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Very Short-term Electric Load Forecasting for Real-time Power System Operation

Hyun-Woo Jung*, Kyung-Bin Song†, Jeong-Do Park and Rae-Jun Park*****

Abstract – Very short-term electric load forecasting is essential for real-time power system operation. In this paper, a very short-term electric load forecasting technique applying the Kalman filter algorithm is proposed. In order to apply the Kalman filter algorithm to electric load forecasting, an electrical load forecasting algorithm is defined as an observation model and a state space model in a time domain. In addition, in order to precisely reflect the noise characteristics of the Kalman filter algorithm, the optimal error covariance matrixes Q and R are selected from several experiments. The proposed algorithm is expected to contribute to stable real-time power system operation by providing a precise electric load forecasting result in the next six hours.

Keywords: Very short-term electric load forecasting, Kalman filter algorithm

1. Introduction

Very short-term electric load forecasting is basic technology required to systemize real-time power system operation. The need for very short-term electric load forecasting is gradually becoming essential for real-time power system operation, but research on the very short-term electric load forecasting techniques is insufficient, unlike areas such as daily electric load forecasting, weekly and monthly electric load forecasting, and medium to long-term electric load forecasting [1-3]. In order to minimize the demand management cost, which is continuously increasing recently, unnecessary demand management cost should be inhibited based on the precise very short-term electric load forecasting. The following algorithms are widely used for the very short-term electric load forecasting : Auto-regressive (AR)Model [4], Autoregressive Moving Average (ARMA)Model [4, 5], Kalman filter technique [6–8], Artificial Neural Network (ANN) [8-10], and Expert System[8,11]. In addition, in order to improve the accuracy of the very short-term electric load forecasting, research on new electric load forecasting is needed. In this paper, a Kalman filter algorithm is applied to the very short-term electric load forecasting. In order to apply the Kalman filter algorithm to the very short-term electric load forecasting, a state space model for a power load forecasting system is designed. In addition, in order to heighten the preciseness of the very short-term electric load forecasting, system noise characteristics are analyzed. Through analyses of case studies for accuracy of the very short term load forecasting, the forecasting time period of the proposed algorithm is decided.

† Corresponding Author: Department of Electrical Engineering, Soongsil University, Seoul, Korea. (kbsong@ssu.ac.kr)
* Economy & Management Research Institute, KEPCO, Korea. (jhw14@kepco.co.kr)
** Division of Energy & Electrical Engineering, Uiduk University, Gyeongju, Korea. (jdpark@uu.ac.kr)
*** Department of Electrical Engineering, Soongsil University, Seoul, Korea. (rejuni@ssu.ac.kr)
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2. The Theory of the Kalman Filter Algorithm

The Kalman filter algorithm is an optimal estimation technique that finds state variables of the system using a probabilistic state space model and the observed values of the system [12, 13]. It is used in diverse areas, such as the control area, stock price prediction, the geographical positioning system, weather prediction, population prediction and so forth [14].

The design of a state space model of the system to apply the Kalman filter algorithm is basically defined as the state space model and the observation model in a time domain [15].

$$x_{k+1} = Ax_k + w_k \tag{1}$$
$$z_k = Hx_k + v_k \tag{2}$$

Where, x_k is a state variable, z_k is an observed value, A is a state transition matrix, H is an output matrix, w_k is system noise, and v_k is measurement noise. In a state space model for a system, the statistics are used to express the noise covariance, and it is assumed that noise of the Kalman filter algorithm follows the standard normal distribution.

The Kalman filter algorithm consists of a prediction process and a correction process[17]. In the prediction process, the value estimated right before ($\hat{x}_{k-1}$) and error covariance (P_{k-1}) are the input, and the predicted values ($\hat{x}_k^-$, P_k^-) are the output. The Kalman filter algorithm's prediction process is composed of (3)-(4).

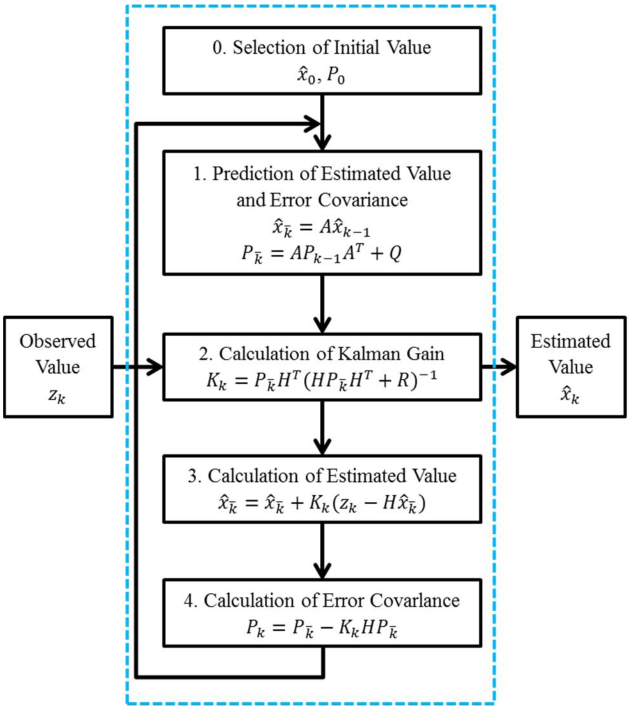

Fig 1. Flow chart of the Kalman filter algorithm [16]

$$\hat{x}_k^- = A\hat{x}_{k-1} + w_k \tag{3}$$
$$P_k^- = AP_{k-1}A^T + Q \tag{4}$$

Where, A is a matrix composed of constants, and Matrix A represents how the system operates according to time. w_k represents noise that flows into the system and affects the state variables, and Q is w_k's covariance matrix. $\hat{x}_k$ and P_k denote the estimated value calculated earlier. When calculating a predicted value from an estimated value, A and Q are used, and these variables have a decisive effect on the predicted value. When the two matrixes are much different from the system, the predicted value and the estimated value become imprecise. In other words, the performance of the Kalman filter is determined by the design of the system state space model.

In the correction process, the predicted value($\hat{x}_k^-$, P_k^-) of the prediction process and the observed value(z_k) are delivered and used as input values for the output estimated value($\hat{x}_k$) and error covariance(P_k). The correction process of the Kalman filter algorithm is composed of formulas (5)-(7).

$$K_k = P_k^- H^T(HP_k^- H^T + R)^{-1} \tag{5}$$
$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \tag{6}$$
$$P_k = P_k^- - K_k H P_k^- \tag{7}$$

Where, K_k is the Kalman gain and represents the weighted value of the Kalman filter algorithm. H is a matrix comprised of constants, and matrix H represents the relationship between the observed value and the state variables. v_k represents noise measured from the sensor, and R refers to the covariance matrix of v_k. Formula (6) represents a formula to calculate the estimated values of the Kalman filter algorithm. The Kalman gain of the Kalman filter algorithm is not fixed and is newly calculated according to the formula (5). In other words, the weight used to calculate the estimated values continues to change according to the predicted situation. The Kalman filter properly corrects the predicted values using the prediction error of the observed value and calculates the final estimated value, and the Kalman gain is a factor to determine how much to correct the predicted value. The formula (7) is a formula to update the error covariance. The error covariance is an indicator that expresses how much the estimated values of the state variables of the Kalman filter differ from the true values. The relationship of $x_k \sim N(\hat{x}_k, P_k)$ is established between the state variable x_k, the estimated value($\hat{x}_k$), and the error covariance(P_k). The state variable x_k follows a normal distribution with an average at $\hat{x}_k$ and a covariance at P_k, and the highest value by examining the probability distribution of the estimated value of the Kalman filter's state variable x_k is selected as an estimated value.

3. Very Short-term Electric Load Forecasting Model

The state space model for the electric load forecasting system to apply the Kalman filter algorithm consists of an observation model and a state space model in a time domain[18]. In order to compose an observation model, an algebraic equation was formed that was expressed as the relationship between the system input values and the state variables. Various algebraic equations were made and a equation with minimum errors was selected.

$$\begin{aligned} y(k) = {} & a_1(k)y(k-1) + a_2(k)y(k-2) + a_3(k)y(k-3) \\ & + a_4(k)y(k-4) + a_5(k)y(k-95) \\ & + a_6(k)y(k-96) \\ & + a_7(k)y(k-97) + a_8(k)y(k-98) \\ & + a_9(k)y(k-191) \\ & + a_{10}(k)y(k-192) + a_{11}(k)y(k-193) \\ & + a_{12}(k)y(k-194) \end{aligned} \tag{8}$$

For the very short-term weekday(Tuesday to Friday) electric load forecasting, electric load data with a 15 minute unit are used. In order to predict the weekday electric load of y(k), a total of 12 data on the previous electric load, y(k-1), y(k-2), y(k-3), y(k-4), y(k-95), y(k-96), y(k-97), y(k-98), y(k-191), y(k-192), y(k-193), and y(k-194), are used as the input data. Where, y(k-1) means the 15 minutes ago electric load leading one time difference from forecasting point y(k). Similarly, y(k-2), y(k-96), y(k-192) respectively denote the 30 minutes ago electric load leading two time differences, the 1,440 minutes (one day) ago electric load leading 96 time differences, the 2,880 minutes(two day) ago electric load leading 192 time differences.

Generally, electric load patterns are similar without effect of weather changes, or social events or abrupt economic variations in 10 days. The data of one day and two days ago are used to model for the load pattern and the data of fifteen minutes, 30 minutes, 45 minutes and 60 minutes ago are used to reflect for variation rate of load at predicting time t. The way of selecting input data is various. The authors tried several cases and investigated the accuracy of load forecasting for the test cases. Then, the best input data selection is decided.

For weekend (Saturday, Sunday and Monday) load forecasting, input data are gathered from the recent two weekends electric load data having the similar electric load profile to the forecasting day. That is, a total of 12 data on the previous electric load, y(k-1), y(k-2), y(k-3), y(k-4), y(k-671), y(k-672), y(k-673), y(k-674), y(k-1343), y(k-1344), y(k-1345) and y(k-1346), are used as the input data. The input data y(k-2), y(k-672), y(k-1344) respectively show the 30 minutes ago electric load leading two time differences, the one week ago electric load leading 672 time differences, the two weeks ago electric load leading 1344 time differences. The weekend load forecasting equation is as follows:

$$\begin{aligned} y(k) &= a_1(k)y(k-1) + a_2(k)y(k-2) + a_3(k)y(k-3) \\ &+ a_4(k)y(k-4) + a_5(k)y(k-671) + a_6(k)y(k-672) \\ &+ a_7(k)y(k-673) + a_8(k)y(k-674) \\ &+ a_9(k)y(k-1343) + a_{10}(k)y(k-1344) \\ &+ a_{11}(k)y(k-1345) + a_{12}(k)y(k-1346) \end{aligned} \quad (9)$$

The formula (10) and (11) represents the matrix expression of the formula (8) and (9).

The measurement equation composed in the manner of the formula (10) and (11) may be expressed as a measured observation model in the form of the formula (12).

$$y(k) = \begin{bmatrix} y(k-1) \\ y(k-2) \\ y(k-3) \\ y(k-4) \\ y(k-95) \\ y(k-96) \\ y(k-97) \\ y(k-98) \\ y(k-191) \\ y(k-192) \\ y(k-193) \\ y(k-194) \end{bmatrix}^T \begin{bmatrix} a_1(k) \\ a_2(k) \\ a_3(k) \\ a_4(k) \\ a_5(k) \\ a_6(k) \\ a_7(k) \\ a_8(k) \\ a_9(k) \\ a_{10}(k) \\ a_{11}(k) \\ a_{12}(k) \end{bmatrix} \quad (10)$$

$$y(k) = \begin{bmatrix} y(k-1) \\ y(k-2) \\ y(k-3) \\ y(k-4) \\ y(k-671) \\ y(k-672) \\ y(k-673) \\ y(k-674) \\ y(k-1343) \\ y(k-1344) \\ y(k-1345) \\ y(k-1346) \end{bmatrix}^T \begin{bmatrix} a_1(k) \\ a_2(k) \\ a_3(k) \\ a_4(k) \\ a_5(k) \\ a_6(k) \\ a_7(k) \\ a_8(k) \\ a_9(k) \\ a_{10}(k) \\ a_{11}(k) \\ a_{12}(k) \end{bmatrix} \quad (11)$$

$$z(k) = H(k)x(k) + v(k) \quad (12)$$

Because the electric loads are complex and nonlinear things which are related with various variables, those are very difficult to express an accurate model with a mathematical equation. Therefore, because it is difficult to perform the state space modeling of the system clearly and to express it mathematically, a pre-state matrix $A(k)$ of the state variable model was composed of unit matrixes. In this case, because changes in the state variables could not be verified through the state space model, the state variables were updated through the probabilistic changes of system noise w(k).

$$x(k+1) = A(k)x(k) + w(k) \quad (13)$$

In order to enhance the preciseness of very short-term electric load forecasting, an error covariance matrix (P_k) with the state variables and the noise characteristics of the noise covariance matrix (Q, R) should be precisely designed. The error covariance matrix (P_k) with state variables and the noise covariance matrix (Q, R) have an influence when the Kalman gain K_k is determined under the Kalman filter algorithm. The design of the value is determined by applying great weight to either the system value or the observed value. In particular, different errors are complexly engaged in the noise characteristics of Q and R, and it is difficult to analytically determine the variables. Therefore, based on the predictor's experiences, an appropriate value should be found while correcting the variables.

In order to find the values of Q and R, more than 30 data sets are required in case of weekdays and weekends very short-term load forecasting. However, due to a change of seasons, obtaining 30 data sets of good quality for weekends forecasting is difficult.

Furthermore, due to lack of 30 data sets of good quality for special days, the authors could not performed very short term load forecasting by using the Kalman filter algorithm for special days. Currently, authors have researched to find good way to forecast very short-term load for special days. In the near future, good research results will be presented for very short term load forecasting for special days.

4. Case Studies

The electric load forecasting error rate is calculated with a mean absolute percentage error(MAPE).

$$\text{MAPE} = \left| \frac{\text{the actual load} - \text{the forecasted load}}{\text{the actual load}} \right| \quad (14)$$

Particular dates in February, June, August, and October of 2013 are selected as case study periods, and then the case studies were performed. First, in order to precisely reflect the noise characteristics of the Kalman filter algorithm, Q and R were selected to minimize errors by performing electric load forecasting for the periods of the case studies. Q and R were searched for by adjusting the value from zero to one in the unit of 0.01. Because electric loads have monthly different characteristics according to temperatures, Q and R are selected monthly to reflect these characteristics. Table 1 shows the monthly Q and R estimation results during the periods in which the case studies are performed.

Table 1. Selection of optimal monthly Q and R (2013)

Month	Q	R
February	0.72	0.01
June	0.14	0.01
August	0.02	0.01
October	0.33	0.01

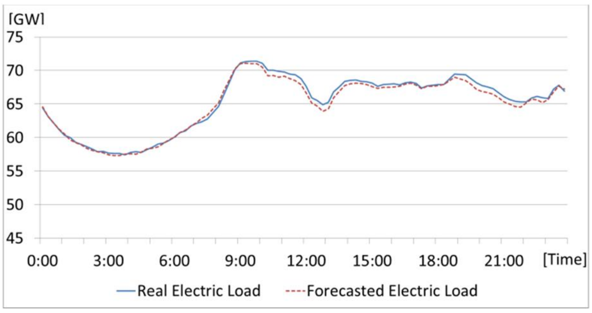

Fig. 2. The error of electric load forecasting at zero O'clock of February 19

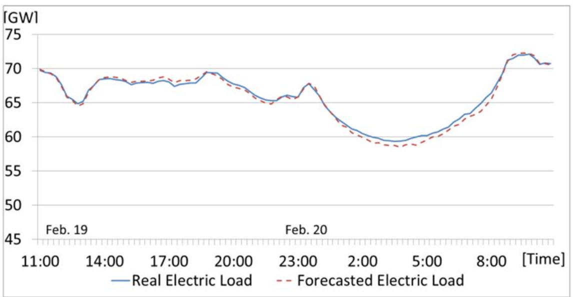

Fig. 3. The error of electric load forecasting at 11 O'clock of February 19

Using the selected Q and R, 24 hour electrical load forecasting is performed in units of 15 minutes from 00:00 a.m. and 11:00 a.m. on February 19, 2013.

Fig. 2 and 3 show the results of 24 hour electric load forecasting performed in units of 15 minutes at 0 and 11 a.m. using the Kalman filter algorithm. The predicted values follow the actual values very well during early 6 hours in figure 2. However, after 6 a.m. the errors occur as the prediction progresses. Similarly, the forecasted values follow the actual values very well during early 6 hours in figure 3.

The proposed Kalman filter algorithm performs a forecasting based on real-time data processing. When the forecasting time period increases, the real-time data processing becomes difficult because the proposed algorithm have to use the forecasted value containing prediction errors as input data. Hence, the forecasting errors after early 6 hours occur much bigger than that of early 6 hours.

Although there are slight differences according to the prediction time, the electric load forecasting results in figure 2 and 3 are excellent during early 6 hours. Therefore, the prediction time-period of the very short-term electric load forecasting technique that applied the Kalman filter algorithm is effective for up to the next six hours, and the results of the very short-term electric load forecasting is quite precise. In addition, electric load forecasting for particular dates in February, June, August, and October of 2013 is performed, and the results are presented in table 2 and table 3.

To verify the accuracy of the proposed algorithm, forecasting results of exponential smoothing are compared and analyzed. The average error rate of proposed algorithm is 0.54%, the average error rate of exponential smoothing

Table 2. The error of weekday electric load forecasting at 00:00 a.m

Date	6h	24h
2013.02.19	0.29%	0.62%
2013.02.20	1.18%	0.82%
2013.06.18	0.53%	0.55%
2013.06.19	0.26%	0.58%
2013.08.20	0.19%	0.95%
2013.08.21	0.47%	0.66%
2013.10.22	0.67%	0.65%
2013.10.23	0.45%	0.55%

Table 3. The error of weekday electric load forecasting at 11:00 a.m

Date	6h	24h
2013.02.19	0.35%	0.64%
2013.02.20	0.34%	1.42%
2013.06.18	0.53%	0.49%
2013.06.19	0.51%	0.70%
2013.08.20	0.75%	0.91%
2013.08.21	0.27%	0.68%
2013.10.22	0.62%	0.69%
2013.10.23	1.19%	0.72%

Table 4. The error of weekend electric load forecasting at 00:00 a.m.

Date	6h	24h
2013.06.15(Sat)	0.27%	0.99%
2013.06.16(Sun)	0.38%	1.50%
2013.06.17(Mon)	0.34%	0.92%
2013.08.17(Sat)	0.40%	1.38%
2013.08.18(Sun)	0.56%	2.32%
2013.08.19(Mon)	0.49%	2.80%
2013.10.19(Sat)	0.64%	0.67%
2013.10.20(Sun)	0.34%	1.55%
2013.10.21(Mon)	0.66%	1.79%

Table 5. The error of weekend electric load forecasting at 11:00 a.m.

Date	6h	24h
2013.06.15(Sat)	0.51%	1.03%
2013.06.16(Sun)	0.77%	0.55%
2013.06.17(Mon)	0.49%	0.79%
2013.08.17(Sat)	0.71%	1.31%
2013.08.18(Sun)	3.81%	3.59%
2013.08.19(Mon)	0.49%	1.58%
2013.10.19(Sat)	0.50%	1.119%
2013.10.20(Sun)	1.30%	3.39%
2013.10.21(Mon)	1.78	1.33

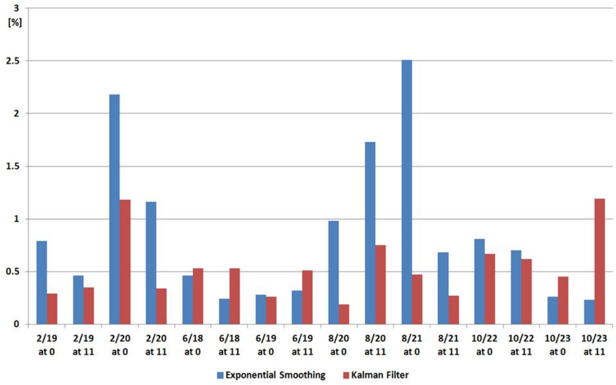

Fig 4. Comparisons of weekday forecasting results between Kalman Filter and Exponential Smoothing

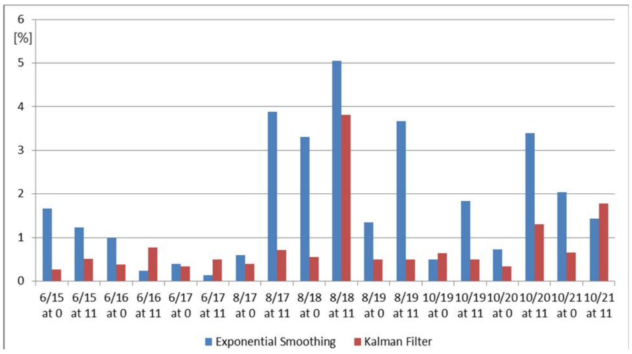

Fig. 5. Comparisons of weekend forecasting results between Kalman filter and exponential smoothing

is 0.86%. At the analysis results, the proposed algorithm is verified the excellence of forecasting results.

Also weekend load forecasting is performed and the results are compared with that of exponential smoothing.

The precise very short-term electric load forecasting is essential for a real-time power system and its operation. The proposed algorithm is expected to greatly contribute to the stable real-time power system operations by providing precise electric load forecasting for the next six hours.

5. Conclusion

In order to apply the Kalman filter algorithm to very short-term electric load forecasting, the precise state space modeling of the system is very important. The very short-term electric load forecasting system based on the Kalman filter algorithm is designed by composing a system measurement observation model and a state space model in a time domain. In addition, in order to precisely reflect the noise characteristics of the Kalman filter algorithm, the optimal error covariance matrixes Q and R are selected through experiments.

According to the forecasting results, the accuracy of the proposed algorithm shows excellent performance especially for the next 6 hours. Therefore, it is expected that the proposed algorithm will contribute to the stable real-time power system operations by providing the accurate very short-term load forecasting results.

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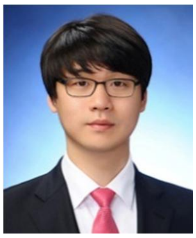
Hyun-Woo Jung He received his B.S. and M.S. degree in Electrical Engineering from Soongsil University, Seoul, Korea, in 2013 and 2015. He is currently a researcher in Economy & Management Research Institute at KEPCO.

Kyung-Bin Song He received his B.S. and M.S. degrees in Electrical Engineering from Yonsei University, Seoul, Korea, in 1986 and 1988, respectively. He received his Ph.D. degree in Electrical Engineering from Texas A&M Uni-versity, College Station, Texas in 1995. He is currently a Professor in Electrical Engineering at Soongsil University, Seoul, Korea. His research interests include load forecasting, load modeling, power system operation and power system economics.

Jeong-Do Park He received his B.S., M.S., and Ph.D. degree in Electrical Engineering from Yonsei University, Seoul, Korea in 1992, 1994 and 2000 respectively. In 2001, he joined the faculty of Uiduk University, GyeongJu, Korea. His research interests include load forecasting, generation scheduling and economic dispatch in electric power systems.



Rae-Jun Park He received his B.S. and M.S. degree in Electrical Engineering from Soongsil University, Seoul, Korea, in 2011 and 2013. Currently, he is pursuing Ph.D. degree at Soongsil University, Seoul, Korea.