

건물 에너지 절감을 위한 실내 온도 추정 시스템

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Indoor Temperature Estimation System for Reduction of Building Energy Consumption

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Abstract

In this paper, a new strategy for estimating building temperature based on the modified resistance capacitance (R - C) network thermal dynamic model is proposed. The proposed method gives accurate indoor temperature estimation using minimum variance finite impulse response filter. Our study is clarified by the experimental validation of the proposed indoor temperature estimation method. This experiment scenario environment is composed of a demand response (DR) server and home energy management system (HEMS) in a test bed.

1. Introduction

The prediction of energy consumption is the most complex issue of the smart grid projects. Daily building energy consumption depends on the randomness of occupant comfort and temperature changes [1-5]. However, the exact estimation of building appliance load is necessary to optimize energy consumption between electricity supply and electricity demand. Through smart meters, which are installed in many buildings nowadays, there are several opportunities to predict energy load more accurately for building appliances to improve energy consumption efficiency [6-7]. Building energy load prediction is a difficult issue. In particular, the Kalman filter is used for estimating the building energy consumption. The building appliance load model plays an important role in understanding and estimating building energy consumption [8-9].

However, the Kalman filter may show poor performance in an unexpected condition. One of the alternative method for Kalman filter is finite impulse response (FIR) filter that does not use infinite impulse response (IIR) estimation [10-15]. Because IIR estimation, such as the Kalman filter, uses all past input and output data to calculate the estimated state, poor estimation performance or divergence phenomenon may occur due to the incorrect initial state in

formation, modeling, and computational error accumulation. However, with its given structural characteristics, FIR estimation can prevent the error accumulation problem, because it estimates the state only with recent finite measurement information. Furthermore, the advantages of FIR guarantee bounded-input bounded-output (BIBO) stability and robustness against temporary model uncertainties, such as incorrect noise information and quantization effects [16-24].

The dynamics of a building are slow and disturbances are unavoidable (e.g., thermal noise of appliances and occupants). Because of the occupant's comfort requirement as well as the limited capacity of appliances, constrained control is required. The goal of our paper is to predict weather in order to make use of the thermostorage capacity of a building using FIR filter.

The rest of this paper is organized as follows. Section II provides indoor temperature estimation based on the resistance -capacitance (R - C) network model. The experiment results gives robustness of the proposed method in Section III. Finally we conclude our paper in Section IV.

2. Indoor Temperature Estimation

In this paper, the experiment is carried out in

the test bed. The walls of the test bed are heavy enough to interrupt the heat flow of neighbor rooms, and the windows of the test bed are too thin to interrupt the heat flow of outdoor temperature. Therefore, the influence of neighboring room temperature can be ignored when comparing the influence of outdoor temperature. Additionally, this test bed has fixed thermal noise from three computers and three residents. Because the activity patterns of residents are the same every day, this thermal noise can be used as a parameter. With these assumptions, the modified R - C network thermal model can be written as follows.

$$T_{inn}(K+1) = T_{inn}(K) + \alpha(T_{out} - T_{inn}(K)) + \beta P_{HVAC}(K) + \gamma(\chi - T_{inn}(K)).$$

Define the output state $y(k)$ as the indoor temperature and the sampling time as 10 minutes. The discrete-time building R - C network thermal model can be written in the following simple state-space form:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + \omega(k), \\ y(k) &= Cx(k) + Du(k), \end{aligned}$$

where

$$A = [1 - \alpha - \gamma], B = [\alpha \ \beta \ \gamma], C = 1, D = 0, \\ x(k) = T_{in}, \text{ and } u(k) = [T_{out}(t) \ P_{HVAC} \ 1]^T.$$

$\omega(k)$ denotes white Gaussian noise, and the numerical values. A, B and C can be calculated based on experiment data.

We can verify the accuracy of the R - C network model with different experiment data sets based on the parameter matrices. The state-space model of the R - C network thermal model can predict the indoor temperature of the test bed with the obtained parameters.

$$\hat{x}(k+1) = \hat{A}\hat{x}(k) + \hat{B}u(k) + \omega(k),$$

\hat{x} , \hat{A} , and \hat{B} are the estimation value of indoor temperature, the accuracy of the model can be obtained by the mean squared error (MSE) e , which is as follows:

$$e = \frac{1}{N} \sum_{k=1}^N \|\hat{x}(k-1) - x(k-1)\|^2.$$

Even if the state-space model can provide more accurate indoor temperature estimation, modeling errors, which can cause poor estimation performance, still remain. In much of the literature, for the estimation of the temperature of a battery with a Kalman filter and electric circuits, a filtering method is proposed to

improve the estimation performance. Therefore, a minimum variance finite impulse response (MVFIR) method is proposed in this section to decrease the accumulation of modeling and measurement errors.

The MVFIR filter is implemented to estimate indoor temperature with a horizon size of 10. With the experimental data, a horizon size of 10 for the FIR filter shows the best estimation performance and calculation time, the finite number of measurements is represented in terms of the state vector at current time k as follows:

$$Y(k-1) = \bar{C}_{10}x(k) + \bar{B}_{10}U(k-1) + \bar{G}_{10}W(k-1) + V(k-1)$$

where

$$Y(k-1) = [y^T(k-10) \ y^T(k-9) \ y^T(k-8) \ \dots \ y^T(k-1)]^T,$$

$$U(k-1) = [u^T(k-10) \ u^T(k-9) \ u^T(k-8) \ \dots \ u^T(k-1)]^T,$$

$$W(k-1) = [\omega^T(k-10) \ \omega^T(k-9) \ \omega^T(k-8) \ \dots \ \omega^T(k-1)]^T,$$

$$V(k-1) = [v^T(k-10) \ v^T(k-9) \ v^T(k-8) \ \dots \ v^T(k-1)]^T,$$

$$y(k) = T_{in}(k), \text{ and } u(k) = [T_{out}(k) \ P_{HVAC}(k) \ 1]^T.$$

The MVFIR filter estimated state can be written as following equation with gain H_B :

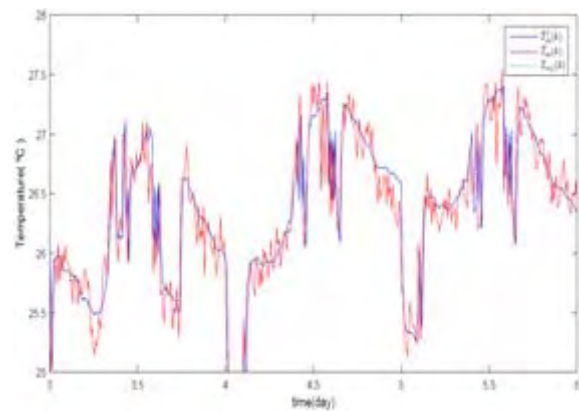
$$\hat{y}(k | k-1) = H_B(Y(k-1) - \bar{B}_{10}U(k-1)).$$

The filter gain can be written as follows:

$$H_B = (\bar{C}_{10}^T \Xi_{10}^{-1} \bar{C}_{10})^{-1} \bar{C}_{10}^T + 10 \Xi_{10}^{-1},$$

3. Experiment Results

In this section, we showed the performance of the proposed method and existing method (i.e. Kalman filter) via experiment result.



(그림 1 Indoor Temperature estimation comparison; blue line : proposed method, redline: Kalman filter)

Figure 1 represents Real temperature and its

estimation at DR level 0 signal for occupant over 30 days. During peak time, HEMS determine energy consumption same as previous pattern. Two estimated temperature results are similar with real indoor temperature. The Kalman filter shows good performance, but in 4.5 or 5.5 times in graph Kalman filter shows poor performance. Nevertheless, our proposed method shows better performance than Kalman filter method in peak time. In other words, the performance of both estimators worsened as the typical pattern of the occupant was modified. However, the MVFIR method demonstrated better performance in temperature prediction.

4. Conclusion

This paper evaluates a new approach to indoor temperature estimation, which is especially helpful for peak times. With the modified R-C network thermal model, a new approach employing MVFIR uses recent finite horizon measurement information and minimizes the estimation error variance to estimate indoor temperature. The modified R-C network thermal model and MVFIR were integrated in the HEMS to overcome difficulties of temperature estimation due to its random nature of turning on/off and energy reduction with the DR level. We implement the HEMS, which includes communication between the DR server and building HEMS to demonstrate its purposes in a test bed.

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Reference

- [1] U.S. Department of Energy, "2011 Buildings Energy Data Book," 2012, http://buildingsdatabook.eren.doe.gov/docs/DataBooks/2011_BEDB.pdf.
- [2] C. Ghiaus, I. Hazyuk, "Calculation of optimal thermal load of intermittently heated buildings," *Energy and Buildings*, vol. 42, no. 8, pp. 1248 - 1258, 2010.
- [3] Y. Y. Hong, J. K. Lin, C. P. Wu, and C. C. Chuang, "Multi-Objective Air-Conditioning Control Considering Fuzzy Parameters Using Immune Clonal Selection Programming," *IEEE Trans on Smart Grid*, vol. 3, no. 4, pp. 1603 - 1610, 2012.
- [4] D. M. Han and J. H. Lim, "Design and Implementation of Smart Home Energy Management Systems based on Zigbee," *IEEE Trans. Consumer Electronics*, vol. 56, no. 3, pp. 1417 - 1425, 2010.
- [5] C. T. Costanzo, G. Zhu, M. F. Anjos, and G. Savad, "A SystemArchitecture for Autonomous Demand Side Load Management in Smart Buildings," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 2157 - 2165, 2012.
- [6] A. Mohesenan-Rad, and A. Leon-Garcia, "Optimal Residential Load Control with Price Prediction in Real-Time Electricity Pricing Environments," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 120 - 133, 2010.
- [7] J. Han, C. S. Choi, and I. Lee, "More efficient home energy management system based on ZigBee communication and infrared remote controls," *IEEE Trans. on Consumer Electronics*, vol. 57, no. 1, pp. 85 - 89, 2011.
- [8] J. S. Han, C. S. Choi, and W. K. Park, "Smart home energy management system including renewable energy based on zigbee and plc," *IEEE Trans. Consumer Electronics*, vol. 60, no. 2, pp. 198 - 202, 2014.
- [9] Y. S. Son, and K. D. Moon, "Home energy management systembased on power line communication," *IEEE Trans. Consumer Electronics*, vol. 56, no. 3, pp. 1380 - 1386, 2010.
- [10] S. H. You, J. M. Pak, C. K. Ahn, P. Shi, and M. T. Lim. Unbiased finite-memory digital phase-locked loop. *IEEE Trans. on Circuits and Systems-II:Express Briefs*, 63(8):798 - 802, Aug. 2016.
- [11] C. K. Ahn, P. Shi, and S. H. You. A new approach on design of a digital phase-locked loop. *IEEE Signal Processing Letters*, 23(5):600 - 604, May. 2016.
- [12] C. K. Ahn, S. Han, and W. H. Kwon. H^∞ FIR filters for linear continuous-time state-space systems. *IEEE Signal Processing Letters*, 13(9):557 - 560, Sep. 2006.
- [13] C. K. Ahn. Strictly passive FIR filtering for state-space models with external disturbance. *International Journal of Electronics and Communications*, 66(11):944 - 948, Nov. 2012.
- [14] C. K. Ahn, P. Shi, and M. V. Basin. Two-Dimensional Dissipative Control and Filtering for Roesser Mode. *IEEE Transactions on Automatic Control*, 60(7):1745 - 1759, Jul. 2015.
- [15] C. K. Ahn. A new solution to the induced l^∞ finite impulse response filtering problem based on two matrix inequalities. *International Journal of Control*, 87(2):404 - 409, 2014.
- [16] C. K. Ahn, P. Shi, and S. H. You. Optimal memory size formula for moving-average digital phase-locked loop. *IEEE Signal Processing Letters*, 23(12):1844 - 1847, Dec. 2016.
- [17] C. K. Ahn, P. Shi, and M. V. Basin. Deadbeat dissipative FIR filtering. *IEEE Trans. on Circuits and Systems-I: Regular*

Papers, 63(8):1210 - 1221, Aug. 2016.

- [18] C. K. Ahn, Y. S. Shmaliy, P. Shi, and Y. Zhao. Receding horizon $l_2 - l_\infty$ FIR filter with imbedded deadbeat property. IEEE Trans. on Circuits and Systems-II:Express Briefs (In press, DOI:10.1109/TCSII.2016.2555038), 2016. [19] C. K. Ahn, Y. S. Shmaliy, S. Zhao, and H. Li. Continuous-time deadbeat H2 FIR filter. IEEE Trans. on Circuits and Systems-II:Express Briefs (In press, DOI:10.1109/TCSII.2016.2613959), 2016.
- [20] C. K. Ahn, Y. S. Shmaliy, and P. Shi. Generalized dissipativitybased receding horizon FIR filtering with deadbeat property. IEEE Trans. on Circuits and Systems-II:Express Briefs (In press, DOI:10.1109/TCSII.2016.2623644), 2016.
- [21] J. M. Pak, C. K. Ahn, M. T. Lim, and M. K. Song. Horizon group shift FIR filter: alternative nonlinear filter using finite recent measurements. Measurement, 57:33 - 45, Nov. 2014.
- [22] J. M. Pak, C. K. Ahn, Y. S. Shmaliy, and M. T. Lim. Improving reliability of particle filter-based localization in wireless sensor networks via hybrid particle/FIR filtering. IEEE Trans. on Industrial Informatics, 11(5):1089 - 1098, Oct. 2015.
- [23] J. M. Pak, C. K. Ahn, C. J. Lee, P. Shi, M. T. Lim, and M. K. Song. Fuzzy horizon group shift FIR filtering for nonlinear systems with TakagiSugeno model. Neurocomputing, 174(Part B):1013 - 1020, Jan. 2016.
- [24] J. M. Pak, C. K. Ahn, P. Shi, and M. T. Lim. Self-recovering extended Kalman filtering algorithm based on model-based diagnosis and resetting using an FIR filter. Neurocomputing, 173(Part 3):645 - 658, Jan. 2016.