論 文
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電力系統負荷豫測에 관한 研究

A New Appreach to Short Term Load Forecasting

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ABSTRACT

In this paper, a new algorithm is derived for short term load forecasting. The load model is represented by the state variable form to exploit the Kalman filter techniques. The suggested model has advantages that it is unnecessary to obtain the coefficients of the harmonic components and its coefficients are not explicitly included in the model.

Case studies were carried out for the hourly power demand forecasting of the Korea electrical system.

I Introduction

The purpose of short-term load forecasting is to supply electric energy in a secure and economic manner. The knowledge of future load demand is useful in maintenance and economic scheduling of power plants, and more recently as inputs to the real time state monitoring and security programs.

The short-term forecasting systems presently used by utility companies vary considerably in their forecasting methodology, for load models are based on electrical demand characteristics of individual sytem. Toyoda(1)made use of state space model with a stochastic input whose variance is unknown and is identified. Christiaanse (3) developed a fouries series model whose parameters are updated hourly via exponential smoothing. K.L.S Sharma (10) expressed a model which permits the use of Kalman filtering techniques. Gupta(6), Galiana(13), H. P. Van Meeteren(14), D. W. Ross(15) modeled dynamic temperature and random effects through a stochastic time series. K.Srinivasan(12) used multiple correlation models whose parameters are updated using linear estimation theory. Others(2), (4), (5), (7), (8), (9), (11) proposed models with the load dependent on time as well as weather variables.

The first paper to suggest the use of Kalman filtering techniques for load prediction was that of Toyoda et al(1). Based on intuitive arguments, these authors have proposed relatively simple models for the load demand over very short, short and medium term duration. But this method led to fairly large errors of prediction.

This paper deals with another state space model which can be used via Kalman filtering technique.

II Identification of load model

A) General

The modeling of load herein is adequately represented for one hour prediction of real power demand (Mw). In the development of model, following properties were considered:

1) The load is represented by a time sequence with hourly intervals.
2) The model state variables must be easily updated at regular intervals.
3) The on-line computation of the model for prediction purpose does not allow much computing time and storage space.
4) The identification of the models used for the prediction of the load should be such that prediction error is zero mean random process.

For very widely distributed power system it may be advantageous to subdivide the load into

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smaller regions or components, and to analyze each separately. The advantage of this method is that abnormal conditions in growth trends of a certain component can be detected, thus preventing misleading forecast conclusions.

But the method to forecast the total load directly is used in this study. This method has advantage that it uses the total which is much smoother and more indicative of overall growth trends.

B) Forecasting model

In order to identify suitable load models it is advantageous to pay attention to the physical explanation of the load behavior. The important aspect of the electric load behavior is its quasi-periodic characteristic illustrated in Fig 1 for two

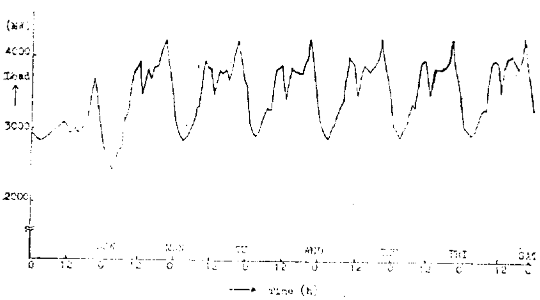

Fig. 1a) Daily load over one week starting May 6, 1979

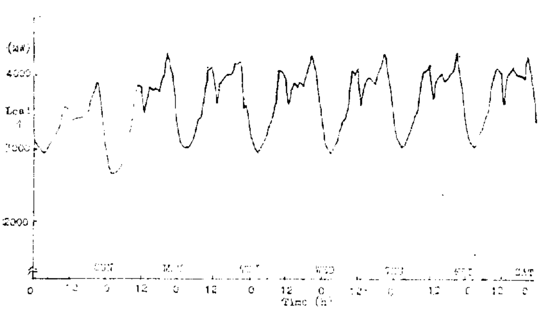

Fig. 1b) Daily load over one week starting May 13, 1979

consecutive weeks. The load behavior is a highly deterministic process. From Monday to Saturday we find a evident daily periodic patterns explained by the periodic consumption habits of power users. Therefore we can hypothesize a load model defined by a periodic time function $Yp\,(t)$. Periodic model $Yp(t)$is represented by a finite fourier series:

$$Yp(t)=\sum_{i=0}^{n}(a_i \sin w_i t+b_i \cos w_i t) \qquad (1)$$

$$w_i=\frac{2\pi . i}{T}$$

T:one week (168 hours)

n: the number of harmonics to be included

The weekly model $Yp(t)$ is superior to a model with a daily period since it does not require different models for week and weekend days, respectively. A model based on a yearly period is impractical because it involves too many parameters.

If we compare load measurements for two consecutive weeks, the weekly load also contains a slow trend component. A weekly period's is superimposed on a trend component caused by the steadily growing demand of electric energy. So, the load model can be represented by the sum of periodic and trend components. The trend component can be represented by the power series. Since the model state variables are updated every an hour, we assume that the trend component is expressed by the power series of three order sufficiently.

In most cases the deterministic analysis is an approximation performed by the need for simplification. If we need a more realistic analysis, the effects of small random variable must be considered. So it is assumed that the load model $Y(t)$ can be written as

$$Y(t)=Y_{trend}(t)+Yp(t)+v(t) \qquad (2)$$

$Y_{trend}(t)$: trend component having power series of three order

$v(t)$: zero mean, a scalar random noise, which accounts for the errors in fit of $Y(t)$ by a finite numer of terms.

The statistics of $v(t)$ can be estimated through historical data. Since the actual load data are received at interval of one hour, Eq. (2) can be represented by the discrete state equation.

$$x(k+1)=Ax(k) \qquad (3)$$
$$y(k)=Cx(k)+v(k)$$

where

$$A=\begin{pmatrix} A^{11} & \vdots\; 4\times 2n \\ & \vdots\; 0 \\ \cdots & \cdots \\ 0 & \vdots\; A^{22} \\ 2n\times 4 & \vdots \end{pmatrix} \quad A^{11}=\begin{pmatrix} 1 & 1 & \frac{1}{2} & \frac{1}{6} \\ 0 & 1 & 1 & \frac{1}{2} \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

$$A^{22}=\begin{pmatrix} B^{11} & \vdots & I \\ \cdots & & \cdots \\ I & \vdots & O \end{pmatrix} \quad B^{11}=\begin{pmatrix} 2\cos w_1 & & & O \\ & 2\cos w_2 & & \\ & & \ddots & \\ O & & & 2\cos w_n \end{pmatrix}$$

$$C=[1,0,0,0 \,\vdots\, 1,1,1,\ldots 1 \,\vdots\, 0,0,0,\ldots 0]$$

$$x(k)=\begin{pmatrix} a_0+c_1k+c_2k^2+c_3k^3 \\ c_1+2c_2k+3c_3k^2 \\ 2c_2+6c_3k \\ 6c_3 \\ a_1 \sin w_1k+b_1 \cos w_1k \\ \vdots \\ a_n \sin w_nk+b_n \cos w_nk \\ a_1 \sin w_1 (k-1)+b_1 \cos w_1(k-1) \\ \vdots \\ a_n \sin w_n (k-1)+b_n \cos w_n(k-1) \end{pmatrix}$$

B^{11}: $n\times n$ dimensional matrix

I: $n\times n$ dimensional identity matrix

O: $n\times n$ dimensional zero matrix

$c_1c_2c_3$: power series coefficients

$a_1..a_n$, $b_1..b_n$: fourier series coefficients

w_i: $\frac{2\pi . i}{168}$　　　$i=1,\ldots n$

$x(k)$: $4+2n$ dimensional state vector

$y(k)$: scalar of observed output

Ⅲ. Implementation of forecasting

A) Selecting algorithm of harmonic components

The knowledge of the number of samplings per period is required to choose the number of harmonics n. The n to be included in eq. (1) should not exceed 84 here since the weekly load curve is given by 168 points at intervals of every an hour. But it is unnecessary to include all the 84 terms since some of the components may be dorminant and the other not.

The power spectrum is used to select the harmonic components required for an adequate description of the load curve.

As we separate the trend component from $Y(t)$ in Eq. (2), the extracting process of the detrended value from load data are described below.

That is,

$$y(T+t)-y(t)=[T,\ T^2+2tT,\ T^3+3T^2t+3Tt^2]\begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} \qquad (4)$$

T: 168 hours

The c_1, c_2 and c_3 are obtained by applying least square estimation technique through historical load data. The left term of Eq. (4) represents the load data which is subtracted from one week posterior load data. Once c_1, c_2 and c_3 are obtained, the trend component is subtracted from the load data which will be used in power spectrum analysis. The detrended values of load data become an input of FFT(Fast Fourier Transform).

B) Forecasting algorithm

Daily real power measurements can be regarded as sequences of random variables that occur consecutively in time. We defined a discrete random process as any sequence of random variables in Eq. (3). Herein, we consider the problem of updating state as optimal estimate of state if additional data become available. Eqs. (5)—(9) below show how an estimate of x is changed if additional measurement data become available.

The estimate of state is given in a recursive manner.

$$\hat{x}(k/k-1)=A\hat{x}\ (k-1/k-1)$$
$$\hat{x}(k/k)=\hat{x}(k/k-1)+K\ (k)\cdot\{y(k)-\hat{y}(k/k-1)\} \qquad (5)$$
$$\hat{y}(k/k-1)=C\hat{x}\ (k/k-1)$$

The $\hat{x}(k/k)$ denotes the estimate of the state $x(k)$ based on measurements up to time k and the $\hat{x}\ (k/k-1)$ denotes the estimate of the state $x(k)$ based on measurements up to time $k-1$.

The factor $y(k)-\hat{y}(k/k-1)$ is called innovation at time k which is multiplied by the vector $K(k)$, which is known as Kalman filter gain vector. This is given by

$$K(k)=P(k/k-1)\ C'[CP\ (k/k-1)\ C'+R(k)]^{-1} \qquad (6)$$

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

$$P(k/k-1)=AP(k/k)\ A' \qquad (7)$$
$$P(k/k)=[I-K(k)C]\cdot P(k/k-1)$$

If we obtain a demand value for j time in advance it is computed as

$$\hat{x}(k+j/k)=(A)^j\ \hat{x}(k/k) \qquad (8)$$
$$\hat{y}(k+j/k)=C\ \hat{x}(k+j/k)$$

Where $\hat{x}(k+j/k)$ is the estimate of state $x(k+j)$ at time k.

If the values of $\hat{x}$ (0/0) and the error covariance $P(0/0)$ are given, we can start at $k=0$ through the recursive Eq. (5) using the $K(k)$ computed from the Eqs. (6) and (7). The initial values of $\hat{x}(0/0)$ and $P(0/0)$ are obtained by the least square estimation through the historical data.

$$\hat{R}(k)=\frac{1}{k}[(k-1)\ \hat{R}\ (k-1)+r^2(k)-CP\ (k/k-1)\ C'] \tag{9}$$

where $r^2(k)=y(k)-C\ \hat{x}\ (k/k-1)$

The block diagram of the load forecasting process is shown in Fig 2.

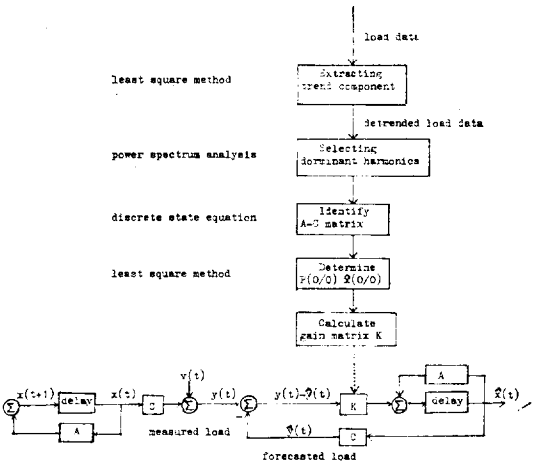

Fig. 2. Block diagram of the load model determination and load prediction

Ⅳ. Tests and Results

In the first place, actual data from the Korea Electric Company system load file for the period of May 1. 1979 to May 6 is used in order to determine the predominant harmonics. The power spectrum computed by the use of the FFT is shown in Fig 3. As expected, very strong components exist at 168, 24 and 12 hours. Also, components at 84, 56 and 42 hours, which are the 2nd, 3rd and 4th harmonics, appear significant. The 5th, 21th, 28th and 35th harmonics also appear significant. Therefore, ten harmonics are selected in this application.

This model was tested over 4 days(May 8—11, 1979). The mean value of prediction error is near zero. Hourly forecasted load curve(···) and actual load curve(—) are shown in Fig 4, and its corresponding percent error (forecast error/actual value) in Fig 5.

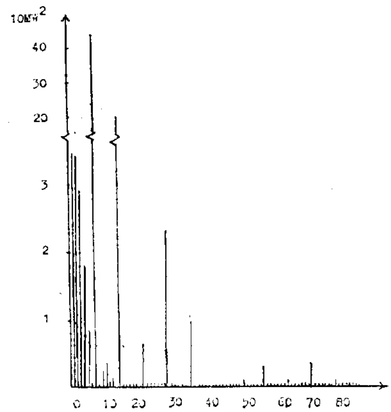

Fig. 3. Power Spectrum of weekly load

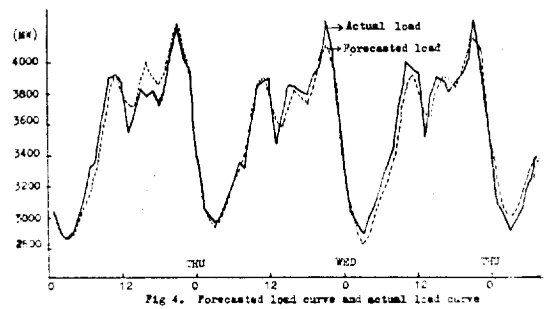

Fig. 4. Forecasted load curve and actual load curve

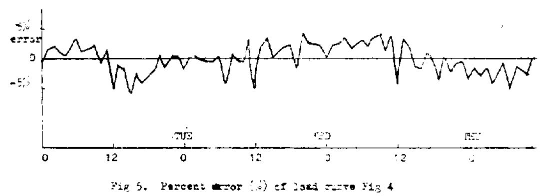

Fig. 5. Percen terror (%) of forecasted load curve Fig 4

The results were evaluated by a standard deviation of one-hour-ahead prediction error. References (3) and (4) show 2.8—2.9% rms error and 2.3% rms error, respectively.

% rms error is defined by

$$\% \text{ rms error} = \frac{100\sqrt{S}}{Y_{average}}$$

S_k is the smoothed value of the squared forecast error, computed according to the formula $S_{k+1}=0.999\ S_k+0.001\cdot\{y(k+1)-\hat{y}(k+1/k)\}$

$Y_{average}$ is the average load of the system while $\sqrt{S}$ is not the smoothed standard deviation value but standard deviation of a day in this paper.

Prediction	TUESDAY May 8	WEDNESDAY May 9	THURSDAY May 10
Hourly prediction (one hour ahead)	2.5%	2.4%	2.6%

V. Conclusions

The test results as evident from the Fig. 4 seem to have anappropriate accuracy, even though the temperature effects have not yet been considered.

The suggested model has advantages that it is unnecessary to obtain the coefficients of the harmonic components and its coefficients arenot explicitly included in the model. The model state variables are automatically corrected to keep track of the changing load conditions.

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