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COMPOSITE MODELING FOR ADAPTIVE SHORT-TERM LOAD FORECASTING

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Abstract - Composite load model is developed for 1-24 hours ahead prediction of hourly electric loads. The load model is composed of three components : the nominal load, the type load and the residual load. The nominal load is modeled such that the Kalman filter can be used and the parameters of the model are adapted by the exponentially weighted recursive least squares method. The type load component is extracted for weekend load prediction and updated by an exponential smoothing method. The residual load is predicted by the autoregressive model and the parameters of the model are estimated using the recursive least squares method. Test results are shown using a utility data for two different years.

keywords - Load forecasting, adaptive filters.

1. INTRODUCTION

In order to supply high quality electric energy to the customer in a secure and economic manner, an electric company faces many economical and technical problems in operation, planning, and control of an electric energy system. For the purpose of optimal planning and operation of this large scale system, modern system theory and optimization techniques are being applied with the expectation of considerable cost savings. In achieving this goal, the knowledge of future power system load is the first prerequisite; therefore, long and short term load predictions are very important subjects.

The load prediction period may be month or year for the long- and the medium-term forecasts[1], and day or hour for the short-term forecast[2-7]. The long- and the medium-term forecasts are used to determine the capacity of generation, transmission, or distribution system additions, and the type of facilities required in transmission expansion planning, annual hydrothermal maintenance scheduling, etc. The short-term forecast is needed for control and scheduling of power system, and also as inputs to load flow study or contingency analysis.

There are two classes of load forecasting models reported in literature[8]. Some load models which use no weather information have been represented by time sequences[2-4]. The other load models have included the effects of weather variables on the power system load[5-7]. The former is based on the extrapolation and the load behavior is represented by Fourier series or trend curves in terms of time functions[2]. More recently state variable models[3] and autoregressive-moving average(ARMA) models[4] have also been developed to describe the load behavior. For the models including weather variables, the total load is decomposed into the weather sensitive load and the non-weather sensitive load[5-7]. The weather sensitive load is mostly predicted using the correlation techniques and the non-weather sensitive load is modeled by the method mentioned above. Each load component is predicted separately and the sum gives the forecast of the total load.

Obiously the electric loads are very much dependent upon weather conditions. But the load models which include weather variables are limited in use by problems such as inaccuracy of weather forecasts and difficulties in modeling the weather-load relationship. The response of the electric loads to changes in weather conditions is observed to be rather slow in Korea and appears in the past load data. In this paper the weather effects on the electric load are not explicitly considered, but small changes in weather will be somewhat reflected by the adaptive prediction algorithm. However, for severe weather changes more accurate weather-sensitive component should be included in future.

A new algorithm is developed to identify the load model which reflects the stochastic behavior of the hourly load demand. The load is decomposed into three components: the nominal load, the residual load, and the type load. The parameters of the model are adapted to the load variations.

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2. CLASSIFICATION AND CHARACTERISTICS OF LOADS

Fig. 1 illustrates the hourly load curves for January 9-22, 1983 and February 8-21, 1987. The figure shows daily and weekly load variations; the load behavior for weekdays (Tuesday through Friday) has a same pattern but small random variations from varing industrial activities, weather conditions, etc. The weekday load pattern is different from Saturday, Sunday, and Monday load patterns. Comparing weekday loads with Saturday loads, the level of Saturday loads is relatively low during p.m.. The level of Monday loads during a.m. influenced by Sunday is very low. Also the 1st and 3rd Sunday loads are lower than the 2nd, 4th, and 5th Sunday loads due to reduction in industrial or commercial activities observed in Korea. These phenomena equally affects Monday loads during a.m.. Therefore daily load curves are classified as six patterns : weekdays, Saturdays, the 1st and 3rd Sundays, the 2nd, 4th, and 5th Sundays, the 1st and 3rd Mondays, the 2nd, 4th, and 5th Mondays, except special holidays. For convenience, weekend-days will include Saturdays, Sundays, and Mondays.

Annual loads variations are shown in Fig. 2 at 0 a.m. (base load) and 6 p.m. (peak load) for 1983 and 1987. Seasonal load variations, load characteristics for special holidays (New Years, Thanksgiving days, etc.), and those of weekend-days are clearly seen. The weekday loads at the same hours are similar to each

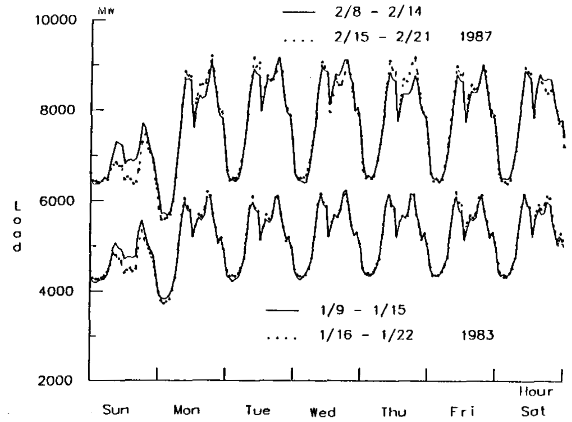

Fig. 1 Hourly load curve over two weeks

other due to daily periodic patterns of the customers, but vary slowly during the year. Factors changing loads are economical, sociological, seasonal and meteorological effects. However, since load variations are slow, loads are sufficiently predicted by the adaptive technique in prediction algorithm.

3. DEVELOPMENT OF LOAD MODELS AND FORECAST METHODOLOGY

A utility load data are analyzed in developing suitable load models. The load is decomposed into three load components. The prediction method for each load component is developed in this section.

3.1 Development of Load Models

If we note that load curves for weekdays are similar to each other in Fig. 1, time series can be composed of the load data for weekdays taken at the same hour of a day for a number of days, resulting in 24 time series. The nominal load is defined from

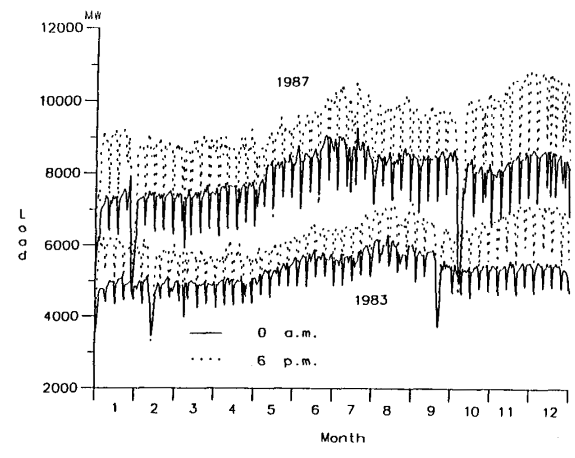

Fig. 2 Daily load curve at the same hour over one year

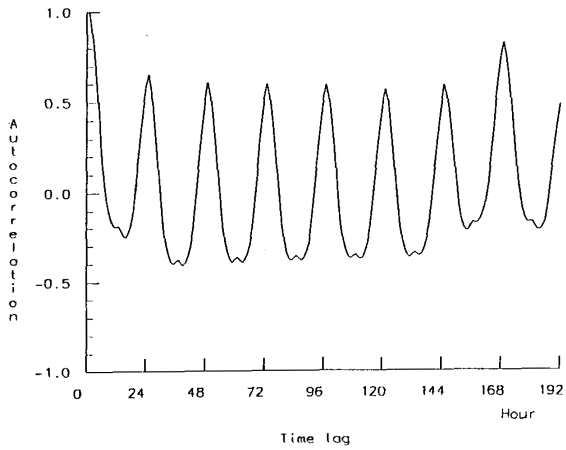

Fig. 3 Autocorrelation of hourly load

load data for ordinary weekdays. For the load prediction of the weekend pattern, time series are composed of the load data which are the differences between the nominal load and the actual load of the weekend pattern. These differences are called the type load and therefore, the load components for the weekend days are found by subtracting the type load from the norminal load.

Another important characteristic of load is shown in Fig. 3 which gives the autocorrelation function of hourly load over four weeks. The function shows peaks at the multiples of 24 hour lags indicating that loads at the same hours have strong correlation with each other independent of the day of the week including weekend-days. Therefore the weekend load data is also used in predicting the nominal load for weekdays. Thus the load is modeled as shown below.

Weekdays.

The loads of weekday pattern are expressed by eq. (1) which is the sum of the nominal load and the residual load:

$$y(i,t) = y_n(i,t) + y_r(i,t), \tag{1}$$

where

$y(i,t)$: the actual load at day i and hour t
$y_n(i,t)$: the nominal load at day i and hour t
$y_r(i,t)$: the residual load at day i and hour t

Weekend-days.

When the forecasted day is either Saturday, Sunday or Monday, the actual load is represented by eq. (2) which is the nominal load minus the type load and plus the residual load:

$$y(i,t) = y_n(i,t) - y_d(i,t) + y_r(i,t), \tag{2}$$

where

$y_d(i,t)$: the type load at day i and hour t
d=1 for Saturday
d=2 for the 1st and 3rd Sunday
d=3 for the 2nd, 4th, and 5th Sunday
d=4 for the 1st and 3rd Monday
d=5 for the 2nd, 4th, and 5th Monday

The nominal load $y_n(i,t)$ is defined as the customer demand under normal conditions of factors, such as economics, business cycle, and meteorological factors, when no special events or blackouts are occurred. This load component is updated with seasonal influences, yearly trends, and weather variations.

The residual load $y_r(i,t)$ corresponds to the modeling error. This error is largely due to the modeling procedure that does not include load data of the preceeding hours of the day. The load models should be identified such that this residual load is a stationary zero mean random process.

The type load $y_d(i,t)$ represents the difference between the weekday loads and the Saturday, Sunday, or Monday loads, which includes the characteristics of the day of the week.

The nominal load is estimated by the Kalman filter to remove random load components from the actual load data. Adaptive prediction technique is applied such that the nominal load is updated with changing conditions. The type load is predicted by the simple exponential smoothing method. Finally, the residual load is predicted by the autoregressive (AR) model using correlation with the load data of preceeding 1-23 hours (the time series at the same hours with time lag of 24 hours have already been exploited in extracting the nominal load).

3.2 The Nominal Load Model

3.2.1 State variable model

To extract the nominal load components from the actual load data $y(i,t)$, the time series are obtained as below. The time series Z_i consisting of load data at the same hours can be expressed as a p-th order AR model. That is,

$$Z_i = \sum_{k=1}^{p} \theta_k Z_{i-k} + a_i, \tag{3}$$

where Z_i is the load demand for day i, θ_k is the parameter of the AR model, and a_i is the white noise, which accounts for the modeling error. To predict the nominal load at hour t, the load demand Z_i is defined as shown below :

$$Z_i = y(i,t). \tag{4}$$

Here, normally the weekday load data is used to find the nominal load model(case 1). However, as mentioned before, the weekend load data can also be used together with the weekday data to improve accuracy(case 2). In order to estimate the nominal load components, the load data must be filtered to reduce the effect of random load fluctuation. Therefore eq. (3) needs to be expressed by the discrete state equation:

$$\begin{aligned} x(i) &= A(i-1)x(i-1) + w(i) \\ y(i) &= Cx(i) + v(i), \end{aligned} \tag{5}$$

where

$$x(i) = (\, Z_i \quad Z_{i-1} \quad \cdots \quad Z_{i-p+1}\,)^T$$

$$A(i-1) = \begin{pmatrix} \theta_1(i-1) & \theta_2(i-1) & \cdots & \cdots & \theta_p(i-1) \\ 1 & 0 & \cdots & \cdots & 0 \\ 0 & 1 & \cdots & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{pmatrix}$$

$$w(i) = (\, a_i \quad 0 \quad \cdots \quad 0\,)^T$$

$$C = (\,1 \quad 0 \quad 0 \quad \cdots \quad 0\,)$$

The system dynamic equation (5) is applicable for all hours and the parameters, $\theta_1(i), \theta_2(i), \cdots, \theta_p(i)$, should be estimated for each hour.

3.2.2 State estimation and forecasting algorithm

It will be assumed that the noise vector $w(i)$ and $v(i)$ are independent zero-mean white Gaussian sequences and their covariance matrices are $Q(i)$ and $R(i)$, respectively. The estimate of the system load vector can be obtained via the Kalman filter algoritm:

$$\hat{x}(i/i-1) = A(i-1)\hat{x}(i-1/i-1) \tag{6}$$

$$\hat{x}(i/i) = \hat{x}(i/i-1) + K(i)[y(i) - \hat{y}(i/i-1)] \tag{7}$$

$$\hat{y}(i/i-1) = C\hat{x}(i/i-1). \tag{8}$$

The $\hat{x}(i/i)$ denotes the estimate of the state $x(i)$ based on measurements up to day i and the $\hat{x}(i/i-1)$ indicates the estimate of the state $x(i)$ based on measurements up to day $i-1$. The scalar $y(i) - \hat{y}(i/i-1)$, which is multiplied by the gain vector $K(i)$, is called innovation at day i. The vector $K(i)$ is given by

$$K(i) = P(i/i-1)C^T[CP(i/i-1)C^T + R(i)]^{-1}. \tag{9}$$

The matrix $P(i/i-1)$ is the covariance of the estimation error $x(i) - \hat{x}(i/i-1)$ and is computed as

$$P(i/i-1) = A(i)P(i/i)A^T(i) + Q(i-1) \tag{10}$$

$$P(i/i) = [I - K(i)C]P(i/i-1). \tag{11}$$

If the values of $\hat{x}(0/0)$ and the error covariance $P(0/0)$ are given, the forecasted load $\hat{y}(i/i-1)$ can be calculated. If there is no prior information for matrix $Q(i)$ and $R(i)$, they can be updated through the following formula [9]:

$$\begin{aligned} \hat{Q}(i) = \frac{1}{i}[&(i-1)\hat{Q}(i-1) + K(i)y(i)y^T(i)K^T(i) \\ &+ P(i/i) - A(i)P(i-1/i-1)A^T(i)] \end{aligned} \tag{12}$$

$$\hat{R}(i) = \frac{1}{i}[(i-1)\hat{R}(i-1) + y(i)y^T(i) + CP(i/i-1)C^T]. \tag{13}$$

Since the parameters of the AR model are updated to the load variations, the parameter estimation must be done by the adaptive algorithm. If we let

$$\theta(i) \underline{\triangle} (\,\theta_1(i) \quad \theta_2(i) \quad \cdots \quad \theta_p(i)\,)^T, \tag{14}$$

then eq. (6) and eq. (8) can be written as

$$\hat{y}(i/i-1) = \theta^T(i-1)\hat{x}(i-1/i-1). \tag{15}$$

The unknown parameter vector $\theta(i)$ is identified by the minimization of the following exponentially weighted cost function:

$$J_1 = \sum_{i=1}^{N}[y(i) - \theta^T(i-1)\hat{x}(i-1/i-1)]^2\alpha^{N-i}, \tag{16}$$

where N is the number of data and α is a weighting factor between 0 and 1. Then the adaptive estimator is obtained as follows [10]:

$$\begin{aligned} \hat{\theta}(i) = \hat{\theta}(i-1) + &\frac{B(i-1)\hat{x}(i-1/i-1)}{\alpha + \hat{x}^T(i-1/i-1)B(i-1)\hat{x}(i-1/i-1)} \\ &\cdot[y(i) - \hat{\theta}^T(i-1)\hat{x}(i-1/i-1)] \end{aligned} \tag{17}$$

$$\begin{aligned} B(i) = \frac{1}{\alpha}\Big[&B(i-1) - \\ &\frac{B(i-1)\hat{x}(i-1/i-1)\hat{x}^T(i-1/i-1)B(i-1)}{\alpha + \hat{x}^T(i-1/i-1)B(i-1)\hat{x}(i-1/i-1)}\Big], \end{aligned} \tag{18}$$

where initial value $\hat{\theta}(i_0)$ and $B(i_0)$ are estimated from the following equations:

$$\hat{\theta}(i_0) = B(i_0) \sum_{k=1}^{i_0} \hat{x}(k/k) y(k) \tag{19}$$

$$B(i_0) = \Big[\sum_{k=1}^{i_0} \hat{x}(k/k)\hat{x}^T(k/k)\Big]^{-1}. \tag{20}$$

If no prior information is availble, the most common choice is to take $\hat{\theta}(0) = 0$ and $B(0) = cI$, where c is a large number. Therefore the prediction of the nominal load at day i and hour t $\hat{y}_n(i,t)$ is given by

$$\hat{y}_n(i,t) = \hat{y}(i/i-1). \tag{21}$$

The adaptive prediction of the nominal load can be constructed as shown in Fig. 4.

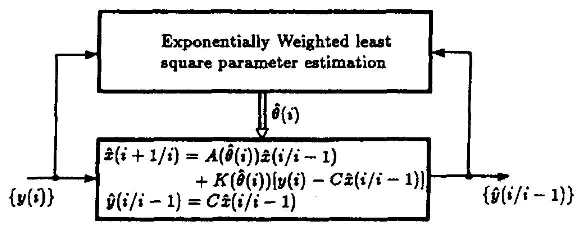

Fig. 4 Adaptive prediction of nominal load

3.3 The Type Load Model

Since the raw load data is filtered through the Kalman filter in predicting the nominal load, another filtering to predict the type load is not needed. The load variation on Saturdays, Sundays and Mondays are larger than those on weekdays. Also, the load data for the weekend is available every week(for Saturdays) or two weeks(for Sundays or Mondays). In this case, the exponential smoothing method can be used as a good estimator because of its simplicity, computational efficiency, and reasonable accuracy. Therefore the type load is modeled as shown below :

$$\hat{y}_d(i_d,t) = \beta_d \hat{y}_d(\underline{i}_d,t) + (1-\beta_d)[y_n(i,t) - y(i,t)], \tag{22}$$

In type load model(22), for each d, i_d represents a type d day and $\underline{i}_d$ represents the previous type d day. For example, i_1 represents the day i of the year which coincides with the Saturday ; i_2 for the day i of the year which coincides with either the 1st or 3rd Sunday ; i_3 for the day i of the year which coincides with the 2nd, 4th, or 5th Sunday, etc. Also, $\hat{y}_d(i_d,t)$ is the prediction of the type load at day i and hour t, and β_d is a smoothing constant. The smoothing constants should be between 0 and 1. Smaller values of β_d give weight to the more recent load data. The constant β_d for each type is chosen such that the sum of the forecast error is minimized.

3.4 The Residual Load Model

If the forecasted day is a weekday, from eq. (1) the residual load is given by

$$y_r(i,t) = y(i,t) - y_n(i,t). \tag{23}$$

If the forecasted day is not a weekday, from eq. (2) the residual load is given by

$$y_r(i,t) = y(i,t) - y_n(i,t) + y_d(i,t). \tag{24}$$

Thus far, the correlation of a load with the loads of the proceeding 1-23 hours has not been considered because the nominal load is modeled by the load data at the same hours. To reflect this, time series $r_t, r_{t-1}, \cdots$ of $y_r(i,t)$ arrayed in time sequence can be written by the q-th order AR model, that is,

$$r_t = \sum_{k=1}^{q} \mu_k r_{t-k} + b_t, \tag{25}$$

where μ_k is the parameter of the AR model and b_t is the white noise. Since the time series r_t can be assumed to be a zero mean stationary process, the parameters μ_k can be estimated by the recursive least squares(RLS) method.
Let

$$\mu = \begin{pmatrix} \mu_1 \\ \vdots \\ \mu_q \end{pmatrix}, \quad \phi(t-1) = \begin{pmatrix} r_{t-1} \\ \vdots \\ r_{t-q} \end{pmatrix}, \tag{26}$$

then eq. (25) can be written as

$$r_t = \mu^T \phi(t-1) + b_t. \tag{27}$$

The estimates μ are computed by minimizing

$$J_2 = \sum_{t=1}^{N} [r_t - \mu^T \phi(t-1)]^2. \tag{28}$$

Then the RLS estimate[11] is given by

$$\hat{\mu}(t) = \hat{\mu}(t-1) + \frac{S(t-1)\phi(t-1)}{1 + \phi(t-1)^T S(t-1)\phi(t-1)} \cdot [r_t - \hat{\mu}^T(t-1)\phi(t-1)] \tag{29}$$

$$S(t) = S(t-1) - \frac{S(t-1)\phi(t-1)\phi(t-1)^T S(t-1)}{1 + \phi(t-1)^T S(t-1)\phi(t-1)}, \tag{30}$$

where initial values may be chosen as $\hat{\mu}(0) = 0$ and S(0)=cI with a large number c. To predict the residual load at time t for lead time ℓ, from eq. (27) the residual load $r_{t+\ell}$ can be written as [12]

$$r_{t+\ell} = \mu_1 r_{t+\ell-1} + \mu_2 r_{t+\ell-2} + \cdots + \mu_q r_{t+\ell-q} + b_{t+\ell}. \tag{31}$$

Taking conditional expectations at time t in eq. (31), we obtain

$$\begin{aligned} E_t[r_{t+\ell}] =& \mu_1 E_t[r_{t+\ell-1}] + \mu_2 E_t[r_{t+\ell-2}] + \cdots \\ &+ \mu_q E_t[r_{t+\ell-q}] + E_t[b_{t+\ell}], \end{aligned} \tag{32}$$

where the brackets imply that the conditional expectation at time t is to be taken. The conditional expectation $E_t[r_{t+\ell}]$ is the expectation of the time series for time $t+\ell$ based on the residual load data $r_t, r_{t-1}, \cdots$. Let $E_t[r_{t+\ell}] \triangle\, \hat{r}_t(\ell)$, then the prediction of the residual load at time t for lead time ℓ is given by

$$\hat{r}_t(\ell) = \mu_1 \hat{r}_t(\ell-1) + \mu_2 \hat{r}_t(\ell-2) + \cdots + \mu_q \hat{r}_t(\ell-q), \quad (33)$$

$$\ell = 1, \cdots, 24$$

where

$$E_t[r_{t-j}] = r_{t-j} \quad j = 0,1,2,\cdots,t-1$$
$$E_t[r_{t+j}] = \hat{r}_t(j) \quad j = 1,2,3,\cdots,24$$
$$E_t[b_{t+j}] = 0 \quad j = 1,2,3,\cdots,24$$

Therefore the prediction of the residual load at day i and hour t $\hat{y}_r(i,t)$ is given by

$$\hat{y}_r(i,t) = \hat{r}_t(\ell) \quad \ell = 1,\cdots,24. \quad (34)$$

Finally, the prediction of the total load at day i and hour t $\hat{y}(i,t)$ is obtained as shown below :

Weekdays.

$$\hat{y}(i,t) = \hat{y}_n(i,t) + \hat{y}_r(i,t). \quad (35)$$

Weekenddays.

$$\hat{y}(i,t) = \hat{y}_n(i,t) - \hat{y}_d(i,t) + \hat{y}_r(i,t), \quad (36)$$

4. TEST AND DISCUSSION

Case studies from the proposed algorithm were carried out for a one-day-ahead prediction of hourly electric loads using the data of Korea Electric Power Company(KEPCO) from January 1 to July 31, 1983 and 1987. The load data for one month(January) were processed to update the parameters of the model. Test results were obtained for the period of Feburary to July. To compare with other papers, the results were evaluated by the following three indices:

(i) Standard deviation $\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[y(i,t) - \hat{y}(i,t)]^2}$

(ii) Root mean square error

$$\varepsilon_1 = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[\{y(i,t) - \hat{y}(i,t)\}/y(i,t)\right]^2} \cdot 100$$

(iii) Percent relative error

$$\varepsilon_2 = \frac{1}{N}\sum_{i=1}^{N}|y(i,t) - \hat{y}(i,t)| \cdot 100/y(i,t),$$

where N is the number of predictions.

To determine the order of the nominal load model, the initial values of the filter were given by $R(0) = 1, Q(0) = I, P(0) = 100I, \hat{x}(0/0) =$ the mean values of the loads at each hour, and $\alpha = 1$. The order of the model is determined such that the prediction error of the norminal load has minimum variance. As the result of the simulation, the 2nd order AR model is used. Also, minimum variance was achieved when the weighting factor α of the norminal load model is equal to 0.95 and in this case the autocorrelation of the forecast error is shown in Fig. 5. Thus the nominal load was extracted such that the residual load was random component.

In prediction of the nominal load, the case of using the weekday data only(case 1) is compared with the case of using both weekday and weekend data(case 2). In 1983, the standard deviation and percent relative error of case 1 are 97.04[MW] and 1.35%, respectively; but for case 2, 96.6[MW] and 1.32%, respectively. Similarly in 1987, the standard deviation and percent relative error of case 1 are 143.96[MW] and 1.24%, respectively; but for case 2, 142.30[MW] and 1.23%, respectively. The use of weekend data in the prediction of the nominal load gave the smaller forecast error. Comparison between the nominal load and the actual load for weekdays is shown in Fig. 6.

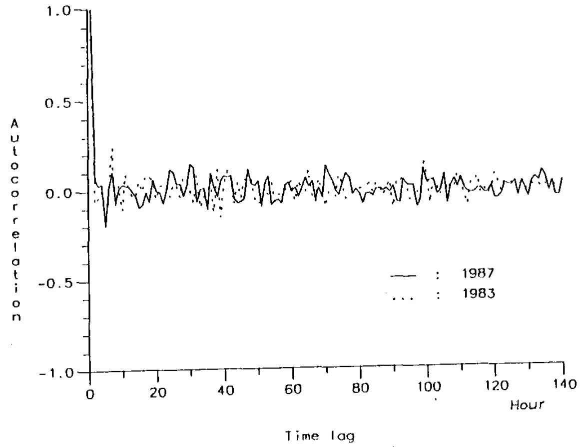

Fig. 5 Autocorrelation of percent prediction error at 12 p.m.

To determine the smoothing constants of the type load model for weekend, the minimum standard deviations were found by increasing β_d from 0.1 to 1. The results are $\beta_1 = 0.9, \beta_2 = 0.9, \beta_3 = 0.8, \beta_4 = 0.7$, and $\beta_5 = 0.8$. To predict the residual load, the time series are rearranged in a time sequence and the standard deviation of prediction error is calculated by increasing the order of the residual model, where the 4th order AR model has the minimum. The type load and residual load are combined with the nominal load to yield the total load forecast and compared with the actual load in Fig. 7. Percent prediction errors are shown in Fig. 8.

Table 1 shows the standard deviations and percent relative errors of the prediction errors for each hour and for all types in 1987. Table 2 shows the summary of the standard deviations and percent relative errors of the prediction errors for 1983 and 1987. Test results for a one-day-ahead predic-

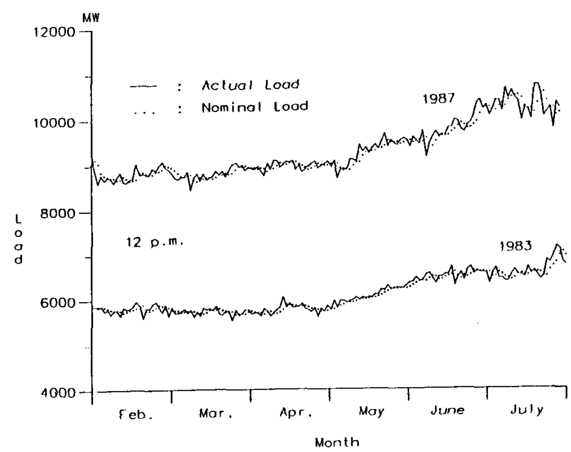

Fig. 6 Comparison of actual load and nominal load for weekdays at 12 p.m.

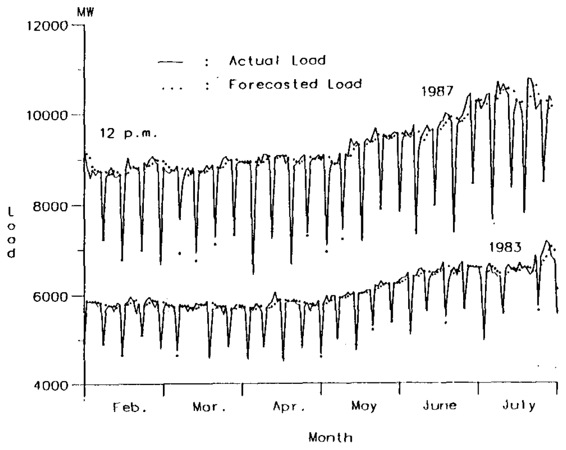

Fig. 7 Comparison of actual load and forecasted load at 12 p.m.

tion over a period of six months in 1983 were given as $\sigma = 104.05[MW], \varepsilon_1 = 1.97\%, \varepsilon_2 = 1.50\%$. Similarly, test results for a one-day-ahead prediction over a period of six months were given as $\sigma = 156.76[MW], \varepsilon_1 = 1.91\%, \varepsilon_2 = 1.40\%$. These are comparable with accuracies reported in other papers[2-7]. The CPU time for six months simulation performed on a VAX 11/780 system is 5.39 sec.

5. CONCLUSION

A new algorithm is developed for a one-day-ahead prediction of hourly electric loads. The load model is decomposed into three components: the nominal load, the type load and the residual load.

The nominal load is extracted from data in such a way that the time series of the residuals obtained with this model can be considered as a stationary process. The nominal load is modeled

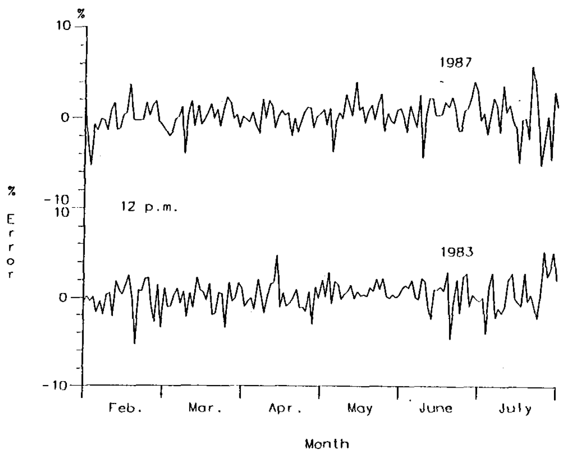

Fig. 8 Percent error at 12 p.m.

by the AR model, which is expressed in the state variable form to exploit the Kalman filter technique for filtering random load components. The states of the system load are estimated for a different number of the order of the nominal model, and the model parameters are updated to load variations by the exponentially weighted least squares method.

The type load for weekend-days is predicted by a relatively simple exponential smoothing method, where the smoothing constants are chosen to minimize prediction errors. The time series of residual load are composed of prediction errors occurring when hourly loads are predicted by the time series of the load data at every same hour. This load is predicted by the AR model, whose parameters are estimated using the recursive least squares method.

In predicting a weekday pattern, the additional use of weekend data shows smaller forecast error. The weather effects on the electric load are not explicitly considered, but small changes in weather will be somewhat reflected by the adaptive prediction algorithm. An advantage of this algorithm is that the load model is automatically adapted with seasonal changes because the nominal and the type loads are updated by the adaptive prediction.

The accuracy of the proposed algorithm is shown in the test results over a period of six months of the data which are comparable with those of load models in literature.

ACKNOWLEDGEMENT

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REFERENCES

[1] C. E. Asbury, "Weather load model for electric demand and energy forecasting," IEEE Trans. on Power Appr. & Sys., vol. PAS-94, pp. 1111-1116, 1975.

[2] W. R. Christiaanse, " Short-term load forecasting using general exponential smoothing," IEEE Trans. on Power Appr. & Sys., vol. PAS-90, pp. 900-910, 1971.

[3] K. L. S. Sharma, A. K. Mahalanabis, "Recursive short-term load forecasting algorithm," Proc. IEE, vol. 121, pp. 59-62, 1974.

[4] Suri Vemuri, Wen Liang Huang and Don J. Nelson, "On-line algorithms for forecasting hourly loads of an electric utility," IEEE Trans. on Power Appr. & Sys., vol. PAS-100, pp. 3775-3784, 1981.

[5] M. Nakamura, "Short term load forecasting using weekday load models and bias models," Proc. PICA Conference, pp. 37-42, 1984.

[6] D. P. Lijesen and J. Rosing, "Adaptive forecasting of hourly loads based on load measurements and weather information," IEEE Trans.on Power Appr. & Sys., vol. PAS-90, pp. 1757-1767, 1971.

[7] H. P. Van Meeteren and P.J.M. Van Son, "Short- term load prediction with a combination of different models," Proc. PICA Conference, pp. 192-197, 1979.

[8] IEEE Committee Report, "Load forecasting bibliography phase I," IEEE Trans. on Power Appr. & Sys., vol. PAS-99, pp. 53-58, 1980.

[9] Peter S. Maybeck, Stochastic models, estimation, and control, Academic Press, vol. 1, 2, 1982.

[10] Goodwin and Sin, Adaptive filtering, prediction and control, Prentice-Hall, 1984.

Table 1 % Relative Error and Standard Deviation of the Prediction Errors

Type	Weekday		Saturday		1, 3rd Sunday		2,4,5th Sunday		1,3rd Monday		2,4,5th Monday		Total	
Hour	% Relative error	MW S.D. (σ)	% Relative error	MW S.D. (σ)	% Relative error	MW S.D. (σ)	% Relative error	MW S.D. (σ)	% Relative error	MW S.D. (σ)	% Relative error	MW S.D. (σ)	% Relative error	MW S.D. (σ)
1	1.11	105.24	0.97	90.62	0.75	64.99	1.30	126.36	1.22	90.58	1.96	160.13	1.18	109.94
2	0.93	84.93	1.09	93.22	0.96	75.66	1.21	108.25	1.73	112.88	1.81	145.85	1.08	95.13
3	0.96	85.93	1.04	90.61	0.83	73.85	1.51	135.44	1.54	102.67	1.79	141.84	1.10	97.37
4	0.90	79.63	0.82	71.04	0.80	72.56	1.01	85.37	1.16	89.15	1.99	135.12	1.01	86.44
5	0.89	79.89	0.95	82.31	0.77	66.51	1.16	101.48	1.21	89.59	1.69	119.28	0.99	85.78
6	0.88	79.35	0.74	67.54	0.89	65.87	1.37	117.33	1.73	124.16	1.57	150.18	1.04	93.64
7	0.96	94.15	0.90	91.12	1.55	130.54	1.31	101.31	1.78	148.45	1.42	140.82	1.12	106.42
8	0.92	99.94	0.73	72.17	0.95	71.85	1.56	145.68	1.62	145.28	1.34	138.05	1.06	109.95
9	1.84	204.18	1.17	126.98	2.85	221.84	1.91	191.75	4.92	416.99	3.88	340.96	1.92	204.56
10	1.37	164.21	1.26	150.88	3.52	283.68	2.38	264.09	2.76	281.43	2.17	232.90	1.61	185.51
11	1.18	143.00	1.16	141.25	3.56	280.06	2.30	266.67	1.89	222.83	1.57	191.66	2.02	169.92
12	1.20	150.02	1.17	135.90	4.26	342.77	2.44	295.65	1.98	211.14	1.52	198.91	1.53	186.63
13	1.42	155.47	1.44	155.90	3.42	270.05	2.57	249.75	1.76	185.32	2.09	216.34	1.66	175.77
14	1.31	160.50	1.52	202.59	3.14	253.62	2.32	264.17	1.69	195.13	1.48	208.51	1.55	185.34
15	1.30	160.76	1.57	199.46	3.59	268.82	2.60	303.59	1.48	191.77	1.43	198.42	1.61	191.44
16	1.33	164.99	1.69	190.96	2.89	219.93	2.99	281.15	1.48	189.80	1.80	217.27	1.63	185.24
17	1.41	173.67	1.64	205.47	2.61	205.93	3.07	292.23	1.48	183.98	1.63	218.21	1.67	193.05
18	1.61	193.38	1.82	211.90	2.03	185.46	3.45	346.76	1.67	198.24	1.80	233.69	1.82	212.09
19	1.56	182.77	1.71	191.20	3.02	257.85	2.60	246.96	1.62	199.42	1.78	202.35	1.78	196.33
20	1.29	148.08	1.44	151.51	2.99	252.82	2.14	189.91	1.07	134.61	1.73	193.30	1.51	162.28
21	1.06	126.96	1.15	126.08	1.31	117.91	1.41	139.77	1.26	151.45	1.42	162.32	1.12	127.29
22	1.21	140.55	1.31	160.39	2.43	229.18	1.87	194.69	1.27	152.13	1.16	130.78	1.37	156.53
23	1.09	128.17	1.32	150.35	2.15	200.74	2.43	236.06	0.79	105.03	1.35	157.12	1.31	149.37
24	1.38	140.35	1.00	110.79	1.33	126.87	2.18	190.94	1.41	135.05	1.72	165.00	1.39	140.55
Mean	1.23	142.30	1.24	144.77	2.23	203.42	2.05	216.95	1.68	183.43	1.75	189.35	1.40	156.76

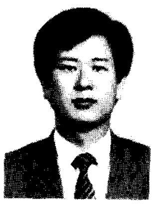
Table 2 Summary of % Relative Error and Standard Deviation of the Prediction Errors

Type	Weekday		Saturday		1, 3rd Sunday		2,4,5th Sunday		1,3rd Monday		2,4,5th Monday		Total	
Error	% Relative error	MW S.D. (σ)	% Relative error	MW S.D. (σ)	% Relative error	MW S.D. (σ)	% Relative error	MW S.D. (σ)	% Relative error	MW S.D. (σ)	% Relative error	MW S.D. (σ)	% Relative error	MW S.D. (σ)
Mean (1983)	1.32	90.84	1.27	94.91	2.41	158.26	1.90	124.13	1.59	105.33	1.77	111.09	1.50	104.05
Mean (1987)	1.23	142.30	1.24	144.77	2.23	203.42	2.05	216.95	1.68	183.43	1.75	189.35	1.40	156.76

[11] Lennart Ljung and Torsten Söderström, Theory and practice of recursive identification, MIT Press, 1983.

[12] G. E. P. Box and G. M. Jenkins, Time series analysis forecasting and control, Holden-Day, 1976.

BIOGRAPHIES



June Ho Park was born in Masan, Korea, on September 17, 1955. He received the B.S., M.S. and Ph.D. degrees in Electrical Engineering from Seoul National University, Seoul, Korea, in 1978, 1980 and 1987, respectively.

He is an Associate Professor of Electrical Engineering at Pusan National University, Pusan, Korea. From 1978 to 1981, he was a researcher at Korea Electrotechnology Research Institute. He has been a faculty of Chung-Nam National University from 1981 to 1984. His areas of interest are power system control, operation and planning.

Dr. Park has been a member of the Korea Institute of Electrical Engineers.

Young Moon Park was born in Masan, Korea, on January 20, 1933. He received the B.S., M.A. and Ph.D. degrees from Seoul National University, Seoul, Korea, in 1956, 1959 and 1971, respectively.

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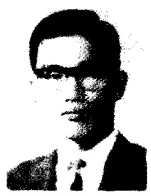
He is a president of the Korea Institute of Electrical Engineers.



Kwang Y. Lee was born in Pusan, Korea, on March 6, 1942. He received the B.S. degree in Electrical Engineering from Seoul National University, Seoul, Korea, in 1964, the M.S. degree in Electrical Engineering from North Dakota State University, Fargo, in 1968, and the Ph.d. degree in System Science from Michigan State University, East Lansing, in 1971.

He has been on the faculties of Michigan State University, University of Houston, and the Pennsylvania State University, where he is an Associate Professor of Electrical Engineering. His areas of interest are system theory and its application to large-scale system, and power system.

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Discussion

A. K. Deb (Innova Corporation, Fremont, Ca): The authors have developed a new method for short term (1-23 hour ahead) electric load forecasting using the state variable approach with Kalman filter and the recursive least square estimation theory. We are working on a related problem of forecasting the overhead transmission line ampacity [1] using a similar technique and hence the interest in this paper. We have a few questions which may help in further clarification of the forecasting method used by the authors and the results that are presented.

1. Weather Modeling

In the introduction it is mentioned that the weather forecasts are inaccurate. We would like to inform that by using the technique of recursive least square estimation and hourly ambient temperature data from two different PG&E locations in California we obtained satisfactory forecasts of ambient temperature 1-24 hours ahead [1].

2. 24 Time Series Models

The forecasting algorithm requires 24 time series for each hour of the day. From these time series the daily variations in load are obtained by extracting the nominal component of load Yn from load measurements Ym. The hourly variations of load are obtained by modeling the residuals Yr = Ym − Yn. While this is a novel approach a more simpler approach would be to consider the hourly and daily variations by the Box-Jenkins multiplicative model (page 322 Box-Jenkins 1976),

Between 24 Hour Period

$$\Phi_p(B^{24})_{\nabla 24} z_t = \beta_q(B^{24})\alpha_t \quad (1)$$

Within 24 Hour Period

$$\phi_p(B)_\nabla \alpha_t = \Theta_q(B) a_t \quad (2)$$

where, B is the backward shift operator and $B^{24} z_t = z_{t-24}$

∇ is the backward difference operator

so that

$$\nabla 24 z_t = (1 - B^{24}) z_t$$

If the authors have considered the above model I would like to request them to show a comparison of the standard deviations of forecast errors with both methods.

3. Memory of AR(p) and AR(q) Models

To understand the storage requirements for this algorithm and its feasibility for implementation in real time it is useful to know the order of the AR(p) and AR(q) model in equation (3) and (25) of the paper respectively. Can the authors please provide this information if possible?

4. Exponential Weighting

Exponential weighting of data is useful, allowing greater weight to recent data and less weight to older data. In Equations (16), (17), (18) an exponential weighting function α^{N-1} was used to estimate the parameters of the AR(p) model. Would the authors please discuss why exponentual weighting was considered in this case and not considered in the estimation of the parameters of the AR(q) model of the residuals given by the equations (29), (30)?

5. Results of Forecast Errors

In Table 1 page 7, the results of the standard deviations of forecasts errors are shown to be less than 2.02 % relative error which is excellent. It is important to clarify they are 24 hour ahead prediction errors for each hour of the day. Since the algorithm is designed for 1-23 hours load prediction it would be interesting to know the SDs and % relative errors of prediction errors at shorter lead hours.

6. Bad and Missing Data

Can the authors please discuss the impact of bad and missing data in the implementation of the algorithm?

7. Typographic Error

In Page 4 para 2 it is stated "...loads of the proceeding 1-23 hours...", obviously it is a typographic error and should be "...loads of the preceding 1-23 hours...".

The authors are congratulated for presenting a well written paper.

Reference

[1] W. J. Steeley, B. L. Norris and A. K. Deb, "Ambient Temperature Corrected Dynamic Transmission Line Ratings at Two PG&E Locations," Paper # 90 SM 403-6-PWRD presented at the IEEE 1990 Summer Meeting, July 14-17 at Minneapolis, Minessota.

Manuscript received August 6, 1990.

J. H. Park, Y. M. Park, and K. Y. Lee: The authors thank the discussor for his interest in the paper and his comments.

Weather forecasts are in general known to be inaccurate. However, special efforts can be made to predict accurate weather variables in the expense of additional resourses. Certainly the paper suggested by the discussor will be a welcome toward improved forecasting. Currently we are developing a load-weather model to use in the event that an accurate weather forecasting is available. In this case, beside temperature, humidity and wind speed may also have to be included.

The discussor mentioned about the use of the Box-Jenkins model which is more simpler than the adaptive prediction model in the paper. An important motivation behind this new approach is to forecast load *adaptively* in spite of the fact that parameters are varying and weather variables are not used. Because of this adaptive nature the % relative error is less than 2.02% and 1.50% (1.40%) in the average for 1983(1987) as shown in Tables 1 and 2.

The orders of AR(p) and AR(q) models in equations (3) and (25), respectively, are determined optimally by increasing the order in an off-line simulation and finding the value which gives the smallest standard deviations(S.D.) in forecasting error. The orders determined are 2 and 4 for AR(p) and AR(q), respectively, as were mentioned in Section 4 of the paper.

The discussor correctly observed that exponential weight is used in the nominal load model, but not in the residual load model. As can be seen in Fig.6 in the paper, the nominal load is nonstationary and changes slowly with seasonal and yearly variations, and exponential weighting is useful in estimating slow-moving system parameters. The residual load, on the other hand, reflects the modeling error as the difference between actual load and the nominal load. Since the nominal load is extracted in such a way that the residual load is a zero mean random process, the residual load is a stationary process, and hence exponential weighting is not necessary.

The discussor mistakenly interpretes the forecasting error in Table 1. Our model is for 1-24 hour ahead load prediction. At zero hour, as the reference, the loads for the next 24 hours are forecasted. Consequently, the load at hour 1 is the 1-hour ahead prediction, the load at hour 2 is the 2-hour ahead prediction, etc. Therefore, the % relative errors and the standard deviations in Table 1 are for all hours, including shorter load hours.

Although the load data is smoothed by Kalman filter to estimate model parameters, bad data can cause the model parameter to change abnormally. Therefore in implementation, when the absolute % error of the filtered data is 5%(for weekday) or 10%(for weekend) from the actual data, the model parameters are not updated. Similarly, for missing data the identification is not performed and parameters are not updated.

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