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An application of adaptive lattice filters to short-term load forecasting in power systems.

Barry L. Norris

AN APPLICATION OF ADAPTIVE LATTICE FILTERS TO SHORT-TERM LOAD FORECASTING IN POWER SYSTEMS

By

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A Thesis

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CERTIFICATE OF APPROVAL

This thesis is accepted and approved in partial fulfillment of the requirements for the degree of Master of Science.

September 5, 1984
(Date)

Professor in Charge

Chairman of Department

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ABSTRACT

Short-term load forecasting in power system applications is a topic of vast interest because of the need to limit operating costs and to avoid major equipment outages. The recent development of adaptive lattice filters and the need for an accurate short-term load forecasting algorithm has led to this research work.

Existing short-term load forecasting methods vary widely in concept and accuracy. It can be easily shown that a method's accuracy is very much related to the complexity of the model or method. Many researchers have included such factors as weather components, harmonic components, and stochastic load components to increase the accuracy of their forecast. Although the inclusion of such elements has in some cases greatly improved the performance of a method, the computational burden of such components can make the algorithm cumbersome to use.

The proposed method of this paper attempts to develop an accurate short-term load forecasting procedure while limiting the number of computations. This method uses a time-varying base load and a recently developed adaptive lattice filter to predict the load at a substation on an hourly basis.

Both the base load and the digital lattice filter are established by processing historical load data. The amount of historical data to be processed is at the discretion of the researcher, though the results of previous work show that increasing the amount of historical data

used generally improves a method's accuracy. This research employed two weeks of historical data. The hourly base load and the stochastic load predicted by the lattice filter are summed to arrive at an actual substation forecast.

The results of the research compare favorably with recent state-of-the-art methods. The proposed method appears to be quite suitable for on-line applications as it requires minimal input data and is computationally efficient.

Chapter I

INTRODUCTION TO LOAD FORECASTING

Load forecasting is a critical part in the operation of a power system. Two distinct types of load forecasting are discussed in the literature and are very much needed by utilities and operators of power systems. The two types of load forecasting are:

- Long-term load forecasting
- Short-term load forecasting

This chapter discusses the inherent differences between the two techniques. However, this paper focuses on short-term forecasting and proposes a new method to arrive at an accurate short-term load forecast. This proposed method involves the use of adaptive digital filtering techniques which were highly developed in the 1970's for use in communication systems.

Long-Term Load Forecasting

In the long-term, a utility or an operator of a power system must be able to estimate the future MW and MVAR requirements on his system. Usually, incorporating such items as 1) previous years total MWH sales; 2) previous years peak demand; and 3) available census data, the load projections for each substation on the power system are estimated from one to ten years.

A utility power system engineer will usually take the load projections and input them into his available load flow program. This load flow program allows the engineer to determine the voltage, current, real power flow, reactive power flow, and power factor at various points on the system. By simulating the normal system and various contingency conditions for each of the years for which he has load projections, the engineer will be able to properly determine what, if any, system reinforcements will need to be made before the load level is actually realized.

Other programs such as stability analysis algorithms also incorporate future load projections to correctly study the future characteristics of the system.

Long-term load projections or forecasts are usually updated at least once a year in order to reflect any changes in system load due to economic growth, economic recession, or a change in plans by consumers of electricity from the power system.

Short-Term Load Forecasting

Short-term load forecasting differs entirely from the previously discussed long-term forecasting methods. Short-term load forecasting is generally interested in projecting the system load from a few minutes to a few hours. Note that long-term forecasting is interested in projections years in advance.

Essentially, in the short-term, system load must be known so that the power output requirements may be established at each generating station. An accurate estimate of the future system load allows the operator to economically adjust for any load fluctuations. Since a more accurate estimate of system load will allow for a more economical schedule for starting-up and shutting-down generating plants, the costs for providing spinning reserve capacity can be minimized.

Also, short-term forecasted loads may be used in on-line load flow or state estimation algorithms to analyze single and multiple-contingency operations in the immediate future. The operator may use these results to make system adjustments in order to avoid future potential problems.

Short-term load forecasting basically is needed for:

- On-line commitment - the commitment of equipment to specific operating conditions.
- Maintenance scheduling - to establish a schedule in which major generating units and/or supply lines may be maintained without impacting the reliability of the power system.
- Security analysis - on-line detection of problem configurations and the analysis of single and multiple-contingency operations.

Load Pattern Characteristics

To fully understand the problems imbedded in short-term load forecasting (and load forecasting in general), the characteristics of the load should be analyzed.

Power system load is generally composed of thousands of electrical devices, all with different power-consuming characteristics. These devices range from a household light bulb to a large air conditioning system in a commercial building to an arc furnace used in steel production.

In order to better deal with such diversity, the power system engineer looks at the MW sum total of all the devices at any one time. This leads to a load pattern or a load curve. It will be shown that this load curve is not constant over time but is quite dependent on such variables as:

- Day of the week
- Season of the year
- Holidays
- Daily or hourly weather changes

Figure 1 clearly shows various time characteri[illegible] load. This graph shows a typical winter weekday and winter weekend for a Pennsylvania Power and Light substation in central eastern Pennsylvania. As outlined in F.D. Galiana's summary report, the "work-rest" cycle of our society gives rise to the vast difference in the weekday and weekend load levels. Typically factories and businesses may be closed on weekends, thereby reducing the demand for electricity at this time. However, when society returns to work on Monday, load levels tend to be at their greatest. During a winter weekend, heat may be reduced to conserve energy and to cut down on heating costs. Upon returning to work on Monday, heating and lighting load will naturally increase quite substantially; this similarly applies to summertime air conditioning.

It must be pointed out that this leads directly to seasonal variations of load patterns. That is, during the winter, heating systems are needed; during the summer, cooling systems are needed while during the spring and the fall seasons neither of these systems will be needed

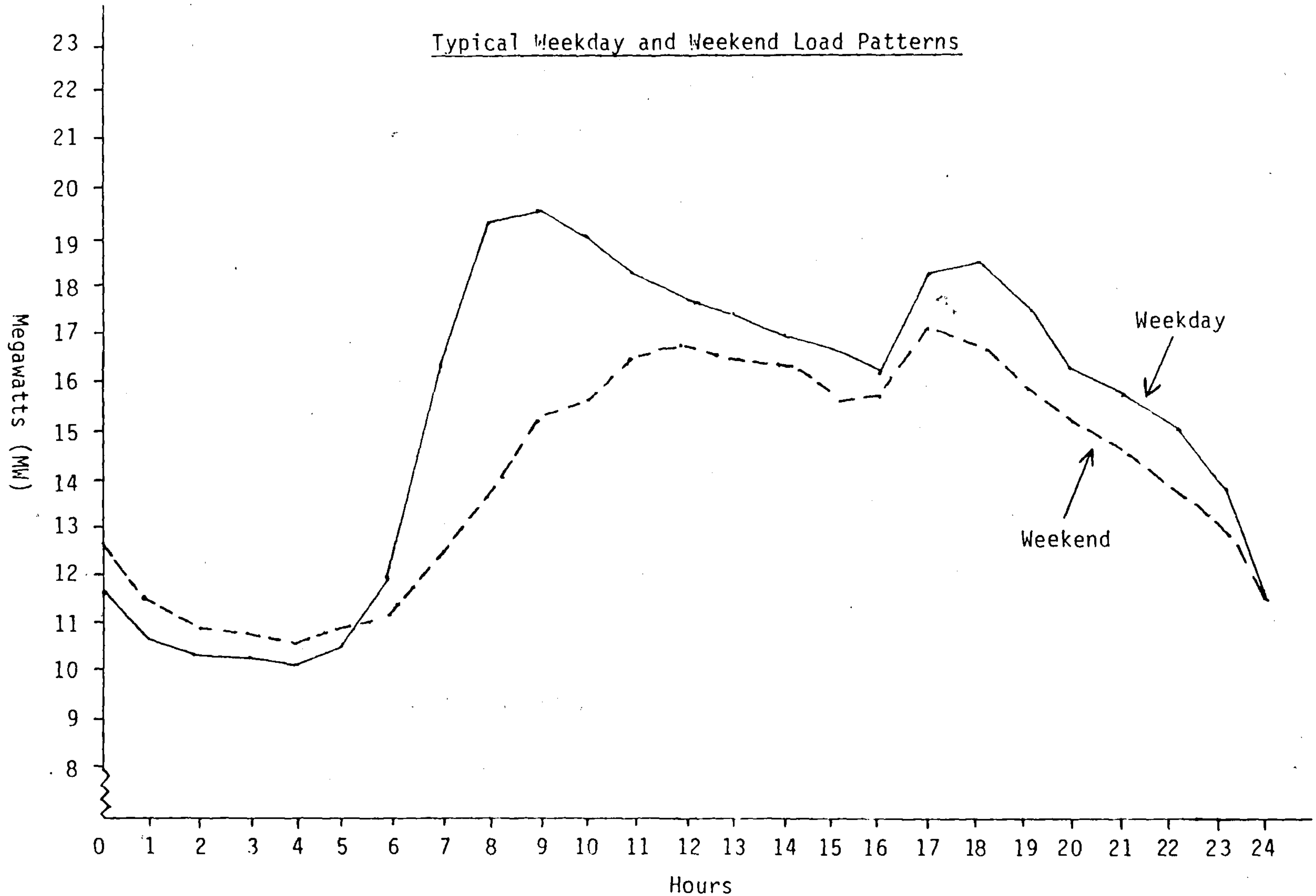
Typical Weekday and Weekend Load Patterns
Megawatts (MW)
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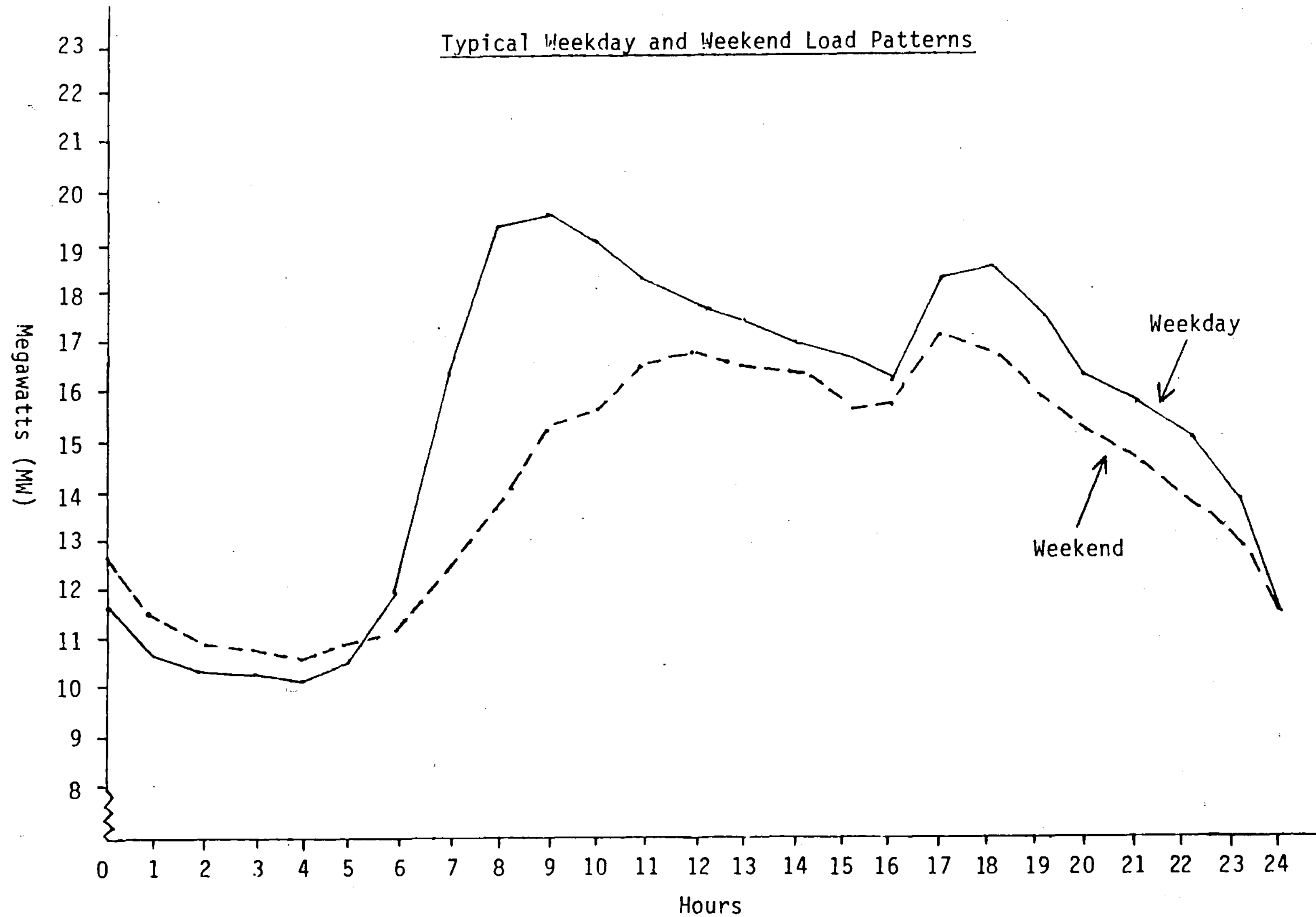
Figure 1



Typical Weekday and Weekend Load Patterns
Megawatts (MW)
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Hours
Weekday
Weekend

Figure 1

substantially (see Figure 2). Because of this, most power systems in North America are either summer or winter peaking systems.

Immediate weather changes also play a significant role in demand curves. Temperature and humidity play the largest role in affecting the total demand. Table 1 shows how temperature can effect the peak load of a substation on a day-to-day basis.

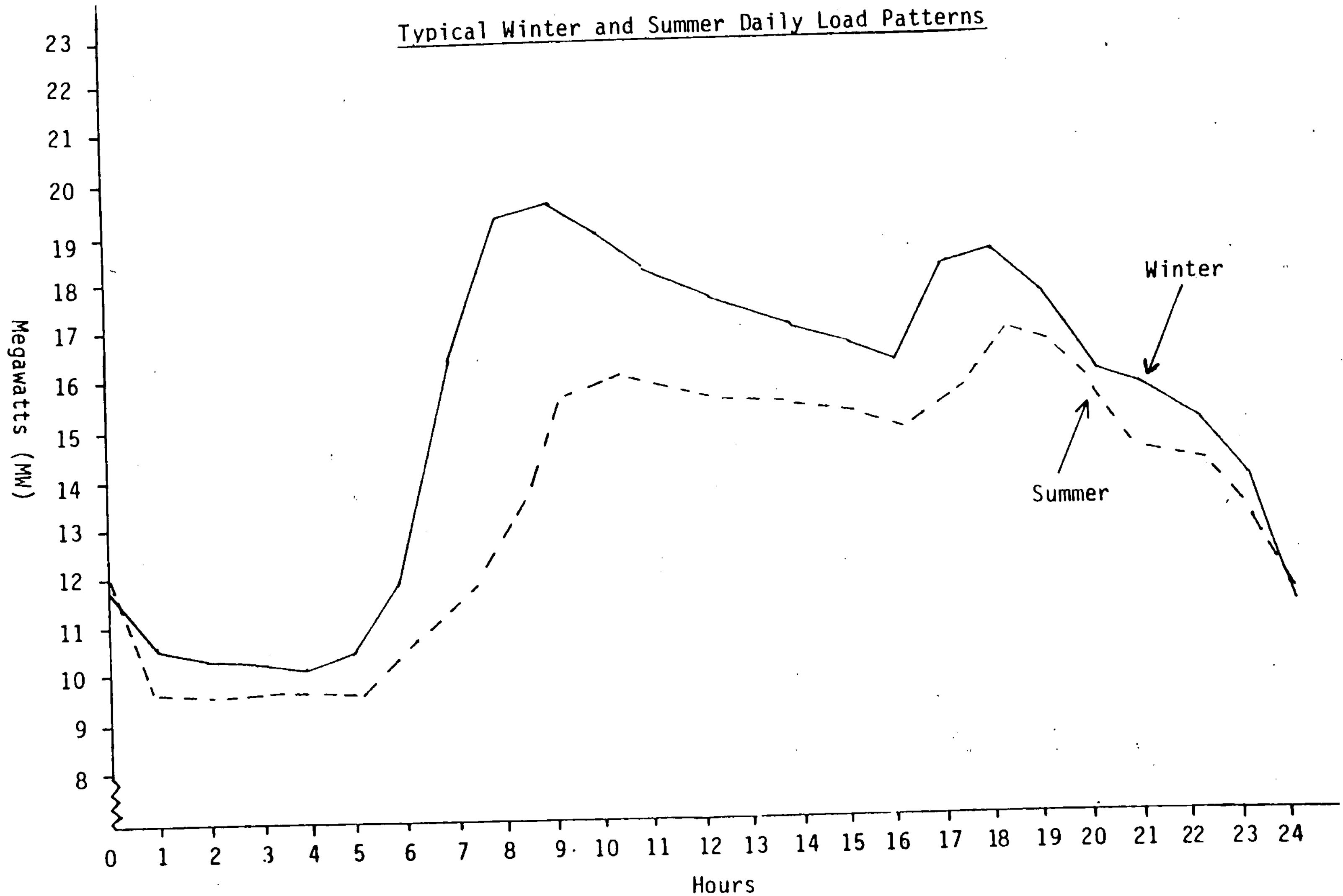
Modeling Short-Term Load

In order to accurately estimate or predict the system load, a precise model must be developed. As pointed out in the previous section, many different factors may effect the actual load level realized on the system.

A researcher must decide what parameters or variables he wishes to include in his short-term model. Once the form of the model is established, any unknown coefficients must be calculated by processing past data. Such techniques as the well-known least-squares approach can be used at this stage. (The least-squares approach is fully discussed in Chapter III.) And, finally, after the model is completely known, it must be tested in a real or simulated situation. At this stage the correctness and validity of the model is tested. If the model tests poorly, the researcher may make adjustments to improve his model or ultimately he may disregard the model if he feels his results are too inaccurate.

State of the Art in Short-Term Load Forecasting

The problem of short-term load forecasting began approximately


Typical Winter and Summer Daily Load Patterns
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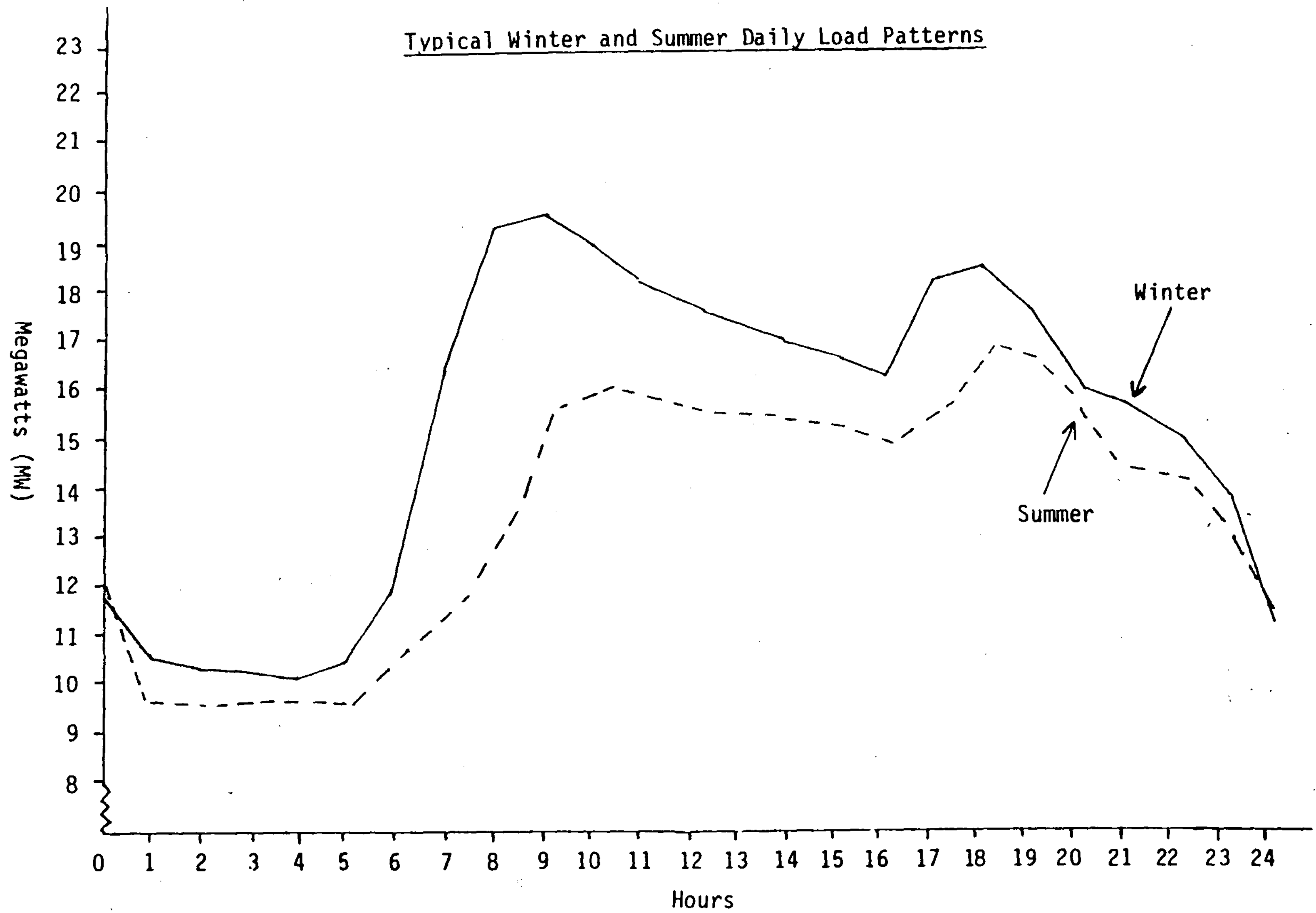
Hours
Winter
Summer

Figure 2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Hours
Winter
Summer

Figure 2

PEAK LOAD VS. AMBIENT TEMPERATURE

FOR PP&L SUBSTATION OVER TWO WEEK PERIOD

Day	Date	Peak Load (MW)	Temperature (^{o}F)
Monday	05 December 1983	19.7	38^{o}
Tuesday	06 December 1983	18.8	43^{o}
Wednesday	07 December 1983	21.2	35^{o}
Thursday	08 December 1983	21.0	31^{o}
Friday	09 December 1983	20.7	36^{o}
Monday	12 December 1983	19.5	40^{o}
Tuesday	13 December 1983	19.3	44^{o}
Wednesday	14 December 1983	18.9	41^{o}
Thursday	15 December 1983	18.3	48^{o}
Friday	16 December 1983	19.7	39^{o}

Table 1

two and a half decades ago with a paper written by Farmer and Patton. This paper set the stage for many of the more developed theories in years to come.

F.D. Galiana's status report on short-term load forecasting (approximately 9 years ago) shows that the load model chosen is usually composed of a number of components. These components relate to the discussion in the previous sections on effects to the load curve. Deterministic functions of time, purely stochastic components, and weather-dependent components are examples of some of the components used to model short-term load.

Weather-Dependent Models

It has been said that a 1^{o} F change in temperature could cause a 200 MW load change on a 10,000 MW peak load system. Thus, it is quite evident that weather (temperature, in this case) can have a profound effect on the immediate load level of a given power system.

One method of including weather in the model is as follows. A base load is assumed which is completely weather insensitive, that is, it is constant. A separate function, highly dependent on weather variables, is added to allow for any variations from the base load at any given time. This model is as in Equation 1.

$$L_T(t) = L_B + L(w,t) \qquad \text{Eq. 1}$$

where:

$L_T(t)$ is the total load at any given time.
L_B is the assumed base load.
$L(w,t)$ is the weather-dependent component.

If need be, the base load, L_B, can be adjusted to relate directly to the time of year for which the model is being used. That is, L_B can be made time-dependent. In equation form:

$$L_T(t) = L_B(t) + L(w,t) \qquad \text{Eq. 1a}$$

Note that in either model a separate weather forecast is needed to calculate the term L(w,t). This may or may not be beneficial to the accuracy of the model.

Time Series Representation

The method of time series representation or time series models relies on the fact that the load curve is basically consistent in terms of shape. The idea of this method is to fit some type of function to the curve. A typical example is that of Equation 2.

$$L(t) = \sum_{i=1}^{k} a_i f_i(t) + L_0(t) \qquad \text{Eq. 2}$$

where:

L(t) is the total load at any time, t.
$L_0(t)$ is a weekly or daily trend at any time, t.

The remaining term of the model represents the functions of time that must be fit to the shape of the curve. Thus, f_i represents the functions used while a_i are the coefficients of the functions.

The functions of time, f_i, must be selected by the researcher in such a way as to achieve the highest level of accuracy. One popular method is that of harmonic decomposition. Equation 2 can be rewritten as:

$$L(t) = \sum_{i=0}^{k} (a_i \sin iwt + b_i \cos iwt) + L_0(t) \qquad \text{Eq. 3}$$

In this way, sinusoidal functions are used as the functions of time in Equation 2. Past load data is processed in such a way as to determine the necessary harmonic components and their associated Fourier coefficients.

The problem with time series modeling is that in order to take advantage of immediate past load data, the coefficients of the model must be updated as each new data point is retrieved. This leads to a great number of calculations, but must be done as the load curve is not a stationary (time-invariant) process and, thus, a constant model is not valid. The model parameters will change in time.

Dynamic Model Representation

Dynamic models differ from time series models in that they use the immediate past load data and various other effects to describe the present load. One possible model is shown in Equations 4 and 5.

$$L_T(t) = L_0(t) + \sum_{i=1}^{i} a_i f_i(t) + Z(t) \qquad \text{Eq. 4}$$

$$Z(t) = \sum_{k=1}^{m} c_k Z(t - k) + \sum_{j=1}^{n} d_j u(t - j) + w(t) \qquad \text{Eq. 5}$$

Note the difference between the time series model of Equation 2 and the dynamic model of Equation 4 is the term $Z(t)$ in Equation 4. This term is used to describe the immediate random trend of the load. The term $u(t - j)$ of Equation 5 is used to include immediate weather trends and may or may not be included by the researcher. The term $w(t)$ is simply the random error component.

With this model, the a_i's are assumed constant over time. Therefore, the Z(t) term is used to make any adjustments in the load by looking at immediate past trend patterns.

Three separate models or algorithms which have recently been developed will be discussed in the next chapter. Each of these models uses the concepts presented in this chapter to attain accurate short-term load forecasts. These methods will be compared and contrasted to the proposed method of this paper in Chapters III and IV.

Chapter II

RECENTLY DEVELOPED SHORT-TERM LOAD FORECASTING ALGORITHMS

A number of short-term load forecasting algorithms have been discussed in the literature during recent years. Each algorithm differs somewhat in the way it models the load, yet each is a valid representation. Three of the most recent algorithms will be discussed here and their advantages and disadvantages are stressed. Each of these algorithms is to be used for on-line applications.

Method #1 - "An Accurate Model for Short-Term Load Forecasting"

A September, 1981 "IEEE Transaction on Power Apparatus and Systems" paper developed a dynamic model to be used adaptively for the prediction of load on an hourly basis.

The authors point out that this algorithm is generally to be used for the monitoring and controlling of a power system. The authors have applied the algorithm to lead times of one hour to one week. This thesis paper concerns itself only with the results on a one hour lead time.

The model is very similar to the discussion on dynamic models in Chapter I. The authors decomposed the load into a number of components:

- Daily pattern reflecting hourly fluctuations during the day
- Weekly pattern showing day-of-the-week effects

· Seasonal trend pattern

· Weather fluctuation component

In equation form, the model is shown to be as follows:

$$Y(i,j) = ADP(j) + AWP(k,j) + WSC(i,j) + TR(i) + SEC(i,j) \qquad \text{Eq. 6}$$

where:

$Y(i,j)$ is the hourly forecast at hour j and day i.

$ADP(j)$ is the average daily load at hour j.

$AWP(k,j)$ is the average weekly load increment at hour j and the k^{th} day of the week.

$WSC(i,j)$ is the weather component at hour j and day i.

$TR(i)$ is the trend component at day i.

$SEC(i,j)$ is the stochastic error component.

Figure 3 shows a flow chart given in the paper which clearly defines the procedure used to forecast the load at any given time.

As with all methods, the various model parameters or coefficients are calculated by processing past load data. Here, the available historical weather data must also be inputted to find the weather component, WSC. The flow chart in Figure 3 shows that the method proposed uses an iterative procedure to calculate the model parameters. Initially, all unknown coefficients are assumed zero, that is, AWP = WSC = TR = 0. Then Equations 7 through 14 are sequentially manipulated to arrive at values for ADP, AWP, WSC, and TR.

$$ADP(j) = 1/n \sum_{i=1}^{n} (y(i,j) - AWP(k,j) - WSC(i,j) - TR(i)) \qquad \text{Eq. 7}$$

Flow Chart for Method 1

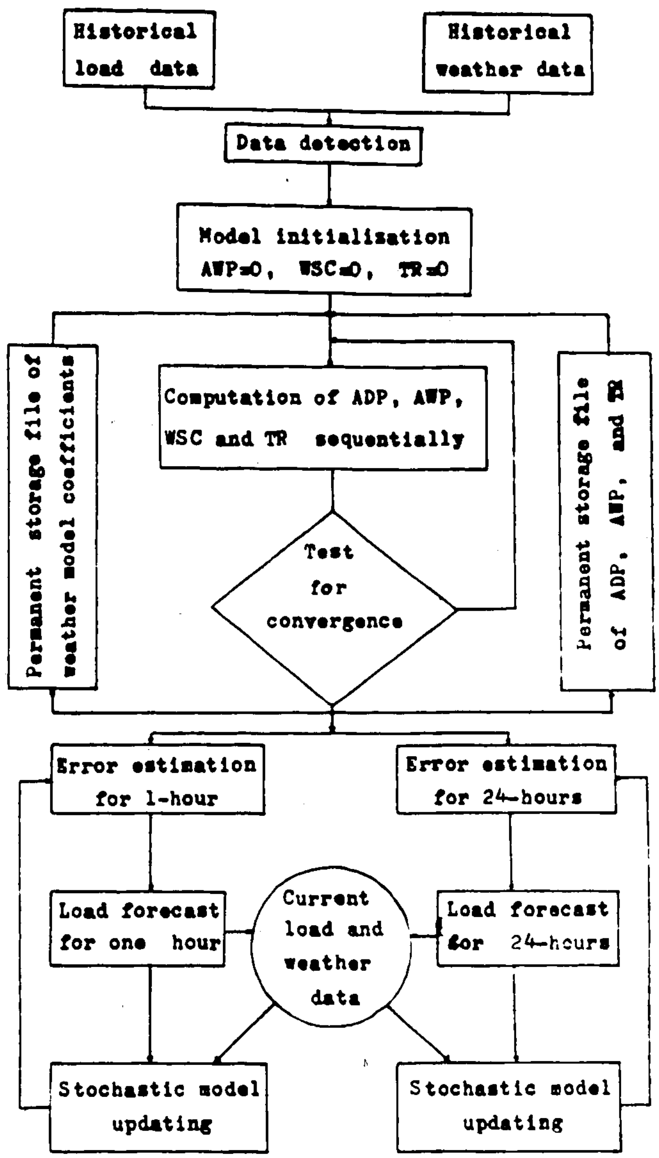

Figure 3

Flow Chart for Method 1

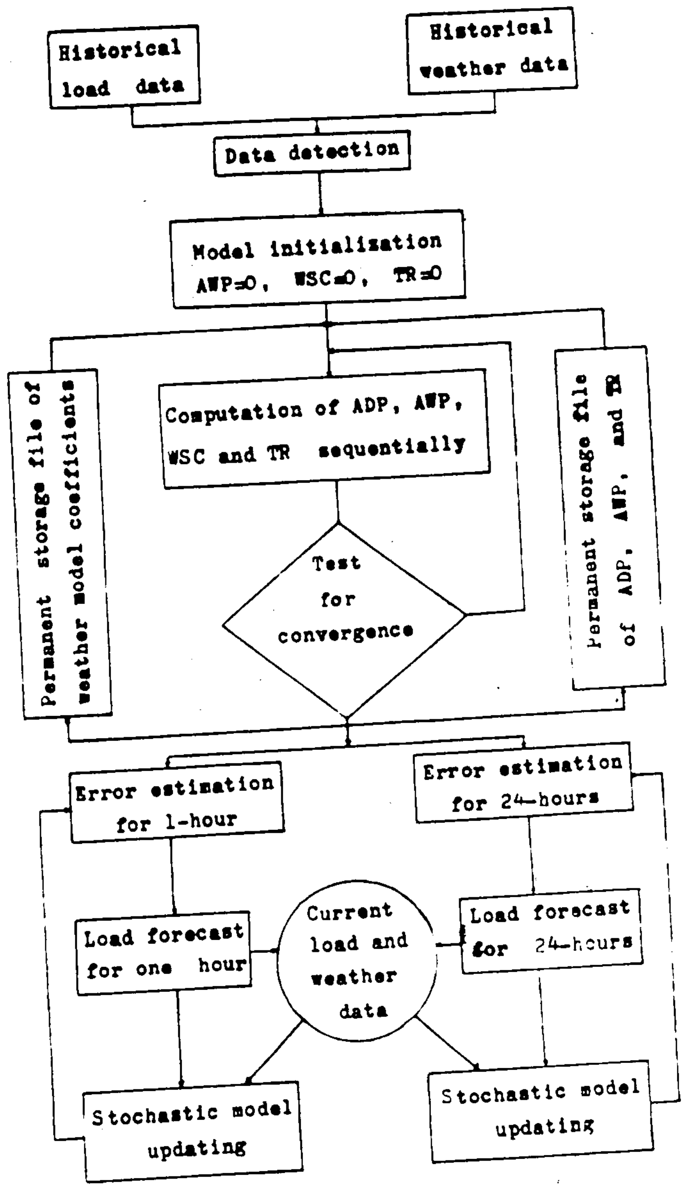

Figure 3

where:

n is the number of days of historical data.
y(i,j) is the hourly load at hour j and day i.

$$AWP(k,j) = 1/m \sum_{i=k}^{m} (y(i,j) - ADP(j) - WSC(i,j) - TR(i)) \qquad \text{Eq. 8}$$

where:

$i = k, k+7, \ldots, k+(m-1)7$

$$x(i,j) = y(i,j) - ADP(j) - AWP(k,j) - TR(i) \qquad \text{Eq. 9}$$

This calculated estimate is fitted to a temperature model outlined below.

$$WSC(i,j) = a_0 + a_1(T_{j-1} - T_s) + a_2(T_{j-1} - T_s)^2 \qquad T > T_s \qquad \text{Eq. 10}$$

$$WSC(i,j) = 0 \qquad T_s > T > T_w \qquad \text{Eq. 11}$$

$$WSC(i,j) = b_0 + b_1(T_w - T_{j-1}) + b_2(T_w - T_{j-1})^2 \qquad T_w > T \qquad \text{Eq. 12}$$

where:

T_j is temperature at hour j.
$T_w = 60^o$ F
$T_s = 70^o$ F
a_0, a_1, a_2, b_0, b_1, b_2 are unknown parameters calculated by the Method of Least Squares.

$$G(i) = 1/24 \sum_{j=1}^{24} (y(i,j) - ADP(j) - AWP(k,j) - WSC(i,j)) \qquad \text{Eq. 13}$$

This function is fitted to a second order polynomial in time to represent a smoothed trend.

$$TR(i) = c_0 + c_1 + c_2t^2 \qquad \text{Eq. 14}$$

where:

c_0, c_1, c_2 are unknown parameters calculated by the Method of Least Squares.

Results of Method #1

The proposed model was tested by the General Egyptian Electricity Corporation Dispatching Incorporate on the Northern Egypt Power System. The load forecasting was done on a total system load basis.

The authors indicate that four weeks worth of data was needed to derive an accurate model. Test results show the model performed with a maximum error of 3.8% and a standard deviation of 1.2%. The authors state the errors are normally distributed on the long term.

Potential Disadvantages of Method #1

The algorithm presented in Method 1 appears to perform fairly well. However, some potential disadvantages of this method seem to make it a questionable algorithm for most on-line power systems. Some of the potential disadvantages follow.

- The method requires a vast amount of historical and current weather data. Temperature variations over a large system can be quite great and thus obtaining the correct weather data is questionable. Also, most systems are not set up to record vast amounts of weather information. Implementation of the necessary equipment to gather this information could be quite costly.

- Using the algorithm adaptively appears quite cumbersome, especially when predicting loads one hour in advance. Tests show the algorithm needs a number of iterations to converge and thus would appear slow and computationally inefficient.

Method #2 - "On-Line Load Forecasting for Energy Control Center Application"

A January, 1982 "IEEE Transaction on Power Apparatus and Systems" paper developed an on-line short-term load forecasting model to be used on American Electric Power Service Corporation's system. The model developed is used to forecast total internal system load, however AEP stresses this algorithm will eventually be used for bus load forecasts.

AEP had four objectives when developing their forecasting procedure:

- Develop an accurate load model and forecast model for AEP's system data
- Develop adaptive models and techniques
- Develop computationally efficient techniques
- Develop easy-to-use techniques

With these four objectives in mind, AEP felt the Bohlin and Generalized Least Squares Algorithm would allow their goals to be met.

With this approach, the internal system load is divided into two parts:

- Nominal load component
- Residual load component

The nominal load component is considered the deterministic portion of the load, while the residual component is considered to be weathersensitive and essentially random. The model developed assumes temperature is the greatest factor in the weather component.

AEP's method develops a load profile model and a temperature profile model which are used for forecasting load in the short-term. The IEEE paper thoroughly discusses the intricasies of the algorithm. This thesis paper attempts only to show the generalities of the algorithm and to stress its advantages and disadvantages.

Load Profile Model of Method #2

The nominal load is modelled with 24 hour load profiles for each day of the week. In equation form, the load profile model is given as:

$$y_k(t) = x_1(t) + a_2(k)x_2(t) + \ldots + a_9(k)x_9(t) + n_t \qquad \text{Eq. 15}$$

where:

$a_i(k) = 1$ for $i = k \quad i = 2, 3, \ldots, 9$
$\quad = 0$ otherwise

$x_1(t)$ is the reference load at hour t

$x_2(t)$ is the Sunday incremental load at hour t different from $x_1(t)$

.
.
.

$x_8(t)$ is the Saturday incremental load at hour t different from $x_1(t)$

$x_9(t)$ is the odd day incremental load different from $x_1(t)$ at hour t

AEP developed a load profile model using state variable concepts and Kalman filtering techniques. The general form of the model is described below.

It is assumed that:

$$x_i(t + 24) = x_i(t) + w_i(t) \qquad \text{Eq. 16}$$

where:

x_i represents the model's state variables

w_i is random error of zero mean

Using Kalman filtering techniques, the estimated nominal load is calculated for each hour of the day. Subtracting the estimated load (load profile) from actual observed load will give rise to the residual load. The following are the governing equations for this method.

$$\underline{H}(k) = (1 \quad a_2(k) \; . \; . \; . \; a_9(k)) \qquad \text{Eq. 17}$$

$$\underline{R}_1 = \text{diag}(d_1^{\,2}, d_2^{\,2} \; . \; . \; . \; d_9^{\,2}) \qquad \text{Eq. 18}$$

$$R_{yy}(k/k-1) = \underline{H}(k)R_{xx}(k/k-1)\underline{H}^T(k) + d_y^{\,2} \qquad \text{Eq. 19}$$

$$R_{xx}(k+1/k) = \underline{R}_1 + R_{xx}(k/k-1) - k(k)R_{yy}(k/k-1)k^T(k) \qquad \text{Eq. 20}$$

where:

R_{yy} is the variance of the Kalman Filter residual sequence Y_k

R_{xx} is the covariance matrix of the estimated state variables

k is the Kalman filter gain for load model

Therefore, as stated previously the residual load is simply:

$$n_t = \hat{Y}_k(t/t-24) = Y_k(t) - H(k)x(t/t-24) \qquad \text{Eq. 21}$$

The state variable matrix is then updated.

$$x(t+24/t) = x(t/t-24) + k(k)\hat{Y}_k(t/t-24) \qquad \text{Eq. 22}$$

Temperature Profile Model of Method #2

This model does not concern itself with separate models for each day of the week. Rather, this model's main concern is 24 hour periodic patterns.

The model is given in equation form as:

$$YT(t) = XT(t) + T_t \qquad \text{Eq. 23}$$

$$XT(t + 24) = XT(t) + wT(t) \qquad \text{Eq. 24}$$

where:

$YT(t)$ is temperature observed at hour t

$XT(t)$ is temperature profile state variable at time t

wT is the random daily temperature variation

T_t is random component for temperature model

As with the load profile model, Kalman filtering techniques are used to arrive at an estimated model. The following outlines the governing equations for the Kalman filter;

$$R_{YTYT}(k/k-1) = R_{XTXT}(k/k-1) + d_{YT}^{2} \qquad \text{Eq. 25}$$

$$KT(k) = R_{XTXT}(k/k-1)/R_{YTYT}(k/k-1) \qquad \text{Eq. 26}$$

$$R_{XTXT}(k+1/k) = RT_1 + R_{XTXT}(k/k-1) - KT(k)^2 R_{YTYT}(k/k-1) \qquad \text{Eq. 27}$$

Similar to the load profile model method, the residuals are computed.

$$T_t = \hat{YT}(t/t-24) = YT(t) - XT(t/t-24) \qquad \text{Eq. 28}$$

The state variables are updated also.

$$XT(t+24/t) = XT(t/t-24) + KT(k)\hat{YT}(t/t-24) \qquad \text{Eq. 29}$$

Manipulation of these two models gives a forecast of the load at time t. The actual procedure is fully documented in the IEEE paper.

<u>Results of Method #2</u>

AEP developed a model for short-term load forecasting based on data obtained from January, 1977 to August, 1977. It should be noted that meteorological forecasts of temperature were used to arrive at a satisfactory temperature model to use for forecasting purposes. The authors show their forecast algorithm behaved with the following characteristics (note only one hour lead time is shown.)

Season	RMS Error
Winter	1.8%
Summer	2.7%

The authors indicate the model performed equally well for every day of the week.

Potential Disadvantages of Method #2

The results of AEP's tests show that their proposed algorithm performed extremely well on their system. However, it appears there are a number of potential disadvantages with their approach.

- A vast amount of weather data is required to develop a weather model. As in Method 1, the accuracy and availability of this data is questionable.
- Weather forecasts are required to implement this algorithm. Depending on this forecast, the weather component of our load forecast may be inaccurate.
- Due to the vast amount of information required and the large number of computations involved, adaptive implementation of this algorithm appears cumbersome.

Method #3 - "On-Line Algorithms for Forecasting Hourly Loads of an Electric Utility"

An August, 1981 "IEEE Transaction on Power Apparatus and Systems" paper outlined a method for forecasting hourly loads using both an autoregressive (AR) model and an autoregressive moving average (ARMA) model. Both of the models developed attempt to account for the stochastic behavior of power system load. As in the previous methods, historical data is processed to derive all the parameters of the describing model.

The IEEE paper fully develops and completely discusses the governing equations and methods for developing both the AR and the ARMA models. The following discussion attempts only to present the basics of each approach. Note, the next chapter will fully discuss time series analysis used in these methods.

Autoregressive Model

The AR model attempts to simulate a time series, such as a load curve in discrete form, where it is assumed that successive points in time are highly dependent. The theory says that the current value of the discrete signal, y(t), can be written as a linear combination of previous values of the signal and some input, u_t. That is,

$$h_p(B)y_t = u_t \qquad \text{Eq. 30}$$

where:

$$h_p(B) = \sum_{i=0}^{p} h_i B^i, \; h_0 = 1 \qquad \text{Eq. 31}$$

A backward shift operator is defined as $By_t = y_{t-1}$. Thus:

$$B^k y_t = y_{t-k} \qquad \text{Eq. 32}$$

Past historical data are then processed so that accurate values for the model's coefficients can be calculated. Here, the least squares estimator is used to find the proper coefficients.

Autoregressive Moving Average Model

Similar to the AR model, the ARMA model attempts to simulate a time series. The ARMA model differs, however, from the AR model in that past inputs are also included in the development of the model. That is,

$$h_p(B)y_t = w_q(B)u_t \qquad \text{Eq. 33}$$

where:

$$w_q(B) = \sum_{j=0}^{q} w_j B^j, \; w_0 = 1 \qquad \text{Eq. 34}$$

and $h_p(B)$ is defined as in the AR model.

Results of Method #3

The authors tested both the AR and ARMA models to forecast the hourly loads on the Lincoln Electric System of Lincoln, Nebraska. The table presented below was taken from the IEEE paper and summarizes the results of these tests.

Table of Results for Method 3

Sample Size	30 Days		60 Days		90 Days		120 Days	
Hour	AR	ARMA	AR	ARMA	AR	ARMA	AR	ARMA
0	6.75%	6.42%	5.81%	4.53%	5.42%	5.34%	5.40%	5.66%
3	7.32	6.23	5.44	1.37	4.69	4.65	4.54	5.39
6	7.81	6.92	6.88	1.80	4.65	4.86	3.77	4.79
9	-0.34	-0.47	0.56	-3.79	-1.45	-1.24	-1.16	-0.32
12	-1.00	-0.63	0.84	-4.37	-1.23	-1.11	-0.92	-0.14
15	-2.83	-1.66	0.97	-4.18	-2.63	-2.57	-2.83	-2.23
18	-5.60	-4.16	1.05	-3.76	-4.74	-4.64	-4.77	-4.15
21	-4.59	-3.01	5.24	0.55	-2.96	-2.68	-3.22	-2.53
RMS Value	5.28	4.44	4.20	3.37	3.79	3.74	3.66	3.75%

Table 2

As is clearly shown in Table 2, the authors looked at the effects of the amount of historical data used to derive the AR and ARMA models. The RMS value of the hourly error is reduced as the amount of sample points is increased.

A comparison of the differences between the AR and ARMA models shows that there is little improvement seen with the increased complexity of the ARMA. Because of this result, the proposed method of the fourth chapter will not concern itself with the ARMA model, but only with an AR model.

Potential Disadvantages of Method #3

The algorithms shown in Method 3 introduced AR and ARMA models to short-term load forecasting. Although the models performed with reasonable accuracy, there appears to be some disadvantages with this approach.

- The algorithm does not appear to easily change model parameters when a new load is measured and recorded. Numerous calculations and iterations are needed for each update.
- The algorithms presented do not take advantage of base load patterns. Including these patterns in an algorithm should increase the accuracy of the method.

Chapter III

GENERAL THEORY OF LINEAR PREDICTION

This chapter fully discusses the theory involved in linear prediction. As noted in Chapter I, the General Least Squares Approach to estimate model parameters is outlined, as is its application to various models. The mathematics presented here are used as a basis for the derivation of the adaptive filters to be proposed in Chapter IV.

Linear Prediction - Analysis of Discrete Signals

The study of dynamic system behavior has been quite extensive. "Time series analyses" began in the fields of statistics, econometrics and communications. Since the recent development of state-space concepts and time domain analysis in control theory applications, time series analysis has been expanded to other fields. John Makhoul's April, 1975 paper thoroughly discusses the theory of linear prediction.

In time series analysis, a continuous signal, s(t), is sampled to obtain a discrete signal, s(nT). This discrete signal is known as a time series. If an accurate model for this time series can be developed, then it would be possible to use this model for forecasting or prediction applications.

It has been shown that one of the most powerful time series models is as follows:

$$s_n = \sum_{k=0}^{p} a_k s_{n-k} + G \sum_{l=0}^{k} b_l u_{n-l} \qquad \text{Eq. 35}$$

where:

$$b_0 = 1.$$

Note s_n is the system output while u_n is some unknown system input. This model says the system output is a linear combination of past outputs and present and past inputs. The term "linear prediction" stems from the fact that the output is predictable from a knowledge of past outputs and inputs. In control system terminology, this model is known as the "pole-zero" model or an "autoregressive moving average (ARMA)" model.

This thesis paper is concerned with a special case of this model. This case is known as the "all-pole" or "autoregressive (AR)" model. This occurs when $b_l = 0$ for all l. As stated before, the results of Vermuri's work indicate an AR model is sufficient for short-term load forecasting.

In the all-pole model, it is assumed the signal, s_n, is given by a linear combination of past values and some input, u_n. This model is shown in Equation 36.

$$s_n = -\sum_{k=0}^{p} a_k s_{n-k} + G u_n \qquad \text{Eq. 36}$$

In the frequency domain, the transfer function for this model is:

$$H(Z) = \frac{S(Z)}{U(Z)} = \frac{G}{1 + \sum_{k=1}^{p} a_k z^{-k}} \qquad \text{Eq. 37}$$

Figure 4 shows diagrams of both the time and frequency models.

(a)

(b)

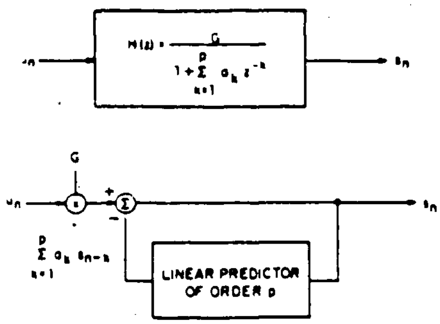

Figure 4. Frequency (a) and Time (b) Models

Once a signal s_n is known, the problem becomes finding values for the predictor coefficients, a_k, and the gain, G (whenever needed.)

Parameter Estimation - Least Squares Approach

This discussion begins by assuming a time series, s_n, has been found in some manner. It is also assumed that there is no information regarding the system input, u_n. (This is essentially true in power system load forecasting.) Letting $\hat{s}_n$ be the prediction of the output, we see that:

$$\hat{s}_n = - \sum_{k=0}^{p} a_k s_{n-k} \qquad \text{Eq. 38}$$

Thus, it follows that the error in the approximation is simply:

$$e_n = s_n - \hat{s}_n \qquad \text{Eq. 39}$$

Combining Equations 38 and 39 we obtain Equation 40.

$$e_n = s_n + \sum_{k=0}^{p} a_k s_{n-k} \qquad \text{Eq. 40}$$

Still, the predictor coefficients must be calculated. This is accomplished by minimizing the squared error with respect to all the model parameters. That is:

$$E = \text{squared error} = \sum_n e_n^2 = (s_n + \sum_{k=0}^{p} a_k s_{n-k})^2 \qquad \text{Eq. 41}$$

To minimize the squared error with respect to all the coefficients, the derivative of the squared error with respect to each predictor coefficient is taken and set equal to zero. Thus:

$$\frac{dE}{da_i} = 0 \qquad \text{for } 1 \leq i \leq p \qquad \text{Eq. 42}$$

This yields the "normal equations" which give the a_k's that minimize the squared error. The normal equations are as follows:

$$\sum_{k=1}^{p} a_k \sum_n s_{n-k} s_{n-i} = - \sum s_n s_{n-i} \qquad \text{Eq. 43}$$

Several methods have been documented for solving the normal equations. The autocorrelation and covariance methods are two of the more popular and complex methods documented.

<u>Autocorrelation Method for Solving Normal Equations</u>

With the autocorrelation method, a global error criterion is satisfied. That is, the squared error, E, is minimized over an infinite region, $-\infty \leq n \leq +\infty$.

Letting $R(i) = \sum s_n s_{n+1}$, we note that Equation 43 reduces to:

$$\sum_{k=1}^{p} a_k R(i-k) = - R(i) \qquad 1 \leq i \leq p \qquad \text{Eq. 44}$$

Also,

$$E = R(0) + \sum_{k=1}^{p} a_k R(k) \qquad \text{Eq. 45}$$

It is noted that $R(-i) = R(i)$ since $R(i)$ is an even function.

Because we have only finite information concerning the signal s_n, the autocorrelation must be limited to a finite interval. This is generally accomplished by windowing the data. The signal outside of this window is assumed to be zero. In equation form:

$$s_{n_{window}} = \begin{cases} s_n w_n & \text{for } 0 \leq n \leq N-1 \\ 0 & \text{otherwise} \end{cases} \qquad \text{Eq. 46}$$

The new autocorrelation function becomes:

$$R(i) = \sum_{n=0}^{N-1-i} s_{n_{window}} s_{n+i_{window}} \qquad \text{Eq. 47}$$

The selection of the window, w_n, is dependent on the application and is fully discussed in Makhoul's "Linear Prediction: A Tutorial Review."

Covariance Method for Solving Normal Equations

This method differs from the autocorrelation method in that it minimizes the squared error, E, over a finite interval and thus no windowing of the signal is required.

The covariance function is written as:

$$\sum_{k=1}^{p} a_k h_{ki} = -h_{oi} \qquad \text{Eq. 48}$$

Also

$$E = h_{oo} + \sum_{k=1}^{p} a_k h_{ok} \qquad \text{Eq. 49}$$

where we define:

$$h_{ik} = \sum_{n=0}^{N-1} s_{n-i} s_{n-k} \qquad \text{Eq. 50}$$

It can be shown that the matrix formed by the last equation, the covariance matrix, is symmetric. That is, $h_{ik} = h_{ki}$. The off-diagonal terms are not equal, however, which is different from the autocorrelation method which has the elements along each diagonal equal.

Method of Calculating Coefficients, a_k's, from Autocorrelation and Covariance Methods

In both the autocorrelation and covariance methods previously outlined, a set of p equations and p unknowns has been found. To find the predictor coefficients, a_k's, of the model these equations must be solved. As Makhoul's paper states, either method or set of equations can be solved using the Gauss reduction method.

The Gauss reduction method would require approximately $p^3/3 + O(p^2)$ operations and p^2 storage or memory locations. It is noted that by using the square-root method to solve the autocorrelation or covariance equations, the computations and memory locations could be reduced to about half of the Gauss reduction method.

A method recently developed by Durbin requires only 2p memory locations and $p^2 + O(p)$ computations. Durbin proposed the recursive procedure outlined below to solve the autocorrelation equations:

$$E(0) = R(0) \qquad \text{Eq. 51}$$

$$K_i = \left(R(i) + \sum_{j=1}^{i-1} a_j^{(i-1)} R(i-j)\right) / E_{i-1} \qquad \text{Eq. 52}$$

$$a_i^{(i)} = K_i \qquad \text{Eq. 53}$$

$$a_j^{(i)} = a_j^{(i-1)} + K_i a_{i-j}^{i-1} \qquad 1 \leq j \leq i-1 \qquad \text{Eq. 54}$$

$$E_i = (1 - K_i^2) E_{i-1} \qquad \text{Eq. 55}$$

Recursively solving these equations the final result is:

$$a_j = a_j^{(p)} \qquad \text{Eq. 56}$$

Disadvantages of the Autocorrelation and Covariance Methods for Solving the Normal Equations

In theory, the autocorrelation method of linear prediction guarantees the stability of the AR model previously described. In practice, however, when this method is limited to finite wordlength computations (that is, a finite number of decimal places in each computation) the stability of this model is not always guaranteed. Also, the necessary windowing of the signal reduces the chances of obtaining the proper spectral properties.

The covariance method does not require windowing of the signal, thus spectral resolution is no problem. Yet, this method in no way guarantees a stable filter. Such methods as floating-point computation were not successful in providing a stable filter.

A class of recursive lattice methods are presented in the next chapter which guarantees the stability of the filter. These methods have been shown to work properly with or without signal windowing and with or without finite wordlength computations.

Chapter IV

ADAPTIVE LATTICE FILTERS AND THE PROPOSED METHOD

As discussed in Chapter III, finding the predictor coefficients from the normal equations is a necessity in linear prediction schemes. It was stated that two of the more popular techniques of solving the normal equations, the autocorrelation method and the covariance method, have certain disadvantages which make them difficult to use. A recursive lattice method has been shown to function well in solving for the predictor coefficients. This method is thoroughly discussed as is the proposed method for short-term load forecasting which incorporates this filter.

MATHEMATICS OF LATTICE FORMULATION

An October, 1977 "IEEE Transactions on Accoustics, Speech, and Signal Processing" paper written by John Makhoul thoroughly discusses the mathematics involved in forming a stable and efficient lattice method for linear prediction. This lattice is an extension of the discussion in Chapter III on analysis of discrete signals.

As previously discussed, the all-pole or AR model is shown to be:

$$H(z) = \frac{S(z)}{U(z)} = \frac{G}{1 + \sum_{k=1}^{p} a_k z^{-k}} \qquad \text{Eq. 57}$$

where:

G is the gain factor.

a_k are the predictor coefficients.

p is the number of filter poles.

The lattice filter defines "reflection coefficients", K_m, which are indirectly related to the predictor coefficients, a_k's. The relation between the reflection coefficients and the predictor coefficients is as follows:

$$a_m^{(m)} = K_m \qquad \text{Eq. 58}$$

$$a_j^{(j)} = a_j^{(m-1)} + K_m a_{m-j}^{(m-1)} \qquad \text{Eq. 59}$$

Solving Equation 59 in a recursive fashion, the final solution is shown to be:

$$a_j = a_j^{(p)} \qquad \text{for } 1 \leq j \leq p \qquad \text{Eq. 60}$$

Filter stability occurs when:

$$K_m \leq 1 \qquad \text{for } 1 \leq j \leq p \qquad \text{Eq. 61}$$

Figure 5 shows the filter described in Makhoul's paper. Note, in this diagram q^{-1} is a filter time delay.

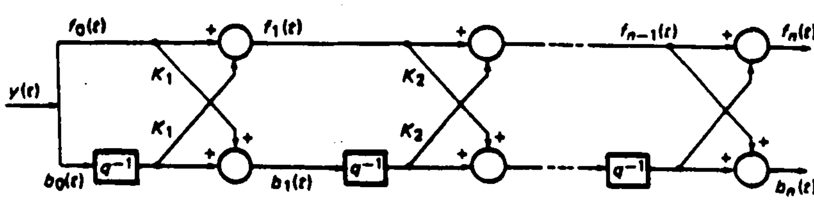

Figure 5. Adaptive Lattice Filter

Similar to minimizing the normal equations with respect to the predictor coefficients, the reflection coefficients are computed by minimizing the forward residual $f_m(t)$ and/or the backward residual $b_m(t)$. The governing equations for the filter of Figure 5 are shown below.

$$f_0(t) = b_0(t) = y(t) \qquad \text{Eq. 62}$$

$$f_{m+1}(t) = f_m(t) + K_{m+1}b_m(t - 1) \qquad \text{Eq. 63}$$

$$b_{m+1}(t) = K_{m+1}f_m(t) + b_m(t - 1) \qquad \text{Eq. 64}$$

Note that $y(t)$ is the input signal to the lattice filter while $f_p(t)$ is the output error residual.

The IEEE paper outlines a number of methods in which the reflection coefficients are calculated. This paper is concerned with the "minimum method." That is, a reflection coefficient, K^f, is calculated which minimizes the mean squared forward residual and another reflection coefficient, K^b, is calculated which minimizes the mean squared backward residual. The reflection coefficient with the smallest absolute value is chosen as the filter coefficient. This guarantees the stability of the filter.

The following definitions are given:

$$F_m(t) = E(f_m^{\,2}(t)) \qquad \text{Eq. 65}$$

$$B_m(t) = E(b_m^{\,2}(t)) \qquad \text{Eq. 66}$$

$$C_m(t) = E(f_m(t)b_m(t - 1)) \qquad \text{Eq. 67}$$

$$K_{m+1} = - C_m(t)/B_m(t - 1) \quad \text{Eq. 68}$$

$$K^b_{m+1} = - C_m(t)/F_m(t) \quad \text{Eq. 69}$$

$$K_m = \min(K^f, K^b) \quad \text{Eq. 70}$$

Note, the notation $E(\cdot)$ indicates the expected value of a variable and denotes the processing of historical data.

An extension of this lattice filter allows the lattice to be used as a one-step-ahead predictor. Equation 63 was previously shown to be:

$$f_{m+1}(t) = f_m(t) + K_{m+1}b_m(t - 1) \quad \text{Eq. 71}$$

Rewritten in summation form we obtain:

$$f_m(t) = f_0(t) + \sum_{m=1}^{p} K_{m+1}b_m(t - 1) \quad \text{Eq. 72}$$

It was previously stated that the forward residual was actually the error between the input and what is realized by the filter. In equation form,

$$f_m(t) = y(t) - \hat{y}_m(t) \quad \text{Eq. 73}$$

Therefore,

$$\hat{y}_m(t) = - \sum_{m=1}^{p} K_{m+1}b_m(t - 1) \quad \text{Eq. 74}$$

The lattice structure is shown in Figure 6 and will be incorporated in predicting the hourly load on a power system. This lattice filter method is fully discussed in G.C. Goodwin and K.S. Sin's book, "Adaptive Filtering Prediction and Control."

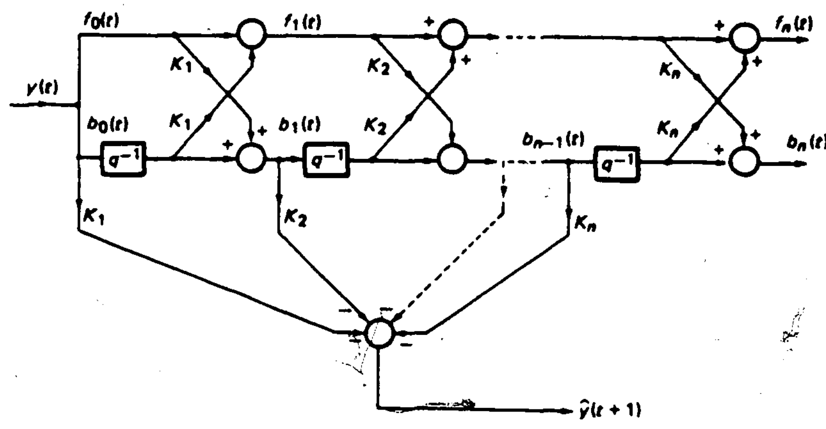

Figure 6. <u>One-Step-Ahead Predictor</u>

PROPOSED METHOD

The method of short-term load forecasting proposed in this thesis paper develops an adaptive hourly algorithm for predicting the load on a power system one hour in advance.

The model proposed can be written as:

$$L_T(t) = L_B(t) + n(t) \qquad \text{Eq. 75}$$

where:

L_T is the total load at time t.
L_B is the base load at time t.
n is the trend component at time t.

The trend component is composed of two parts - an average value of load at time t and a stochastic component which is generated by the previously discussed lattice filter. The steps below outline the procedure to calculate the load on an hourly basis.

Step-by-Step Procedure

Step 1 Obtain and input historical data. (Two weeks of data is used in the research shown here.)

Step 2 Analyze the given historical data and develop a time-varying base load for the given power system. Thus, a specific base load is found for each hour of the day.

Step 3 Choose the order of the filter to be used. (p = 3 in this research.)

Step 4 Revise the historical data by subtracting the base load for each hour from the corresponding data points.

Step 5 Find the average value of the revised data over the specified window size for time t. The window size corresponds to the filter order and is representative of the number of past loads linearly combined to predict the load at time t.

Step 6 Generate a zero-mean historical data set by subtracting the average value of the data from each corresponding data point.

Step 7 Using Equations 62-70, process, in a bootstrap fashion, the modified historical data set (zero-mean sequence) to generate the reflection coefficients for each hour of the day. That is, 24 separate filters are developed; one for each hour of the day.

Step 8 Modify the recent data needed for prediction by subtracting the average value and base load.

Step 9 Input the modified recent load information into the lattice structure to predict the stochastic component one hour in advance.

Step 10 Calculate $L_T(t)$ by summing the base load, the average over the window, and the stochastic component generated by the lattice filter.

Results of Tests on Proposed Method

The proposed method was tested with data gathered from a Pennsylvania Power and Light Company substation for December, 1983. As stated previously, two weeks worth of data was used to develop the base load and filter coefficients. A prediction was then made on an hourly basis for Monday, December 19, 1983. A third order lattice was used.

Table 3 shows the base load values used in the test. Table 4 shows the values of the reflection coefficients calculated as well as the average over the data window. The results for the test day are shown in Table 5.

The absolute average error over this 24-hour period is 4.29% while the RMS error value is 4.8%.

Time-Varying Base Load Given by

Data for Period 12/05-12/16

Time	Base Load (MW)
Midnight	11.5
1 AM	10.3
2	9.3
3	9.2
4	9.2
5	9.7
6	11.2
7	15.2
8	17.4
9	18.2
10	17.9
11	18.1
Noon	17.0
13	16.5
14	15.7
15	15.6
16	14.8
17	17.0
18	17.7
19	17.5
20	16.7
21	15.5
22	15.0
23	13.7

Table 3

Reflection Coefficients and Average Over Data Window

Time	$\underline{K}_1$	$\underline{K}_2$	$\underline{K}_3$	Average (MW)
Midnight	-.295	-.190	-.304	1.0
1 AM	-.727	-.108	-.309	0.9
2	-.795	-.622	-.015	1.0
3	-.782	-.606	-.097	1.0
4	-.857	-.258	-.983	1.1
5	-.833	-.002	-.410	1.1
6	-.788	-.178	+.234	1.1
7	-.815	-.048	-.747	1.2
8	-.905	-.041	-.172	1.3
9	-.728	-.681	-.383	1.3
10	-.650	-.169	-.566	1.3
11	-.588	+.057	-.359	1.2
Noon	-.680	-.537	+.173	1.2
13 PM	-.802	+.151	-.385	1.2
14	-.754	+.243	+.140	1.4
15	-.803	-.305	+.002	1.7
16	-.684	-.206	+.256	1.9
17	-.351	-.449	-.546	1.9
18	-.568	+.301	-1.0	1.7
19	-.642	+.045	+.396	1.4
20	-.687	+.061	+.115	1.1
21	-.760	-.130	-.248	1.0
22	-.660	-.476	-.636	0.9
23	-.720	-.223	-.982	1.0

Table 4

Test Results for Monday, 12/19/83

Time	Predicted (MW)	Actual (MW)	% Error
Midnight	12.2	12.7	-3.9
1 AM	11.5	12.0	-4.1
2	10.9	11.8	-7.6
3	11.6	12.0	-3.3
4	11.8	12.5	-5.6
5	13.1	12.9	+1.5
6	14.2	14.6	-2.7
7	18.1	18.9	-4.2
8	21.5	21.1	+1.8
9	21.9	22.3	-1.8
10	19.7	21.8	-9.6
11	20.6	21.7	-5.0
Noon	19.8	20.5	-3.4
13 PM	19.7	20.0	-1.0
14	18.5	19.5	-5.1
15	18.5	19.7	-6.0
16	18.6	19.4	-4.1
17	20.6	21.5	-4.1
18	21.4	22.1	-3.1
19	23.7	21.8	+8.7
20	20.2	21.4	-5.6
21	19.2	20.7	-7.2
22	19.3	19.6	-1.5
23	18.0	18.4	-2.1

Table 5

Chapter V

CONCLUSIONS AND OBSERVATIONS ON THE USE OF LATTICE FILTERS FOR SHORT-TERM LOAD FORECASTING

A complete study of short-term load forecasting has been researched and reviewed in this paper. A new technique which incorporates the use of adaptive lattice filters was discussed and greatly researched. This chapter attempts to provide an account of observations and thoughts of further research in this area. A discussion of the results and a comparison to the three previously discussed methods also follows.

Discussion of Results

An attempt was made in this research to use the recently developed adaptive lattice filters to predict the load at a power system substation one hour in advance. During the research, numerous changes and experiments were done with the filter in an attempt to reduce the prediction error. Some experimental "observations" are listed below.

- The filter performed much better when a zero-mean sequence was input rather than using the original signals. Modifying the signal reduced the chance of error.
- Despite experimenting with varying orders of filters (3rd, 4th, 5th), a third order filter performed just as well as a fourth or fifth order model. The increased accuracy was greatly outweighed by the increased number of computations.
- The relatively few computations needed to develop a filter seem to make it very acceptable as an on-line adaptive process.

It is noted that the results of Table 5 are not as accurate as originally hoped. Method #1 and Method #2 of Chapter II seemed to perform with much more accuracy. Taking a closer look at these methods, however, shows the proposed method may not be as inaccurate as the results may lead one to believe.

First, both Method #1 and Method #2 rely heavily on weather data and information. As previously noted, Method #1 requires temperature data and was developed to predict system load. Attempting to use the algorithm for substation or bus load forecasting would require numerous temperature readings corresponding to each substation or region. Acquiring this meteorological information could prove to be quite costly and quite difficult. Method #2 also requires a vast amount of weather information as it develops a weather profile model. To make an actual prediction, weather forecasts are required which could introduce some degree of error to the overall load forecast. The proposed method does not require weather information in any form and thus proves to be much easier to use in terms of data collection, storage, and calculations. The only data required for the proposed method is a collection of historical data and the immediate past hourly load values. Thus, despite the increased accuracy of Method #1 and #2, the amount of data and the number of calculations necessary seem to make them unadaptable to bus load forecasting.

Method #3 is in many ways very similar to the proposed model. The filter in Method #3 is not a lattice filter but is the linear filter described by Equation 36. To solve for the predictor coefficients of this model, the normal equations must be solved as discussed in Chapter III. Thus, methods such as the autocorrelation method are involved. It was mentioned previously that this method and the covariance method were at times inefficient in guaranteeing stability and finding the correct coefficients. The lattice filter method, on the other hand, has been shown to guarantee the stability of the algorithm and can be used with a windowed or non-windowed signal. This was proven in this research as Table 4 shows no reflection coefficient has an absolute value exceeding one. A comparison of the accuracies of Method #3 and the proposed method shows that they were quite similar. Further investigation of Method #3 shows that increasing the data length to initialize the filter parameters improved the accuracy of the model substantially. It is believed the same would be seen with the proposed method.

Future Research Considerations

It is felt that the results of this research show promise for using lattice filters in short-term load forecasting. However, it should be noted that there is room for further research in this area. Some thoughts follow on potential future research topics.

This research employed two weeks worth of data to create a filter to predict the hourly load at a power system substation. This same two week historical data base was used to establish a time-varying base load and the average component previously described.

Expansion of the amount of historical data used to develop the filter and base load may lead to an improved prediction. A more precise approximation of a base load curve will allow a more precise "modified" historical data set to be generated thereby providing a better filter.

It is felt that results similar to those of Vermuri will be found.

To be used on a large power system, the algorithm shown previously would have to be modified to account for all the substations of the system. The research here concerned itself with a single substation. The describing equations previously discussed for the lattice filter would need to be expanded from a "scalar operation" filter to a "vector operation" filter.

Final Remarks

This research was undertaken in hopes of developing a short-term load forecasting algorithm or technique which was accurate, adaptive, and computationally efficient. The proposed method in this paper seems to satisfy these criteria.

As originally noted, short-term load forecasting is a critical component in monitoring and controlling a power system. The method outlined in this paper can be incorporated into the on-line control systems of a power system control center to provide this critical component.

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