)/FLOAT(MCOUNT)
18800  89   MCOUNT=MCOUNT+1
18900      YOLD=YW
19000      MCOUNT=MCOUNT+1
19100      REWIND 6
19200      WRITE(6,*) MCOUNT,MCOUNT,YOLD,WVAR
19300  *    PRINT80,WVAR
19400  80   FORMAT(10X,'WVAR',F12.5/)

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00100 *****
00200 C      PROGRAM FOR IDENTIFICATION AND INITIALISATION
00300 C      OF PARAMETERS OF STOCHASTIC LOAD MODEL AND
00350 C      WEATHER LOAD MODEL
00400 *****
00500 C      IF INTERMEDIATE RESULTS ARE DESIRED THEN REMOVE
00600 C      '*' FROM THE FIRST COLUMN OF RESPECTIVE
00650 C      PRINT STATEMENTS IN THE PROGRAM
00675 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
00700      DIMENSION Z(365,24),T(365,24),WC(365,24),TOW0(24,24),
00800      1 TOW1(24,24),X(365,24),A(24,24),AT(24,24),
00900      2 ATO(24,24),TOINV(24,24),Q(24,24),ATOAT(24,24),
01000      3 TMP(365),WV(2,365),P(7,365),Y(365),POBAR(7),
01100      4 YMIN(365),WVMIN(2,365),PMIN(7,365),DELY(365),
01200      5 PHAIT(365,9),A0(9),AE(365,9),
01300      6 AZERO(9),PEE(365,9,9),TAM1(9,9),HMDTY(365),
01400      7 P0(9,9),POINV(81),JL(81),JM(81),WVOBAR(2)
01500 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
01600 C      Z(N,J)          LOAD IN AMPERS ON N TH DAY
01700 C      AND JTH HOUR
01800 C      HMDTY(N)        HUMIDITY ON N TH DAY
01900 C      TMP(N)          TEMPERATURE ON N TH DAY
02000 C      Y(N)            PEAK LOAD ON N TH DAY
02100 C      NDAY           NUMBER OF DAYS FOR WHICH LOAD
02200 C                    DATA IS AVAILABLE
02300 C      NHOOR           HOURS PER DAY,24
02400 C      N1             LOAD DATA FOR FIRST TO N1 DAY
02500 C                    CONSTITUTE THE FIRST PART OF LOAD DATA
02600 C      N2             LOAD DATA FOR N1+1 TO N2 DAY
02700 C                    CONSTITUTE THE SECOND PART OF LOAD DATA
02800 C                    THIRD PART OF LOAD DATA IS FROM N2+1
02900 C                    TO NDAY
02950 C      LDAY           DAY ON THE LAST DATE OF AVAILABLE DATA
02975 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
03000      OPEN(UNIT=1,FILE='LOD1.DAT')
03100      OPEN(UNIT=4,DEVICE='DSK',FILE='RES1.DAT')
03200      OPEN(UNIT=7,DEVICE='DSK',FILE='RES2.DAT')

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03300      OPEN(UNIT=9,DEVICE='DSK',FILE='RES3.DAT')
03400      OPEN(UNIT=10,DEVICE='DSK',FILE='RES4.DAT')
03500      READ(1,*) NHOUR,NDAY,N1,N2,ALPHA,BEETA,TS,TW,LDAY
03600      READ(1,*)((Z(I,J),J=1,NHOUR),I=1,NDAY),(TMP(I),I=1,NDAY)
03700      READ(1,*) (HMDTY(I),I=1,NDAY)
03800 *****
03850 C      SECTION 1: STOCHASTIC LOAD MODEL
03875 C      IDENTIFICATION OF PARAMETERS
03887 *****
03900 C      CALCULATION OF BASIC LOAD COMPONENTS
04000 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04100      DO10 I=7,NDAY
04200      DO 10 J=1,NHOUR
04300      SUM=0.0
04400      DO5 K=(I-6),I
04500      SUM=SUM+Z(K,J)
04600 5      CONTINUE
04700      T(I,J)=SUM/7.
04800 10     CONTINUE
04900 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
05000 C      CALCULATION OF BASIC LOAD COMPONENTS FOR THE
05100 C      FIRST SIX DAYS OF AVAILABLE DATA
05200 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
05300      DO 20 I=1,6
05400      DO20 J=1,NHOUR
05500      T(I,J)=T(7,J)
05600 20     CONTINUE
05700 *      PRINT49
05800 49     FORMAT(T10,'BASIC LOAD COMPONENT')
05900 *      PRINT31.( T(I,J),J=1,NHOUR),I=1,NDAY)
06000 31     FORMAT(5X,3(5X,8F13.5/)/)
06100 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
06200 C      CALCULATION OF WEEKLY LOAD COMPONENTS
06300 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
06400      DO30 K=1,7
06500      DO 30 J=1,NHOUR
06600      WC(K,J)=Z(K,J)-T(7,J)

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06700 30 CONTINUE
06800 DO 35 I=8,NDAY
06900 DO 35 J=1,NHOUR
07000 WC(I,J)=WC((I-7),J)+ALPHA*(Z(I,J)-T(I,J)-WC((I-7),J))
07100 35 CONTINUE
07200 * PRINT51
07300 51 FORMAT(T10,'WEEKLY COMPONENT')
07400 * PRINT31,((WC(I,J),J=1,NHOUR),I=1,NDAY)
07500 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
07600 C CALCULATION OF RESIDUAL COMPONENTS
07700 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
07800 DO40 I=1,NDAY
07900 DO40 J=1,NHOUR
08000 X(I,J)=Z(I,J)-T(I,J)-WC(I,J)
08100 40 CONTINUE
08200 * PRINT71
08300 71 FORMAT(T10,'RESIDUAL COMPONENT')
08400 * PRINT31,((X(I,J),J=1,NHOUR),I=1,NDAY)
08500 WRITE(4,*) ((Z(I,J),J=1,NHOUR),I=(NDAY-5),NDAY)
08600 WRITE(4,*) ((WC(I,J),J=1,NHOUR),I=(NDAY-6),NDAY)
08700 WRITE(4,*) (X(NDAY,J),J=1,NHOUR)
08800 F=FLOAT(NDAY)
08900 DO50 J=1,NHOUR
09000 DO50 K=1,NHOUR
09100 TOW0(J,K)=0.0
09200 DO60 I=1,NDAY
09300 TOW0(J,K)=TOW0(J,K)+X(I,J)*X(I,K)
09400 60 CONTINUE
09500 TOW0(J,K)=TOW0(J,K)/F
09600 50 CONTINUE
09700 * PRINT33
09800 33 FORMAT(20X,'TOW0')
09900 * PRINT31,((TOW0(J,K),K=1,NHOUR),J=1,NHOUR)
10000 DO70 J=1,NHOUR
10100 DO 70 K=1,NHOUR
10200 TOW1(J,K)=0.0
10300 DO 65 I=2,NDAY

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10400      TOW1(J,K)=TOW1(J,K)+X(I,J)*X((I-1),K)
10500  65      CONTINUE
10600      TOW1(J,K)=TOW1(J,K)/(F-1.0)
10700  70      CONTINUE
10800  *      PRINT69
10900  69      FORMAT(T15,'TOW1')
11000  *      PRINT31,((TOW1(J,K),K=1,NHOUR),J=1,NHOUR)
11100      WRITE(7,*) ((TOW0(I,J),J=1,NHOUR),I=1,NHOUR)
11200      WRITE(7,*) ((TOW1(J,J),J=1,NHOUR),I=1,NHOUR)
11300      NH=NHOUR
11400      CALL MATINV(TOW0,TOINV,NH)
11500      CALL MATMUL(TOW1,TOINV,A,NH,NH,NH)
11600  *      PRINT6
11700  6      FORMAT(/T10,'A'/)
11800  *      PRINT300,((A(I,J),J=1,NHOUR),I=1,NHOUR)
11900  300    FORMAT(5X,4(5X,6E15.7/))
12000      DO80 I=1,NHOUR
12100      DO80 J=1,NHOUR
12200      AT(I,J)=A(J,I)
12300  80      CONTINUE
12400      CALL MATMUL(A,TOW0,ATO,NH,NH,NH)
12500      CALL MATMUL(ATO,AT,ATOAT,NH,NH,NH)
12600      DO90 J=1,NHOUR
12700      DO90 K=1,NHOUR
12800      Q(J,K)=TOW0(J,K)-ATOAT(J,K)
12900  90      CONTINUE
13000  *      PRINT7
13100  7      FORMAT(/T10,'Q'/)
13200  *      PRINT300,((Q(J,K),K=1,NHOUR),J=1,NHOUR)
13300 *****
13400 CC      SECTION 2: WEATHER LOAD MODEL
13500 CC      INITIALISATION OF PARAMETERS
13600 *****
13700 C      CALCULATION OF DAILY PEAK LOAD
13800 C::::::::::::::::::::::::::::::::::::::::::::::::::
13900      DO4 I=1,NDAY
14000      Y(I)=0.0

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14100      DO4 J=1,NHOUR
14200      IF(Z(I,J).GT.Y(T)) Y(I)=Z(I,J)
14300  4      CONTINUE
14400 C:.....
14500 C      NON-LINEAR TRANSFORMATION OF THE WEATHER VARIABLE
14600 C:.....
14700      DO8 I=1,NDAY
14800      IF(TMP(I).GE.TS) WV(1,I)=TMP(I)-TS
14900      IF(TMP(I).GT.TW.AND.TMP(I).LT.TS) WV(1,I)=0.0
15000      IF(TMP(I).LE.TW) WV(1,I)=TW-TMP(I)
15100      WV(2,I)=100.0-HMDTY(I)
15200  8      CONTINUE
15300 *      PRINT296
15400  296    FORMAT(38X,'WV(I,I)'/)
15500 *      PRINT308,(( WV(I, I),I=1,NDAY),J=1,2)
15600  308    FORMAT(30X,2E13.5/)
15700 C:.....
15800 C      CALCULATION OF P(J,I)
15900 C:.....
16000      NDAY=NDAY/7
16100      KDAY=NDAY-(NDAY*7)
16200      IF(LDAY.GT.KDAY) GO TO 12
16300      LDAY=LDAY+7
16400  12     IDAY=LDAY-KDAY
16500      IDD=IDAY+1
16600      DO16 K=1,NDAY
16700      IDAY=IDAY+1
16800      IF(IDAY.GT.7) IDAY=IDAY-7
16900      DO16 J=1,7
17000      IF(J.EQ.IDAY) GO TO 24
17100      P(J,K)=0.0
17200      GO TO 16
17300  24     P(J,K)=1.0
17400  16     CONTINUE
17500 *      PRINT 184
17600  184    FORMAT(/T20,'P(J,K)'/)
17700 *      PRINT 188,((P(J,K),J=1,7),K=1,NDAY)

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17800 188   FORMAT(T5.7F5.1)
17850 C:.....:
17900 C     CALCULATOIN OF INITIAL VALUES, YOBAR, WVOBAR(K)
17950 C     AND POBAR(K)
17975 C:.....:
18000     YOBAR=0.0
18100     DO28 N=1, N1
18200     YOBAR=YOBAR+Y(N)
18300 28    CONTINUE
18400     G=FLOAT(N1)
18500     YOBAR=YOBAR/G
18600     DO32 K=1, 7
18700     POBAR(K)=0.0
18800     DO36 N=1, N1
18900     POBAR(K)=POBAR(K)+P(K, N)
19000 36    CONTINUE
19100     POBAR(K)=POBAR(K)/G
19200 32    CONTINUE
19300     DO34 K=1, 2
19400     WVOBAR(K)=0.0
19500     DO39 N=1, N1
19600     WVOBAR(K)=WVOBAR(K)+WV(K, N)
19700 39    CONTINUE
19800     WVOBAR(K)=WVOBAR(K)/G
19900 34    CONTINUE
20000 *    PRINT228, YOBAR
20100 228   FORMAT(/15X, 2F12.6)
20200 *    PRINT252
20300 252   FORMAT(30X, 'POBAR(K)'/)
20400 *    PRINT256, (POBAR(K), K=1, 7)
20500 256   FORMAT(27X, E15.7)
20550 C:.....:
20600 C     CALCULATION OF MEAN VALUES
20700 C     FOR THE SUCCESSTVE DAYS
20750 C:.....:
20800     YHIN(N1)=YOBAR
20900     DO45 K=1, 2

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21000      WVMIN(K,N1)=WV0BAR(K)
21100  45    CONTINUE
21200      DO44 I=1,7
21300      PMIN(I,N1)=P0BAR(I)
21400  44    CONTINUE
21500      N1DAY=NDAY+1
21600      N11DAY=N1+1
21700      DO48 N=(N1+2),N1DAY
21800      YMIN(N-1)=ALPHA*Y(N-1)+(1.0-ALPHA)*YMIN(N-2)
21900      DO53 K=1,2
22000      WVMIN(K,(N-1))=ALPHA*WV(K,(N-1))+(1.0-ALPHA)*
22100      1WVMIN(K,(N-2))
22200  53    CONTINUE
22300      DO52 I=1,7
22400      PMIN(I,(N-1))=ALPHA*P(I,(N-1))+(1.0-ALPHA)*PMIN(I,(N-2))
22500  52    CONTINUE
22600  48    CONTINUE
22700  *     PRINT248,(YMIN(N),N=N1,NDAY)
22800  248   FORMAT(/15X,'YMIN',5X,E15.7)
22900  *     PRINT249,((WVMIN(K,N),K=1,2),N=N1,NDAY)
23000  249   FORMAT(/15X,'WVMIN',5X,2E15.7)
23100  *     PRINT270
23200  270   FORMAT(/30X,'PMIN(I,J)')/
23300  *     PRINT274,((PMIN(I,J),I=1,7),J=N1,NDAY)
23400  274   FORMAT(5X,7E12.5)
23500      WRITE(9,*) YMIN(NDAY),(WVMIN(K,NDAY),K=1,2),
23600  1     (PMIN(J,NDAY),J=1,7)
23700      WRITE(9,*) (P(J,NDAY),J=1,7)
23750  C:::::
23800  C     CALCULATION OF DELTA Y(N)
23850  C:::::
23900      DO56 N=N11DAY,NDAY
24000      DELY(N)=Y(N)-YMIN(N-1)
24100  56    CONTINUE
24200  *     PRINT280
24300  280   FORMAT(30X,'DELY(N)')/
24400  *     PRINT284,(DELY(N),N=N11DAY,NDAY)

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24500 284   FORMAT(25X,2E13.5/)
24550 C:.....:
24600 CC    MATRIX PHAI AND ITS TRANSPOSE
24650 C:.....:
24700      DO72 N=N11DAY,NDAY
24800      DO72 I=1,9
24900      IF(I.GT.7) GO TO 76
25000      PHAIT(N,I)=P(I,N)-PMIN(I,(N-1))
25100      GO TO 72
25200 76    JD=I-7
25300      PHAIT(N,I)=WV(JD,N)-WVMIN(JD,(N-1))
25400 72    CONTINUE
25500 *    PRINT212
25600 212   FORMAT(25X,'PHAIT(N,I)'/)
25700 *    PRINT216,((PHAIT(N,I),I=1,9),N=N11DAY,NDAY)
25800 216   FORMAT(5X,9F12.6/)
25900 CC    CALCULATION OF P0
26000      NC=9
26100      DO82 J=1,NC
26200      DO82 K=1,NC
26300      P0(J,K)=0.0
26400      DO84 N=N11DAY,N2
26500      P0(J,K)=P0(J,K)+PHAIT(N,J)*PHAIT(N,K)
26600 84    CONTINUE
26700 82    CONTINUE
27200      CALL ARRAY(2,NC,NC,NC,NC,P0INV,P0)
27300      CALL MINV(P0INV,NC,C,JL,JM)
27400 *    PRINT288
27500 288   FORMAT(25X,'DETERMINANT' '/')
27600 *    PRINT292,C
27700 292   FORMAT(35X,E13.5/)
27800      CALL ARRAY(1,NC,NC,NC,NC,P0INV,P0)
27900 *    PRINT240
28000 240   FORMAT(30X,'P0(I,J)'/)
28300 *    PRINT244,((P0(I,J),J=1,NC),I=1,NC)
28400 244   FORMAT(5X,9(E12.5))
28450 C:.....:

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CALCULATION OF A(O)

.....

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DO89 J=1,NC
A0(J)=0.0
DO88 N=N11DAY,N2
A0(J)=A0(J)+PHAIT(N,J)*DELY(N)
8 CONTINUE
9 CONTINUE
PRINT264
54 FORMAT(/30X,'A0(J)'/)
PRINT260,(A0(J),J=1,NC)
50 FORMAT(25X,E14.6)
51 CONTINUE
DO91 I=1,NC
AZERO(I)=0.0
DO91 J=1,NC
AZERO(I)=AZERO(I)+PO(I,J)*A0(J)
1 CONTINUE
PRINT232
32 FORMAT(30X,'AZERO(J)'/)
PRINT236,(AZERO(J),J=1,NC)
16 FORMAT(25X,E15.7)

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.....

CALCULATION OF PEE MATRIX FOR SUCCESSIVE DAYS

.....

```

DO92 I=1,NC
DO92 J=1,NC
PEE(N2,I,J)=PO(I,J)
1 CONTINUE
N21DAY=N2+1
DO152 N=N21DAY,NDAY
SUM4=0.0
DO124 I=1,NC
SUM3=0.0
DO128 J=1,NC
SUM3=SUM3+PHAIT(N,J)*PEE((N-1),J,I)
8 CONTINUE

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31900      SUM4=SUM4+SUM3*PHAIT(N,I)
32000  124   CONTINUE
32100      SUM4=1.0+SUM4/BEETA
32200      SUM4=1.0/SUM4
32300      DO132 I=1,NC
32400      SUM5=0.0
32500      DO136 J=1,NC
32600      SUM5=SUM5+PEE((N-1),I)*PHAIT(N,J)
32700  136   CONTINUE
32800      DO140 J=1,NC
32900      TAM1(I,J)=SUM5*PHAIT(N,J)
33000  140   CONTINUE
33100  132   CONTINUE
33200      DO148 I=1,NC
33300      DO148 K=1,NC
33400      PEE(N,I,K)=0.0
33500      DO144 J=1,NC
33600      PEE(N,I,K)=PEE(N,I,K)+TAM1(I,J)*PEE((N-1),J,K)
33700  144   CONTINUE
33800      PEE(N,I,K)=PEE(N,I,K)/(BEETA**2)
33900      PEE(N,I,K)=PEE((N-1),I,K)/BEETA-PEE(N,I,K)*SUM4
34000  148   CONTINUE
34100  152   CONTINUE
34200 *      PRINT204
34300  204   FORMAT(T20,'PEE(N,I,K)')
34400 *      PRINT208,(((PEE(N,I,K),K=1,NC),I=1,NC),N=N2,NDAY)
34500  208   FORMAT(5X,9(5X,9E12.5//))
34550 C:.....:
34600 CC      CALCULATION OF AE MATRIX FOR SUCCESSIVE DAYS
34650 C:.....:
34700      DO156 J=1,NC
34800      AE(N2,J)=AZERO(J)
34900  156   CONTINUE
35000      DO176 N=N21DAY,NDAY
35100      SUM7=0.0
35200      DO164 J=1,NC
35300      SUM7=SUM7+PHAIT(N,J)*AE((N-1),J)

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35400 164 CONTINUE
35500 SUM7=DELY(N)-SUM7
35600 DO168 I=1,NC
35700 AE(N,I)=0.0
35800 DO172 J=1,NC
35900 AE(N,I)=AE(N,I)+PEE(N,I,J)*PHAIT(N,J)
36000 172 CONTINUE
36100 AE(N,I)=AE(N,I)*SUM7+AE((N-1),I)
36200 168 CONTINUE
36300 176 CONTINUE
36400 WRITE(10,*) ((PRE(NDAY,I,J),J=1,NC),I=1,NC)
36500 WRITE(10,*) (AE(NDAY,J),J=1,NC)
36600 * PRINT180
36700 180 FORMAT(15X/T15,'AE'/)
36800 * PRINT185,((AE(I,J),J=1,NC),I=N2,NDAY)
36900 185 FORMAT(5X,9E12.5/)
37000 STOP
37100 END
37200 C.....
37250 C.....
37300 SUBROUTINE MATINV(X,A,L)
37350 C THIS SUBROUTINE CALCULATES THE INVERSE
37375 C OF MATRIX,X.
37387 C ORIGINAL MATRIX,X IS NOT DESTROYED
37400 DIMENSION X(24,24),A(24,24),B(24,48)
37500 DO5000 J=1,L
37600 DO5000 K=1,L
37700 B(J,K)=X(J,K)
37800 5000 CONTINUE
37900 N1=2*L
38000 N2=L+1
38100 DO101 M=1,L
38200 DO201 N=N2,M1
38300 B(N,M)=0.0
38400 201 M1=M+1
38500 101 B(M,M1)=1.0
38600 DO450 J=1,L

```

```

38700      IF(B(J,J).EQ.0) GO TO 102
38800      DO450 M=1,L
38900      IF(M.EQ.J) GO TO 450
39000      C=B(M,J)
39100      C=C/B(J,J)
39200      DO105 N=1,N1
39300  105  B(M,N)=B(M,N)-B(J,N)*C
39400  450  CONTINUE
39900      DO106 J=1,L
40000      R=1./B(J,J)
40100      DO106 N=N2,N1
40200  106  B(J,N)=B(J,N)*R
40300      DO1001 J=1,L
40400      DO1001 K=1,L
40500  1001 A(J,K)=B(J,K+L)
40700  102  RETURN
40800      END
40850 C ::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
40875 C ::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
40900      SUBROUTINE MATMUL(R,S,U,L1,L2,L3)
40950 C      THIS SUBROUTINE CALCULATES THE MULTIPLICATION
40975 C      OF TWO MATRICES R AND S.
40987 C      U IS THE RESULTANT MATRIX
40993 C      L1 IS THE NUMBER OF ROWS IN MATRIX R
40996 C      L2 IS THE NUMBER OF COULMNS IN MATRIX R
40998 C      OR NUMBER OF ROWS IN MATRI S.
40999 C      L3 IS THE NUMBER OF COULMNS IN MATRIX S
41000      DIMENSION R(24,24),S(24,24),U(24,24)
41100      DO13 I=1,L1
41200      DO13 J=1,L3
41300      U(I,J)=0.0
41400      DO19 K=1,L2
41500      U(I,J)=U(I,J)+R(I,K)*S(K,J)
41600  19    CONTINUE
41700  13    CONTINUE
41800      RETURN
41900      END

```

```

41950 C:.....:
41975 C:.....:
42000     SUBROUTINE ARRAY (MODE,I,J,N,M,S,D)
42100     DIMENSION S(81) ,D(81)
42300     NI=N-I
42500 C     TEST TYPE OF CONVERSION
42700     IF(MODE=1) 100, 100, 120
42900 C     CONVERT FROM SINGLE TO DOUBLE DIMENSION
43100 100 IJ=I*J+1
43200     NM=N*J+1
43300     DO 110 K=1,J
43400     NM=NM-NI
43500     DO 110 L=1,I
43600     IJ=IJ-1
43700     NM=NM-1
43800 110 D(NM)=S(IJ)
43900     GO TO 140
44100 C     CONVERT FROM DOUBLE TO SINGLE DIMENSION
44300 120 IJ=0
44400     NM=0
44500     DO 130 K=1,J
44600     DO 125 L=1,I
44700     IJ=IJ+1
44800     NM=NM+1
44900 125 S(IJ)=D(NM)
45000 130 NM=NM+NI
45200 140 RETURN
45300     END
45350 C:.....:
45375 C:.....:
45400     SUBROUTINE MINV(A,N,D,L,M)
45500     DIMENSION A(81),L(81),M(81)
45600 C.....:
45900 C     IF A DOUBLE PRECISION VERSION OF THIS ROUTINE
45950 C     IS DESIRED,THE C IN COULMN 1 SHOULD BE REMOVED
46000 C     FROM THE DOUBLE PRECISION STATEMENT WHICH FOLLOWS
46300 C     DOUBLE PRECISION A,D,BIGA,HOLD

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46500 C      THE C MUST ALSO BE REMOVED FROM DOUBLE PRECISION
46550 C      STATEMENTS APPEARING IN OTHER ROUTINES USED IN
46575 C      CONJUCTION WITH THIS ROUTINE.
46900 C      THE DOUBLE PRECISION VERSION OF THIS SUBROUTINE
46950 C      MUST ALSO CONTAIN DOUBLE PRECISION FORTRAN
47000 C      FUNCTIONS.  ABS IN STATEMENT
47100 C      10 MUST BE CHANGED TO DABS.
47300 C      .....
47500 C      SEARCH FOR LARGEST ELEMENT
47700      D=1.0
47800      NK=-N
47900      DO 80 K=1,N
48000      NK=NK+N
48100      L(K)=K
48200      M(K)=K
48300      KK=NK+K
48400      BIGA=A(KK)
48500      DO 20 J=K,N
48600      IZ=N*(J-1)
48700      DO 20 I=K,N
48800      IJ=IZ+I
48900  10      IF(ABS(BIGA)-ABS(A(IJ))) 15,20,20
49000  15      BIGA=A(IJ)
49100      L(K)=I
49200      M(K)=J
49300  20      CONTINUE
49500 C      INTERCHANGE ROWS
49700      J=L(K)
49800      IF(J-K) 35,35,25
49900  25      KI=K-N
50000      DO 30 I=1,N
50100      KI=KI+N
50200      HOLD=-A(KI)
50300      JI=KI-K+J
50400      A(KI)=A(JI)
50500  30      A(JI)=HOLD
50700 C      INTERCHANGE COLUMNS

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50900      35 I=M(K)
51000      IF(I-K) 45,45,38
51100      38 JP=N*(I-1)
51200      DO 40 J=1,N
51300      JK=NK+J
51400      JI=JP+J
51500      HOLD=-A(JK)
51600      A(JK)=A(JI)
51700      40 A(JI) =HOLD
51900 C      DIVIDE COLUMN BY MINUS PIVOT (VALUE OF PIVOT ELEMENT IS
52000 C      CONTAINED IN BIGA)
52200      45 IF(BIGA) 48,46,48
52300      46 D=0.0
52400      RETURN
52500      48 DO 55 I=1,N
52600      IF(I-K) 50,55,50
52700      50 IK=NK+I
52800      A(IK)=A(IK)/(-BIGA)
52900      55 CONTINUE
53100 C      REDUCE MATRIX
53300      DO 65 I=1,N
53400      IK=NK+I
53500      HOLD=A(IK)
53600      IJ=I-N
53700      DO 65 J=1,N
53800      IJ=IJ+N
53900      IF(I-K) 60,65,60
54000      60 IF(J-K) 62,65,62
54100      62 KJ=IJ-I+K
54200      A(IJ)=HOLD*A(KJ)+A(IJ)
54300      65 CONTINUE
54500 C      DIVIDE ROW BY PIVOT
54700      KJ=K-N
54800      DO 75 J=1,N
54900      KJ=KJ+N
55000      IF(J-K) 70,75,70
55100      70 A(KJ)=A(KJ)/BIGA

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55200      75 CONTINUE
55400 C          PRODUCT OF PIVOTS
55600          D=D*BIGA
55800 C          REPLACE PIVOT BY RECIPROCAL
56000          A(KK)=1.0/BIGA
56100      80 CONTINUE
56300 C          FINAL ROW AND COLUMN INTERCHANGE
56500          K=N
56600      100 K=(K-1)
56700          IF(K) 150,150,105
56800      105 I=L(K)
56900          IF(I-K) 120,120,108
57000      108 JQ=N*(K-1)
57100          JR=N*(I-1)
57200          DO 110 J=1,N
57300          JK=JQ+J
57400          HOLD=A(JK)
57500          JI=JR+J
57600          A(JK)=-A(JI)
57700      110 A(JI) =HOLD
57800      120 J=M(K)
57900          IF(J-K) 100,100,125
58000      125 KI=K-N
58100          DO 130 I=1,N
58200          KI=KI+N
58300          HOLD=A(KI)
58400          JI=KI-K+J
58500          A(KI)=-A(JI)
58600      130 A(JI) =HOLD
58700          GO TO 100
58800      150 RETURN
58900          END

```

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00100 *****
00200 CC      PROGRAM FOR ADAPTIVE FORECASTING
00300 *****
00400      DIMENSION Z(8,24),WC(8,24),TMP(3),WV(2,3),Y(2),
00500      1 X(3,24),TOW0(24,24),TOW1(24,24),T(24),P(7,2),
00600      2 A(24,24),AT(24,24),TOINV(24,24),ATO(24,24),HMDTY(3),
00700      3 DELY(2),TAM1(9,9),PEE(2,9,9),AE(2,9),B(3),
00800      4 ATOAT(24,24),Q(24,24),ZS(24),SVAR(24),YMIN(2),
00900      5 WVMIN(2,2),PMIN(7,2),PHAIT(2,9),CVAR(24),ZC(24)
00950 C::::::::::
01000      OPEN(UNIT=3,DEVICE='DSK',FILE='INP1.DAT')
01100      OPEN(UNIT=4,DEVICE='DSK',FILE='RES1.DAT')
01200      OPEN(UNIT=5,DEVICE='DSK',FILE='INP2.DAT')
01300      OPEN(UNIT=6,DEVICE='DSK',FILE='INTL.DAT')
01400      OPEN(UNIT=7,DEVICE='DSK',FILE='RES2.DAT')
01500      OPEN(UNIT=9,DEVICE='DSK',FILE='RES3.DAT')
01600      OPEN(UNIT=10,DEVICE='DSK',FILE='RES4.DAT')
01650 C::::::::::
01700      READ(3,*) NH,ALPHA,BEETA,TS,TW
01800      READ(4,*)((Z(I,J),J=1,NH),I=2,7)
01900      READ(4,*)((WC(I,J),J=1,NH),I=1,7)
02000      READ(4,*)(X(1,J),J=1,NH)
02100      READ(5,*)(Z(8,J),J=1,NH),TMP(2),TMP(3),HMDTY(2),HMDTY(3)
02200      READ(6,*) NCOUNT,MCOUNT,YOLD,WVAR
02300      READ(7,*)((TOW0(I,J),J=1,NH),I=1,NH),
02400      1 ((TOW1(I,J),J=1,NH),I=1,NH)
02500      READ(9,*) YMIN(1),(WVMIN(K,1),K=1,2),(PMIN(J,1),J=1,7)
02600      READ(9,*)(P(J,1),J=1,7)
02700      READ(10,*)((PEE(1,I,J),J=1,9),I=1,9),(AE(1,J),J=1,9)
02750 C::::::::::
02775 C      UPDATE BASIC , WEEKLY PATTERN COMPONENT AND
02787 C      CALCULATE RESIDUAL COMPONENT
02793 C::::::::::
02800      DO13 J=1,NH
02900      T(J)=0.0
03000      DO15 I=2,8
03100      T(J)=T(J)+Z(I,J)

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03200 15      CONTINUE
03300      T(J)=T(J)/7.0
03400      WC(8,J)=WC(1,J)+ALPHA*(Z(8,J)-T(J)-WC(1,J))
03500      X(2,J)=Z(8,J)-T(J)-WC(8,J)
03600 13      CONTINUE
03700 *      PRINT 14
03800 14      FORMAT(10X,'BASIC LOAD COMPONENT'/)
03900 *      PRINT16,(T(J),J=1,NH)
04000 16      FORMAT(5X,8F12.6)
04050 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04075 C      CALCULATION OF PEAK LOAD
04087 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04100      Y(2)=0.0
04200      DO49 J=1,NH
04300      IF(Z(8,J),GT.Y(2)) Y(2)=Z(8,J)
04400 49      CONTINUE
04450 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04475 C      WEATHER VARIABLE TRANSFORMATION
04487 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04500      DO46 I=2,3
04600      IF(TMP(I).GE.TS) WV(1,I)=TMP(I)-TS
04700      IF(TMP(I).LT.TS.AND.TMP(I).GT.TW) WV(1,I)=0.0
04800      IF(TMP(I).LE.TW) WV(1,I)=TW-TMP(I)
04900 46      CONTINUE
04920      WV(2,2)=100.0-HMDTY(2)
04940      WV(2,3)=100.0-HMDTY(3)
04970 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04985 C      CALCULATION OF P(J,K)
04992 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
05000      DO53 J=1,7
05100      M=J+1
05200      IF(J.EQ.7) M=1
05300      P(M,2)=P(J,1)
05400 53      CONTINUE
05500 *      PRINT 211,(P(M,2),M=1,7)
05600 211     FORMAT(5X,'P(M,2)',5X,7F3.1)
05700      COUNT=FLOAT(NCOUNT)

```

```

03200 15      CONTINUE
03300      T(J)=T(J)/7.0
03400      WC(8,J)=WC(1,J)+ALPHA*(Z(8,J)-T(J)-WC(1,J))
03500      X(2,J)=Z(8,J)-T(J)-WC(8,J)
03600 13      CONTINUE
03700 *      PRINT 14
03800 14      FORMAT(10X,'BASIC LOAD COMPONENT'/)
03900 *      PRINT16,(T(J),J=1,NH)
04000 16      FORMAT(5X,8F12.6)
04050 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04075 C      CALCULATION OF PEAK LOAD
04087 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04100      Y(2)=0.0
04200      DO49 J=1,NH
04300      IF(Z(8,J).GT.Y(2)) Y(2)=Z(8,J)
04400 49      CONTINUE
04450 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04475 C      WEATHER VARIABLE TRANSFORMATION
04487 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04500      DO46 I=2,3
04600      IF(TMP(I).GE.TS) WV(1,I)=TMP(I)-TS
04700      IF(TMP(I).LT.TS.AND.TMP(I).GT.TW) WV(1,I)=0.0
04800      IF(TMP(I).LE.TW) WV(1,I)=TW-TMP(I)
04900 46      CONTINUE
04920      WV(2,2)=100.0-HMDTY(2)
04940      WV(2,3)=100.0-HMDTY(3)
04970 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
04985 C      CALCULATION OF P(J,K)
04992 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
05000      DO53 J=1,7
05100      M=J+1
05200      IF(J.EQ.7) M=1
05300      P(M,2)=P(J,1)
05400 53      CONTINUE
05500 *      PRINT 211,(P(M,2),M=1,7)
05600 211     FORMAT(5X,'P(M,2)',5X,7F3.1)
05700      COUNT=FLOAT(NCOUNT)

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05750 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
05775 C      UPDATE 'A' AND 'Q' MATRIX
05787 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
05800      DO17 J=1,NH
05900      DO17 K=1,NH
06000      TOW0(J,K)=TOW0(J,K)+(X(2,J)*X(2,K)-TOW0(J,K))/COUNT
06100      TOW1(J,K)=TOW1(J,K)+(X(2,J)*X(1,K)-TOW1(J,K))/
06200      2 (COUNT-1.0)
06300  17  CONTINUE
06400      CALL MATINV(TOW0,TOINV,NH)
06500      CALL MATMUL(TOW1,TOINV,A,NH,NH,NH)
06600      DO21 I=1,NH
06700      DO21 J=1,NH
06800      AT(I,J)=A(J,I)
06900  21  CONTINUE
07000      CALL MATMUL(A,TOW0,ATO,NH,NH,NH)
07100      CALL MATMUL(ATO,AT,ATOAT,NH,NH,NH)
07200      DO23 J=1,NH
07300      DO23 K=1,NH
07400      Q(J,K)=TOW0(J,K)-ATOAT(J,K)
07500  23  CONTINUE
07550 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
07600 CC      FORECAST BASED ON STOCHASTIC MODEL
07650 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
07700      DO27 I=1,NH
07800      X(3,I)=0.0
07900      DO29 J=1,NH
08000      X(3,I)=X(3,I)+A(I,J)*X(2,J)
08100  29  CONTINUE
08200      ZS(I)=T(I)+WC(2,I)+X(3,I)
08300  27  CONTINUE
08350 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
08375 C      HOUR CORRESPONDING TO PEAK LOAD
08387 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
08400      ZSP=0.0
08500      DO35 J=1,NH
08600      IF(ZS(J).GT.ZSP) ZSP=ZS(J)

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08700 35    CONTINUE
08800      DO36 J=1,NH
08900      IF(ZS(J).EQ.ZSP) KP=J
09000 36    CONTINUE
09050 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
09075 C      STOCHASTIC VARIANCE
09087 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
09100      DO37 J=1,NH
09200      SVAR(J)=Q(J,J)
09300 37    CONTINUE
09400      REWIND 4
09500      WRITE(4,*) ((Z(I,J),J=1,NH),I=3,8)
09600      WRITE(4,*) ((WC(I,J),J=1,NH),I=2,8)
09700      WRITE(4,*) (X(2,J),J=1,NH)
09800      REWIND 7
09900      WRITE(7,*) ((TOW0(I,J),J=1,NH),I=1,NH),
10000 4    ((TOW1(I,J),J=1,NH),I=1,NH)
10050 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
10075 C      UPDATE WEATHER LOAD MODEL
10087 C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
10100      YMIN(2)=ALPHA*Y(2)+(1.0-ALPHA)*YMIN(1)
10150      DO 50 K=1,2
10200      WVMIN(K,2)=ALPHA*WV(K,2)+(1.0-ALPHA)*WVMIN(K,1)
10250 50    CONTINUE
10300      DO51 J=1,7
10400      PMIN(J,2)=ALPHA*P(J,2)+(1.0-ALPHA)*PMIN(J,1)
10500 51    CONTINUE
10600 *      PRINT212,YMIN(1),YMIN(2),((WVMIN(K,J),K=1,2),J=1,2)
10700 *      PRINT212,((PMIN(J,I),J=1,7),I=1,2)
10800 212   FORMAT(5X,4F12.4/)
10900      REWIND 9
11000      WRITE(9,*) YMIN(2),(WVMIN(K,2),K=1,2),(PMIN(J,2),J=1,7)
11100      WRITE(9,*) (P(J,2),J=1,7)
11150      NC=9
11200      DO57 J=1,NC
11300      IF(J.GT.7) GO TO 59
11400      PHAIT(2,J)=P(J,2)-PMIN(J,1)

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11500      GO TO 57
11550 59    JD=J-7
11600      PHAIT(2,J)=WV(JD,2)-WVMIN(JD,1)
11700 57    CONTINUE
11800 *     PRINT213,(PHAIT(2,J),J=1,NC)
11900 213   FORMAT(5X,'PHAIT',9E12.5/)
12000      DELY(2)=Y(2)-YMIN(1)
12100      SUM4=0.0
12200      DO61 I=1,NC
12300      SUM3=0.0
12400      DO63 J=1,NC
12500      SUM3=SUM3+PHAIT(2,J)*PEE(1,J,I)
12600 63    CONTINUE
12800      SUM4=SUM4+SUM3*PHAIT(2,I)
13000 61    CONTINUE
13100      SUM4=1.0+SUM4/BEETA
13200      SUM4=1.0/SUM4
13400      DO65 I=1,NC
13500      SUM5=0.0
13600      DO67 J=1,NC
13700      SUM5=SUM5+PEE(1,I,J)*PHAIT(2,J)
13800 67    CONTINUE
13900 *     PRINT216,SUM5
14000      DO69 K=1,NC
14100      TAM1(I,K)=SUM5*PHAIT(2,K)
14200 69    CONTINUE
14300 65    CONTINUE
14400 *     PRINT217,((TAM1(I,J),J=1,NC),I=1,NC)
14500 217   FORMAT(5X,'TAM1',3X,9E13.5)
14600      DO71 I=1,NC
14700      DO71 K=1,NC
14800      PEE(2,I,K)=0.0
14900      DO73 J=1,NC
15000      PEE(2,I,K)=PEE(2,I,K)+TAM1(I,J)*PEE(1,J,K)
15100 73    CONTINUE
15200 *     PRINT218,PEE(2,I,K)
15300 218   FORMAT(5X,'PEE',3X,E13.5)

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```

15400      PEE(2,I,K)=PEE(2,I,K)/(BEETA**2)
15500      PEE(2,I,K)=PEE(1,I,K)/BEETA-PEE(2,I,K)*SUM4
15600  71   CONTINUE
15700      SUM7=0.0
15800      DO75 J=1,NC
15900      SUM7=SUM7+PHAIT(2,J)*AE(1,J)
16000  75   CONTINUE
16100      SUM7=DELY(2)-SUM7
16200      DO77 I=1,NC
16300      AE(2,I)=0.0
16400      DO79 J=1,NC
16500      AE(2,I)=AE(2,I)+PEE(2,I,J)*PHAIT(2,J)
16600  79   CONTINUE
16700      AE(2,I)=AE(2,I)*SUM7+AE(1,I)
16800  77   CONTINUE
16900  *    PRINT72,(AE(2,I),I=1,NC)
17000  72   FORMAT(5X,'AE',3X,9F12.6/)
17100  *    PRINT74,((PEE(2,I,J),J=1,NC),I=1,NC)
17200  74   FORMAT(5X,'PEE',3X,9E13.5/)
17300      REWIND 10
17400      WRITE(10,*)((PEE(2,I,J),J=1,NC),I=1,NC),(AE(2,J),J=1,NC)
17500      SUM2=0.0
17600      DO70 J=1,NC
17700      SUM2=SUM2+AE(2,J)*PMIN(J,2)
17800  70   CONTINUE
17900      B(3)=YMIN(2)-AE(2,8)*WVMIN(1,2)-AE(2,9)*WVMIN(2,2)-SUM2
18000      SUM=0.0
18100      DO83 J=1,7
18200      SUM=SUM+AE(2,J)*P(J,2)
18300  83   CONTINUE
18305  *    PRINT 84,AE(2,8),WV(1,3),AE(2,9),WV(2,3)
18310  84   FORMAT(/3X,'AE(2,8)=' ,F10.6,3X,'WV(1,3)=' ,F10.6,3X,
18315      1  'AE(2,9)=' ,F10.6,3X,'WV(2,3)=' ,F10.6/)
18325  C::::::::::
18337  C      PEAK LOAD FORECAST BASED ON WEATHER MODEL
18343  C::::::::::
18400      YW=B(3)+SUM+AE(2,8)*WV(1,3)+AE(2,9)*WV(2,3)

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LOAD (AMPS.) OBSERVED AT RAJNAGAR SUBSTATION
 FROM 1 AUGUST, 87. TO 10 NOVEMBER, 87. ON 33 KV
 FEEDER SUPPLYING POWER TO ROORKEE TOWN

45.0	40.0	40.0	40.0	45.0	50.0	55.0	55.0
60.0	70.0	70.0	75.0	70.0	70.0	70.0	65.0
60.0	65.0	75.0	80.0	80.0	70.0	60.0	50.0
45.0	40.0	38.0	38.0	40.0	42.0	45.0	50.0
60.0	60.0	70.0	65.0	60.0	60.0	60.0	55.0
55.0	60.0	75.0	80.0	80.0	70.0	50.0	50.0
45.0	40.0	45.0	45.0	50.0	50.0	50.0	52.0
60.0	65.0	70.0	70.0	75.0	75.0	70.0	75.0
75.0	50.0	50.0	65.0	75.0	70.0	50.0	45.0
50.0	50.0	50.0	50.0	48.0	50.0	50.0	52.0
60.0	75.0	75.0	80.0	70.0	75.0	75.0	75.0
70.0	65.0	75.0	85.0	75.0	60.0	50.0	50.0
50.0	45.0	45.0	48.0	50.0	50.0	50.0	45.0
50.0	50.0	50.0	60.0	75.0	50.0	50.0	50.0
50.0	55.0	65.0	90.0	80.0	75.0	60.0	70.0
50.0	55.0	50.0	40.0	40.0	50.0	50.0	50.0
65.0	75.0	80.0	80.0	80.0	70.0	70.0	75.0
75.0	70.0	75.0	90.0	85.0	75.0	60.0	60.0
50.0	50.0	45.0	45.0	50.0	50.0	50.0	50.0
60.0	65.0	60.0	75.0	70.0	70.0	70.0	70.0
60.0	55.0	80.0	100.0	90.0	65.0	60.0	55.0
40.0	40.0	50.0	50.0	45.0	50.0	55.0	50.0
45.0	65.0	60.0	75.0	70.0	60.0	65.0	65.0
65.0	65.0	85.0	90.0	95.0	60.0	50.0	40.0
40.0	45.0	45.0	45.0	50.0	50.0	50.0	60.0
60.0	55.0	65.0	65.0	65.0	65.0	50.0	55.0
55.0	65.0	75.0	90.0	85.0	70.0	50.0	50.0
45.0	45.0	48.0	50.0	50.0	52.0	52.0	52.0
55.0	65.0	78.0	78.0	80.0	75.0	70.0	65.0
75.0	70.0	80.0	100.0	85.0	75.0	55.0	50.0
50.0	50.0	50.0	50.0	50.0	55.0	55.0	65.0
60.0	70.0	70.0	80.0	80.0	75.0	75.0	75.0
80.0	75.0	85.0	95.0	90.0	65.0	60.0	50.0
48.0	45.0	40.0	42.0	42.0	45.0	50.0	50.0
55.0	60.0	75.0	70.0	70.0	70.0	70.0	75.0
70.0	60.0	70.0	90.0	85.0	70.0	55.0	50.0
40.0	40.0	38.0	35.0	30.0	28.0	23.0	40.0
45.0	50.0	50.0	50.0	50.0	50.0	56.0	55.0
60.0	60.0	60.0	90.0	75.0	50.0	40.0	40.0
40.0	38.0	36.0	30.0	32.0	35.0	40.0	45.0
60.0	60.0	65.0	65.0	60.0	55.0	60.0	60.0
60.0	60.0	60.0	90.0	80.0	65.0	50.0	45.0
40.0	40.0	45.0	45.0	48.0	50.0	50.0	50.0
50.0	55.0	55.0	60.0	60.0	55.0	50.0	50.0
55.0	60.0	70.0	90.0	90.0	70.0	55.0	50.0
45.0	45.0	48.0	48.0	50.0	50.0	50.0	50.0
60.0	60.0	65.0	65.0	60.0	60.0	65.0	60.0
60.0	65.0	75.0	85.0	80.0	70.0	55.0	45.0

45.0	50.0	40.0	50.0	50.0	50.0	50.0	50.0
55.0	60.0	70.0	60.0	60.0	60.0	60.0	60.0
60.0	60.0	80.0	95.0	90.0	80.0	60.0	50.0
35.0	35.0	40.0	50.0	55.0	55.0	55.0	55.0
60.0	60.0	65.0	70.0	60.0	60.0	60.0	65.0
65.0	70.0	75.0	100.0	90.0	80.0	60.0	55.0
50.0	50.0	55.0	55.0	60.0	60.0	55.0	55.0
55.0	60.0	60.0	65.0	65.0	65.0	60.0	60.0
55.0	50.0	80.0	98.0	95.0	55.0	50.0	50.0
45.0	45.0	50.0	50.0	55.0	55.0	50.0	55.0
50.0	55.0	70.0	70.0	70.0	65.0	65.0	70.0
65.0	62.0	95.0	100.0	75.0	75.0	60.0	50.0
40.0	35.0	50.0	50.0	50.0	50.0	50.0	50.0
55.0	60.0	65.0	65.0	65.0	60.0	60.0	60.0
65.0	60.0	90.0	75.0	90.0	75.0	60.0	50.0
50.0	50.0	50.0	50.0	50.0	55.0	50.0	50.0
50.0	50.0	55.0	55.0	70.0	65.0	70.0	60.0
60.0	65.0	75.0	95.0	90.0	80.0	65.0	50.0
50.0	45.0	48.0	48.0	50.0	50.0	50.0	50.0
52.0	55.0	60.0	60.0	58.0	55.0	50.0	52.0
50.0	60.0	80.0	90.0	85.0	65.0	52.0	45.0
40.0	40.0	40.0	42.0	45.0	50.0	50.0	50.0
55.0	60.0	75.0	75.0	75.0	65.0	65.0	60.0
70.0	60.0	90.0	95.0	90.0	75.0	60.0	50.0
40.0	40.0	40.0	45.0	50.0	55.0	55.0	50.0
65.0	70.0	75.0	75.0	75.0	65.0	75.0	75.0
70.0	70.0	90.0	95.0	90.0	65.0	55.0	50.0
56.0	54.0	50.0	50.0	50.0	50.0	60.0	50.0
65.0	75.0	60.0	75.0	70.0	65.0	60.0	70.0
65.0	60.0	80.0	85.0	35.0	70.0	55.0	50.0
38.0	35.0	35.0	38.0	40.0	50.0	50.0	50.0
60.0	70.0	75.0	80.0	65.0	80.0	70.0	65.0
65.0	65.0	85.0	95.0	90.0	80.0	50.0	45.0
45.0	40.0	40.0	42.0	45.0	50.0	55.0	50.0
45.0	55.0	55.0	50.0	60.0	60.0	65.0	60.0
55.0	55.0	70.0	78.0	70.0	55.0	50.0	45.0
35.0	35.0	35.0	38.0	40.0	45.0	50.0	50.0
60.0	60.0	50.0	60.0	60.0	60.0	60.0	60.0
55.0	60.0	70.0	90.0	60.0	70.0	55.0	50.0
50.0	45.0	50.0	50.0	40.0	40.0	40.0	50.0
55.0	55.0	60.0	65.0	50.0	50.0	50.0	55.0
55.0	60.0	80.0	80.0	65.0	55.0	50.0	40.0
50.0	50.0	45.0	50.0	50.0	50.0	50.0	50.0
60.0	60.0	60.0	50.0	60.0	60.0	60.0	60.0
55.0	55.0	80.0	95.0	60.0	75.0	60.0	45.0
45.0	45.0	50.0	50.0	50.0	50.0	50.0	50.0
50.0	55.0	55.0	60.0	65.0	68.0	60.0	65.0
70.0	60.0	80.0	95.0	90.0	75.0	50.0	45.0

45.0	40.0	40.0	50.0	50.0	50.0	50.0	50.0
55.0	60.0	70.0	60.0	60.0	60.0	60.0	60.0
60.0	60.0	80.0	95.0	90.0	80.0	60.0	50.0
35.0	35.0	40.0	50.0	55.0	55.0	55.0	55.0
60.0	60.0	65.0	70.0	60.0	60.0	60.0	65.0
65.0	70.0	75.0	100.0	90.0	80.0	60.0	55.0
50.0	50.0	55.0	55.0	60.0	60.0	55.0	55.0
55.0	60.0	60.0	65.0	65.0	65.0	60.0	60.0
55.0	50.0	80.0	98.0	95.0	55.0	50.0	50.0
45.0	45.0	50.0	50.0	55.0	55.0	50.0	55.0
50.0	65.0	70.0	70.0	70.0	65.0	65.0	70.0
65.0	62.0	95.0	100.0	75.0	75.0	60.0	50.0
40.0	35.0	50.0	50.0	50.0	50.0	50.0	50.0
55.0	60.0	65.0	65.0	65.0	60.0	60.0	60.0
65.0	60.0	90.0	75.0	90.0	75.0	60.0	50.0
50.0	50.0	50.0	50.0	50.0	55.0	50.0	50.0
50.0	50.0	55.0	55.0	70.0	65.0	70.0	60.0
60.0	65.0	75.0	95.0	90.0	80.0	65.0	50.0
50.0	45.0	48.0	48.0	50.0	50.0	50.0	50.0
52.0	55.0	60.0	60.0	58.0	55.0	50.0	52.0
50.0	60.0	80.0	90.0	85.0	65.0	52.0	45.0
40.0	40.0	40.0	42.0	45.0	50.0	50.0	50.0
55.0	60.0	75.0	75.0	75.0	65.0	65.0	60.0
70.0	80.0	90.0	95.0	90.0	75.0	60.0	50.0
40.0	40.0	40.0	45.0	50.0	55.0	55.0	50.0
65.0	70.0	75.0	75.0	75.0	65.0	75.0	75.0
70.0	70.0	90.0	95.0	90.0	65.0	55.0	50.0
56.0	54.0	50.0	50.0	50.0	50.0	60.0	50.0
65.0	75.0	60.0	75.0	70.0	65.0	60.0	70.0
65.0	60.0	80.0	85.0	35.0	70.0	55.0	50.0
38.0	35.0	35.0	38.0	40.0	50.0	50.0	50.0
60.0	70.0	75.0	80.0	85.0	80.0	70.0	65.0
65.0	65.0	85.0	95.0	90.0	80.0	50.0	45.0
45.0	40.0	40.0	42.0	45.0	50.0	55.0	50.0
45.0	55.0	55.0	50.0	60.0	60.0	65.0	60.0
55.0	55.0	70.0	78.0	70.0	55.0	50.0	45.0
35.0	35.0	35.0	38.0	40.0	45.0	50.0	50.0
60.0	60.0	50.0	60.0	60.0	60.0	60.0	60.0
55.0	60.0	70.0	90.0	80.0	70.0	55.0	50.0
50.0	45.0	50.0	50.0	40.0	40.0	40.0	50.0
55.0	55.0	60.0	65.0	50.0	50.0	50.0	55.0
55.0	60.0	80.0	80.0	65.0	55.0	50.0	40.0
50.0	50.0	45.0	50.0	50.0	50.0	50.0	50.0
60.0	60.0	60.0	50.0	60.0	60.0	60.0	60.0
55.0	55.0	80.0	95.0	60.0	75.0	60.0	45.0
45.0	45.0	50.0	50.0	50.0	50.0	50.0	50.0
50.0	55.0	55.0	60.0	65.0	68.0	60.0	65.0
70.0	60.0	80.0	95.0	90.0	75.0	50.0	45.0

40.0	40.0	40.0	45.0	50.0	50.0	50.0	50.0	50.0
52.0	54.0	55.0	60.0	65.0	55.0	55.0	55.0	55.0
60.0	50.0	80.0	90.0	90.0	70.0	50.0	50.0	50.0
50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0
60.0	70.0	55.0	60.0	50.0	55.0	55.0	55.0	55.0
65.0	80.0	90.0	95.0	65.0	65.0	60.0	60.0	60.0
50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0	55.0
55.0	65.0	65.0	70.0	70.0	60.0	60.0	60.0	60.0
65.0	75.0	90.0	90.0	75.0	55.0	50.0	50.0	45.0
45.0	50.0	45.0	50.0	50.0	55.0	55.0	55.0	55.0
55.0	60.0	65.0	65.0	68.0	55.0	60.0	60.0	60.0
60.0	65.0	90.0	95.0	85.0	70.0	55.0	50.0	50.0
45.0	45.0	50.0	50.0	50.0	55.0	50.0	50.0	58.0
55.0	50.0	58.0	60.0	65.0	60.0	60.0	60.0	50.0
60.0	65.0	70.0	85.0	85.0	65.0	55.0	50.0	50.0
45.0	45.0	50.0	55.0	50.0	50.0	50.0	50.0	40.0
65.0	70.0	70.0	70.0	65.0	70.0	55.0	55.0	75.0
70.0	70.0	95.0	100.0	70.0	65.0	50.0	50.0	50.0
45.0	45.0	48.0	48.0	50.0	50.0	60.0	60.0	52.0
55.0	65.0	70.0	70.0	65.0	60.0	55.0	55.0	60.0
70.0	80.0	80.0	90.0	60.0	60.0	50.0	50.0	45.0
45.0	45.0	45.0	48.0	48.0	50.0	50.0	50.0	52.0
50.0	55.0	65.0	65.0	65.0	65.0	60.0	60.0	65.0
60.0	65.0	80.0	90.0	85.0	70.0	52.0	52.0	45.0
40.0	40.0	42.0	45.0	45.0	50.0	50.0	50.0	50.0
55.0	60.0	60.0	65.0	65.0	65.0	50.0	50.0	65.0
60.0	65.0	75.0	70.0	65.0	70.0	55.0	55.0	50.0
50.0	45.0	40.0	40.0	50.0	50.0	50.0	50.0	60.0
60.0	70.0	70.0	70.0	65.0	50.0	55.0	55.0	50.0
55.0	50.0	80.0	90.0	80.0	60.0	60.0	60.0	55.0
40.0	40.0	35.0	35.0	40.0	50.0	50.0	50.0	50.0
55.0	60.0	60.0	60.0	80.0	80.0	60.0	60.0	55.0
55.0	58.0	85.0	98.0	90.0	75.0	60.0	60.0	45.0
50.0	50.0	45.0	45.0	50.0	50.0	50.0	50.0	55.0
50.0	54.0	55.0	65.0	60.0	60.0	65.0	65.0	60.0
60.0	70.0	98.0	85.0	60.0	70.0	60.0	60.0	50.0
50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0
55.0	65.0	55.0	65.0	60.0	60.0	75.0	75.0	75.0
60.0	58.0	95.0	95.0	95.0	80.0	60.0	60.0	50.0
50.0	50.0	50.0	50.0	50.0	55.0	55.0	50.0	50.0
60.0	70.0	75.0	75.0	70.0	60.0	70.0	70.0	70.0
65.0	60.0	90.0	95.0	90.0	75.0	60.0	50.0	50.0
50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0
55.0	70.0	75.0	75.0	70.0	60.0	70.0	70.0	70.0
75.0	65.0	95.0	95.0	95.0	75.0	60.0	50.0	50.0
40.0	45.0	50.0	50.0	50.0	55.0	60.0	55.0	55.0
60.0	70.0	75.0	75.0	70.0	70.0	70.0	70.0	70.0
45.0	65.0	100.0	95.0	85.0	75.0	55.0	50.0	50.0

40.0	40.0	45.0	45.0	50.0	50.0	50.0	55.0
60.0	55.0	75.0	80.0	80.0	70.0	70.0	75.0
60.0	70.0	100.0	100.0	98.0	60.0	55.0	45.0
40.0	50.0	45.0	50.0	50.0	55.0	55.0	55.0
70.0	65.0	70.0	70.0	65.0	60.0	60.0	60.0
60.0	60.0	100.0	90.0	80.0	75.0	52.0	50.0
45.0	45.0	48.0	48.0	50.0	50.0	52.0	52.0
65.0	60.0	70.0	65.0	60.0	65.0	60.0	60.0
60.0	60.0	90.0	90.0	85.0	65.0	60.0	55.0
40.0	40.0	45.0	45.0	48.0	50.0	55.0	52.0
65.0	70.0	70.0	70.0	70.0	70.0	70.0	70.0
65.0	60.0	100.0	90.0	80.0	70.0	60.0	50.0
45.0	45.0	45.0	48.0	50.0	50.0	52.0	52.0
60.0	60.0	60.0	60.0	60.0	60.0	65.0	65.0
60.0	60.0	95.0	65.0	75.0	70.0	60.0	50.0
40.0	45.0	45.0	50.0	60.0	60.0	50.0	52.0
50.0	55.0	60.0	60.0	60.0	70.0	65.0	65.0
65.0	65.0	100.0	95.0	85.0	65.0	55.0	50.0
45.0	40.0	40.0	40.0	45.0	50.0	50.0	50.0
60.0	65.0	70.0	70.0	70.0	70.0	65.0	65.0
65.0	70.0	100.0	98.0	80.0	65.0	50.0	50.0
40.0	40.0	45.0	45.0	50.0	50.0	50.0	50.0
50.0	65.0	65.0	65.0	65.0	65.0	60.0	85.0
60.0	65.0	95.0	92.0	90.0	85.0	50.0	50.0
50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0
60.0	65.0	65.0	70.0	65.0	65.0	60.0	60.0
60.0	65.0	100.0	100.0	90.0	65.0	55.0	55.0
45.0	45.0	45.0	45.0	45.0	45.0	50.0	50.0
55.0	50.0	65.0	60.0	60.0	60.0	55.0	58.0
65.0	60.0	85.0	85.0	80.0	60.0	50.0	50.0
50.0	50.0	40.0	40.0	40.0	50.0	50.0	50.0
60.0	50.0	65.0	60.0	60.0	60.0	55.0	60.0
60.0	80.0	100.0	95.0	90.0	65.0	50.0	45.0
40.0	35.0	40.0	45.0	45.0	50.0	50.0	55.0
60.0	60.0	55.0	58.0	58.0	60.0	55.0	60.0
60.0	65.0	95.0	95.0	90.0	60.0	50.0	40.0
40.0	40.0	40.0	42.0	45.0	50.0	50.0	50.0
50.0	50.0	55.0	55.0	52.0	50.0	50.0	52.0
55.0	60.0	95.0	90.0	75.0	60.0	75.0	40.0
35.0	35.0	40.0	40.0	40.0	35.0	30.0	40.0
40.0	45.0	45.0	60.0	60.0	55.0	55.0	55.0
55.0	60.0	75.0	80.0	75.0	65.0	50.0	45.0
40.0	40.0	38.0	40.0	42.0	45.0	45.0	48.0
50.0	50.0	50.0	50.0	50.0	50.0	45.0	45.0
40.0	50.0	75.0	80.0	80.0	50.0	48.0	45.0
35.0	35.0	38.0	38.0	40.0	45.0	48.0	50.0
50.0	50.0	50.0	60.0	55.0	50.0	50.0	50.0
55.0	70.0	85.0	85.0	70.0	85.0	50.0	45.0

35.0	35.0	38.0	38.0	45.0	50.0	50.0	50.0
50.0	50.0	60.0	65.0	60.0	50.0	50.0	50.0
50.0	65.0	80.0	80.0	75.0	55.0	50.0	50.0
40.0	35.0	35.0	35.0	35.0	40.0	50.0	50.0
50.0	55.0	55.0	50.0	50.0	50.0	50.0	50.0
50.0	60.0	95.0	90.0	70.0	60.0	50.0	50.0
30.0	30.0	40.0	40.0	40.0	50.0	50.0	50.0
50.0	50.0	60.0	60.0	60.0	60.0	60.0	60.0
58.0	70.0	95.0	95.0	80.0	50.0	45.0	40.0
35.0	35.0	40.0	40.0	40.0	50.0	50.0	45.0
50.0	52.0	55.0	60.0	55.0	50.0	55.0	55.0
52.0	65.0	85.0	85.0	80.0	65.0	60.0	50.0
50.0	50.0	40.0	40.0	50.0	50.0	50.0	50.0
45.0	60.0	60.0	65.0	60.0	60.0	60.0	65.0
65.0	75.0	100.0	100.0	90.0	65.0	50.0	50.0
50.0	40.0	40.0	40.0	45.0	45.0	50.0	50.0
60.0	65.0	60.0	65.0	55.0	55.0	55.0	60.0
60.0	75.0	90.0	85.0	80.0	65.0	60.0	50.0
40.0	40.0	40.0	40.0	40.0	45.0	50.0	50.0
60.0	65.0	60.0	65.0	60.0	55.0	50.0	50.0
70.0	80.0	95.0	95.0	80.0	60.0	50.0	40.0
40.0	40.0	40.0	40.0	40.0	45.0	50.0	45.0
50.0	60.0	60.0	60.0	52.0	50.0	50.0	50.0
65.0	90.0	95.0	95.0	75.0	60.0	50.0	40.0
40.0	40.0	40.0	40.0	45.0	50.0	50.0	50.0
50.0	65.0	70.0	70.0	70.0	65.0	65.0	60.0
65.0	85.0	95.0	90.0	80.0	70.0	50.0	40.0
40.0	45.0	40.0	40.0	50.0	45.0	50.0	50.0
60.0	65.0	50.0	60.0	60.0	30.0	65.0	75.0
70.0	95.0	90.0	95.0	85.0	60.0	50.0	35.0
35.0	35.0	36.0	38.0	45.0	50.0	52.0	52.0
60.0	65.0	60.0	55.0	55.0	55.0	55.0	65.0
65.0	95.0	95.0	95.0	75.0	50.0	40.0	35.0
35.0	35.0	35.0	38.0	40.0	50.0	50.0	52.0
50.0	60.0	60.0	60.0	60.0	60.0	55.0	65.0
70.0	80.0	100.0	90.0	80.0	60.0	50.0	40.0
35.0	35.0	35.0	38.0	38.0	48.0	50.0	50.0
50.0	50.0	60.0	60.0	60.0	60.0	60.0	60.0
60.0	75.0	95.0	90.0	80.0	60.0	50.0	40.0
45.0	45.0	40.0	40.0	50.0	50.0	55.0	55.0
50.0	50.0	50.0	65.0	60.0	60.0	60.0	60.0
65.0	70.0	90.0	90.0	75.0	60.0	50.0	40.0
40.0	35.0	35.0	35.0	45.0	50.0	50.0	50.0
60.0	60.0	50.0	50.0	50.0	50.0	50.0	50.0
55.0	70.0	90.0	80.0	75.0	65.0	55.0	40.0
35.0	35.0	40.0	40.0	50.0	50.0	60.0	50.0
30.0	45.0	60.0	60.0	55.0	55.0	50.0	50.0
55.0	75.0	90.0	85.0	75.0	60.0	50.0	45.0

50.0	40.0	36.0	30.0	40.0	40.0	50.0	50.0
50.0	55.0	55.0	50.0	50.0	40.0	35.0	50.0
50.0	75.0	55.0	30.0	70.0	65.0	50.0	50.0
40.0	40.0	36.0	30.0	30.0	50.0	50.0	55.0
50.0	50.0	52.0	55.0	50.0	50.0	45.0	50.0
70.0	75.0	90.0	85.0	75.0	65.0	60.0	50.0
50.0	50.0	45.0	45.0	45.0	50.0	50.0	55.0
50.0	50.0	45.0	45.0	45.0	40.0	42.0	40.0
50.0	60.0	80.0	75.0	75.0	60.0	60.0	50.0
50.0	50.0	40.0	40.0	40.0	40.0	50.0	55.0
50.0	50.0	45.0	45.0	40.0	30.0	25.0	25.0
50.0	65.0	75.0	75.0	75.0	55.0	35.0	30.0
28.0	30.0	30.0	30.0	35.0	35.0	45.0	45.0
45.0	45.0	45.0	45.0	45.0	40.0	30.0	35.0
50.0	70.0	70.0	70.0	60.0	50.0	45.0	40.0
40.0	40.0	40.0	40.0	45.0	45.0	45.0	50.0
45.0	45.0	48.0	50.0	45.0	45.0	50.0	50.0
50.0	65.0	70.0	70.0	60.0	45.0	35.0	20.0
25.0	25.0	20.0	20.0	30.0	35.0	50.0	50.0
50.0	50.0	55.0	80.0	50.0	50.0	50.0	50.0
50.0	80.0	90.0	80.0	70.0	50.0	40.0	25.0
35.0	35.0	38.0	38.0	38.0	45.0	50.0	50.0
55.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0
60.0	80.0	85.0	70.0	65.0	50.0	38.0	30.0
35.0	35.0	38.0	38.0	40.0	45.0	50.0	55.0
60.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0
55.0	70.0	70.0	70.0	70.0	50.0	45.0	35.0
30.0	30.0	35.0	35.0	35.0	50.0	70.0	60.0
50.0	60.0	50.0	60.0	60.0	50.0	50.0	50.0
50.0	75.0	75.0	75.0	70.0	60.0	50.0	40.0
40.0	40.0	35.0	35.0	40.0	50.0	60.0	60.0
60.0	50.0	50.0	55.0	50.0	50.0	50.0	50.0
55.0	80.0	100.0	90.0	80.0	60.0	40.0	35.0
40.0	40.0	35.0	35.0	40.0	50.0	50.0	60.0
55.0	60.0	50.0	55.0	50.0	55.0	50.0	50.0
50.0	95.0	90.0	80.0	80.0	60.0	50.0	40.0
40.0	30.0	30.0	28.0	30.0	35.0	50.0	50.0
50.0	50.0	55.0	55.0	50.0	50.0	45.0	50.0
50.0	80.0	80.0	75.0	70.0	60.0	50.0	40.0
40.0	40.0	40.0	40.0	40.0	50.0	63.0	50.0
50.0	50.0	60.0	60.0	55.0	50.0	50.0	55.0
55.0	85.0	90.0	80.0	75.0	60.0	50.0	40.0
40.0	40.0	40.0	40.0	40.0	40.0	60.0	60.0
50.0	52.0	50.0	52.0	50.0	50.0	50.0	55.0
60.0	80.0	90.0	85.0	75.0	50.0	40.0	30.0
35.0	30.0	32.0	35.0	35.0	55.0	55.0	55.0
56.0	52.0	52.0	50.0	50.0	50.0	50.0	50.0
60.0	90.0	90.0	90.0	80.0	50.0	40.0	40.0

40.0	35.0	35.0	40.0	40.0	50.0	50.0	55.0
52.0	50.0	50.0	50.0	50.0	45.0	48.0	50.0
55.0	75.0	80.0	80.0	75.0	60.0	50.0	45.0
38.0	30.0	30.0	35.0	40.0	50.0	55.0	65.0
60.0	60.0	50.0	50.0	50.0	55.0	50.0	50.0
50.0	80.0	85.0	80.0	75.0	60.0	65.0	35.0
35.0	35.0	38.0	38.0	40.0	48.0	55.0	60.0
55.0	60.0	55.0	50.0	50.0	50.0	50.0	50.0
50.0	85.0	95.0	85.0	75.0	55.0	48.0	35.0
35.0	35.0	38.0	38.0	40.0	50.0	52.0	55.0
59.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0
55.0	90.0	85.0	75.0	70.0	55.0	45.0	35.0
30.0	30.0	35.0	35.0	38.0	50.0	50.0	55.0
55.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0
60.0	80.0	95.0	95.0	85.0	55.0	50.0	50.0
40.0	35.0	30.0	30.0	35.0	50.0	60.0	65.0
50.0	50.0	50.0	60.0	50.0	50.0	50.0	50.0
50.0	80.0	90.0	85.0	75.0	50.0	40.0	40.0

DAILY AVERAGE TEMPERATURE RECORDED AT
HYDROLOGY DEPARTMENT, UNIVERSITY OF ROORKEE
FROM 1 AUGUST, 87. TO 10 NOVEMBER, 87.

33.25	33.00	32.10	31.00	30.00	30.60	31.00	32.00
33.35	33.25	32.50	33.10	27.10	33.00	29.35	30.15
30.10	33.10	26.00	32.25	30.10	31.25	28.75	28.25
31.50	32.00	28.85	27.80	26.25	30.60	28.65	29.35
31.00	31.60	30.50	28.85	29.25	30.50	28.20	29.20
29.75	27.70	29.50	29.75	29.80	30.25	29.95	30.90
31.75	31.00	30.35	30.75	30.25	29.90	29.95	29.35
29.80	29.00	28.90	29.10	28.50	27.90	28.40	28.50
27.50	27.25	27.35	27.30	28.10	28.35	27.70	28.70
28.40	28.20	27.40	26.55	26.75	26.70	27.80	25.50
20.50	21.45	22.30	22.55	23.35	23.95	24.05	23.75
27.35	24.50	26.00	25.20	23.50	21.25	21.80	22.60
21.75	20.85	20.10	21.50	22.25	22.55		

DAILY RELATIVE HUMIDITY RECORDED AT
HYDROLOGY DEPARTMENT, UNIVERSITY OF ROORKEE
FROM 1 AUGUST, 87. TO 10 NOVEMBER, 87.

65.00	67.00	64.00	74.00	70.00	64.00	67.00	73.00
72.00	65.00	67.00	64.00	74.00	70.00	64.00	67.00
73.00	72.00	62.00	75.00	65.00	87.00	85.00	72.00
55.00	91.00	82.00	95.00	82.00	82.00	77.00	82.00
85.00	79.00	86.00	83.00	81.00	93.00	91.00	81.00
85.00	76.00	79.00	81.00	75.00	71.00	78.00	73.00
85.00	76.00	75.00	71.00	73.00	62.00	70.00	50.00
76.00	73.00	66.00	51.00	63.00	65.00	73.00	72.00
52.00	53.00	64.00	64.00	58.00	63.00	66.00	70.00
63.00	67.00	56.00	62.00	52.00	75.00	67.00	81.00
77.00	71.00	49.00	64.00	62.00	67.00	71.00	70.00
72.00	75.00	68.00	62.00	71.00	60.00	61.00	64.00
53.00	67.00	70.00	62.00	64.00	62.00		

APPENDIX-3

LOAD FORECAST FOR NOV.2,1987.
 INCORPORATING EFFECT OF TEMERATURE
 LEAD TIME = 24 HOURS

STOCHASTIC MODEL FORECAST	VARIANCE	COMPOSITE LOAD FORECAST	VARIANCE
35.58047	11.75080	35.64714	11.74755
35.55842	11.30281	35.11317	11.15779
35.97369	9.67181	35.74727	9.63431
38.74831	9.23400	38.30494	9.09021
41.11955	9.42730	40.72059	9.31087
50.28537	9.23137	49.52908	8.81296
56.80984	9.90273	56.51877	9.84076
56.18791	7.60052	55.95837	7.56198
52.64802	14.55344	52.32492	14.47708
57.40342	15.37038	56.91782	15.19789
58.96393	21.84258	58.33269	21.55110
59.83277	24.53753	58.81046	23.77302
53.65423	14.73419	53.39414	14.68471
55.39155	25.79219	54.77410	25.51331
55.14290	19.60849	54.28445	19.06942
56.47277	21.61483	55.77385	21.25750
57.06711	20.46026	56.41126	20.14562
87.81229	26.79156	86.62767	25.76500
96.97104	33.38753	92.90589	21.29901
85.96086	31.17362	83.49074	26.71033
75.80860	31.07944	74.39875	29.62544
53.88451	22.06274	53.67560	22.03082
43.80680	14.77484	43.64203	14.75498
35.18908	16.10780	35.17769	16.10771

PEAK LOAD FORECAST BASED ON WEATHER LOAD MODEL = 85.74341

APPENDIX-3

LOAD FORECAST FOR NOV.2,1987.
 INCORPORATING EFFECT OF TEMPERATURE
 LEAD TIME = 24 HOURS

STOCHASTIC MODEL FORECAST	VARIANCE	COMPOSITE LOAD FORECAST	VARIANCE
35.58047	11.75080	35.64714	11.74755
35.55842	11.30281	35.11317	11.15779
35.97369	9.67181	35.74727	9.63431
38.74831	9.23400	38.30494	9.09021
41.11955	9.42730	40.72059	9.31087
50.28537	9.23137	49.52908	8.81296
56.80984	9.90273	56.51877	9.84076
56.18791	7.60052	55.95837	7.56198
52.64802	14.55344	52.32492	14.47708
57.40342	15.37038	56.91782	15.19789
58.96393	21.84258	58.33269	21.55110
59.83277	24.53753	58.81046	23.77302
53.65423	14.73419	53.39414	14.68471
55.39155	25.79219	54.77410	25.51331
55.14290	19.60849	54.28445	19.06942
56.47277	21.61483	55.77385	21.25750
57.06711	20.46026	56.41126	20.14562
87.81229	26.79156	86.62767	25.76500
96.97104	33.38753	92.90589	21.29901
85.96086	31.17362	83.49074	26.71033
75.80860	31.07944	74.39875	29.62544
53.88451	22.06274	53.67560	22.03082
43.80680	14.77484	43.64203	14.75498
35.18908	16.10780	35.17769	16.10771

PEAK LOAD FORECAST BASED ON WEATHER LOAD MODEL = 85.74341

APPENDIX-3

LOAD FORECAST FOR NOV.8,1987.
 INCORPORATING EFFECT OF TEMPERATURE
 LEAD TIME = 1 WEEK

STOCHASTIC MODEL FORECAST	VARIANCE	COMPOSITE LOAD FORECAST	VARIANCE
38.09843	10.45588	38.19225	10.38194
32.11634	10.46504	32.28756	10.21873
32.02110	9.00662	32.03035	9.00590
30.04130	8.58199	29.93548	8.48792
32.70704	8.86735	32.58941	8.75110
40.01230	8.64343	40.00938	8.64336
52.56910	9.36676	52.52585	9.35104
53.89843	7.21517	53.87573	7.21084
51.96153	13.50227	52.15696	13.18140
48.47491	13.87326	48.77850	13.09895
49.13355	21.12627	49.64807	18.90230
51.24337	23.90858	51.80264	21.28089
45.30100	14.55949	45.47681	14.29981
46.55671	24.91983	46.66912	24.81369
43.35238	19.04880	43.67102	18.19585
45.00019	21.36379	45.30045	20.60638
47.73059	20.11817	48.35538	16.83868
79.29706	26.13197	80.98432	2.21568
76.86715	31.36696	77.50095	27.99218
70.17398	29.72483	70.70805	27.32854
67.49090	30.73060	67.66405	30.47872
55.96167	21.36624	56.07414	21.25998
45.92212	14.09879	45.93226	14.09792
34.47274	15.33168	34.49542	15.32736

PEAK LOAD FORECAST BASED ON WEATHER LOAD MODEL = 81.14063

APPENDIX-3

LOAD FORECAST FOR NOV.2,1987.
 INCORPORATING EFFECT OF TEMPERATURE AND HUMIDITY
 LEAD TIME = 24 HOURS

STOCHASTIC MODEL FORECAST	VARIANCE	COMPOSITE LOAD FORECAST	VARIANCE
35.74101	11.78330	35.81097	11.77954
35.57708	11.30193	35.15880	11.16772
35.89503	9.67326	35.67881	9.63740
38.71941	9.18967	38.30231	9.05622
41.09866	9.39107	40.72359	9.28315
50.14407	9.22262	49.42705	8.82824
56.51855	10.02229	56.23106	9.95890
56.03846	7.63240	55.81541	7.59424
53.21648	14.31842	52.87455	14.22873
57.05699	15.54117	56.58376	15.36939
58.72188	21.91650	58.11707	21.63590
59.66159	24.57889	58.69172	23.85733
53.55248	14.74889	53.30298	14.70114
55.00433	25.98280	54.40592	25.70811
55.04967	19.62041	54.23768	19.11465
56.32219	21.64722	55.65745	21.30827
56.84657	20.48778	56.22034	20.18696
87.65183	26.80778	86.52862	25.84002
96.67952	33.50584	92.84122	22.20477
86.05322	31.16454	83.73261	27.03363
75.89475	31.08994	74.57248	29.74877
54.01022	22.00983	53.81783	21.98143
43.81393	14.77034	43.65878	14.75187
35.45101	16.19595	35.45215	16.19595

PEAK LOAD FORECAST BASED ON WEATHER LOAD MODEL = 85.29960

APPENDIX-3

LOAD FORECAST FOR NOV.8,1987,
 INCORPORATING EFFECT OF TEMPERATURE AND HUMIDITY
 LEAD TIME = 1 WEEK

STOCHASTIC MODEL FORECAST	VARIANCE	COMPOSITE LOAD FORECAST	VARIANCE
38.01353	10.45090	38.21633	10.37756
32.04951	10.45509	32.42370	10.20540
32.01506	9.00604	32.03271	9.00549
30.02983	8.58396	29.79247	8.48349
32.73195	8.87145	32.46776	8.74699
40.04193	8.64390	40.03825	8.64387
52.58879	9.36115	52.50318	9.34808
53.93337	7.21502	53.88295	7.21049
51.84630	13.49025	52.27328	13.16514
48.22092	13.87738	48.89560	13.06569
48.91124	21.12627	50.05393	18.79787
51.15303	23.93290	52.39973	21.16129
45.21427	14.56994	45.61038	14.29016
46.61071	24.91834	46.85888	24.80852
43.24993	19.04254	43.95498	18.15612
44.83516	21.35678	45.49908	20.57077
47.53774	20.12046	48.92589	16.68428
78.91781	26.20560	82.67042	1.09439
76.75441	31.41256	78.16785	27.85005
70.08097	29.74227	71.26952	27.22319
67.46298	30.73400	67.84517	30.47353
56.04992	21.37103	56.30500	21.25501
45.98029	14.09792	46.00586	14.09676
34.46171	15.33175	34.51378	15.32691

PEAK LOAD FORECAST BASED ON WEATHER LOAD MODEL = 82.83396