Energy usage pattern analysis and AECP(adaptive energy consumption prediction) scheme for efficient office-building energy management

[Seok-Ho Yoon, Seung-yeon Kim, Choong-Ho Cho]

Abstract—The deployment of advanced metering infrastructures on the small-medium scale building facilitates power suppliers and consumers to better control the utility supply and usage chain. Data from these systems are generally used to analyze the utility usage, furthermore we can enable such as smart energy management and distribution of resources of the building. For the efficient demand-response management of building energy, we analyze the results of the energy usage pattern through clustering of the usage data of the office building. Accordingly, in this paper, we propose the RLS-based power usage prediction algorithm, the Adaptive Energy Consumption Prediction (AECP). In order to obtain the validity of our prediction model, we calculate the error rate between the measured and the actual data of the power usage. Based on this, we determine the demand for energy-efficiency with energy consumption forecast.

Keywords—blueding energy management, energy forecasting, energy consumption, energy management, AECP

I. Introduction

In the last 20 years, due to the rapid growth in world energy consumption, keen interest has been paid to energy conservation. The Energy Information Administration (EIA), in its International Energy Outlook [1], analyzes and forecasts that the building energy consumption will grow by 34% in the next 20 years at an annual growth rate of about 1.5%. Buildings are one of the fastest growing energy consuming sectors. It is estimated that the amount of the energy consumed in the Korean buildings reaches 25% of total energy consumption, and the electric energy used was 55.7% of the total building energy usage.

According to the Energy Information Administration of the Institute of Energy Economics Korea, in 2012 the portion of energy consumption by each end-user sector accounted to about 17.7% in transportation, 62% in industry, 7.9% in commercial, and 10.2% in residential sectors, respectively[2].

This study analyzes the data of the actual power usage of the small and medium-sized office buildings, and propose efficient buildings energy demand management measures. To view the daily hourly energy use patterns, we perform a clustering analysis on power usage data of the office building.

Seok-Ho Yoon, Seung-yeon Kim, Choong-Ho Cho
Computer & Information Science / Korea University
Republic of Korea

In order to accurately predict the demand for energy used in buildings, we propose the energy consumption forecast model, AECP. Using the proposed model, we estimate the error of actual data from the predicted value, and show that our AECP model provides high performance in power usage prediction.

II. Data pattern analysis based on the amount of electricity used

In this chapter, to understand the pattern in the energy data on an hourly and daily basis, we perform clustering analysis to determine the similarity of the daily use between the actual power consumption data of office buildings. We use the Euclidean distance as a measure of the similarity, and the distribution of the measured data was analyzed using the average connecting method (e.g., hierarchical cluster analysis[3]). Total amount of energy consumption data over 1 year in 2013 was analyzed for similarity analysis of use pattern.
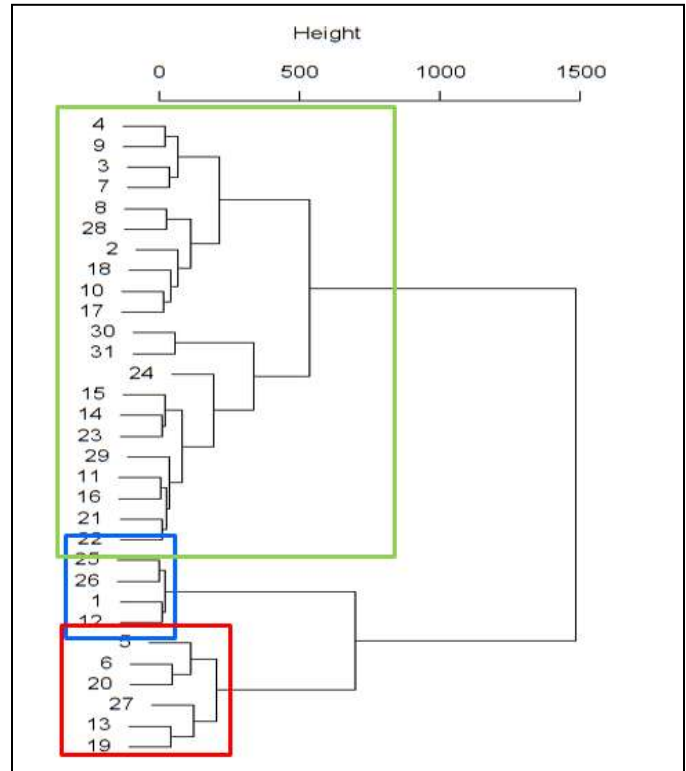

Figure 1.   Daily energy usage pattern in N building during March 2013

Figure 1 shows the daily data clustering results for the total use in N Building for one month in January 2013. In January 2013, 1st day is a holiday, whereas 5th, 6th, 12th, 13th, 19th, 20th, 27th days are each holidays and weekends. We can see that the clustering on weekdays, weekends and holidays are different groups based on similarity of power usage in Figure 1. From the figure, the parts marked by the green box (top), red box (middle) and blue box (bottom) represent the weekdays, holidays, and data error portion respectively. Therefore, this suggests that the clustering analysis has been made properly. Based on the above results, the energy usage tendency is observed to be different on weekdays and holidays. Therefore, the forecast should be considered in both weekdays and holidays for more accurate predictions.
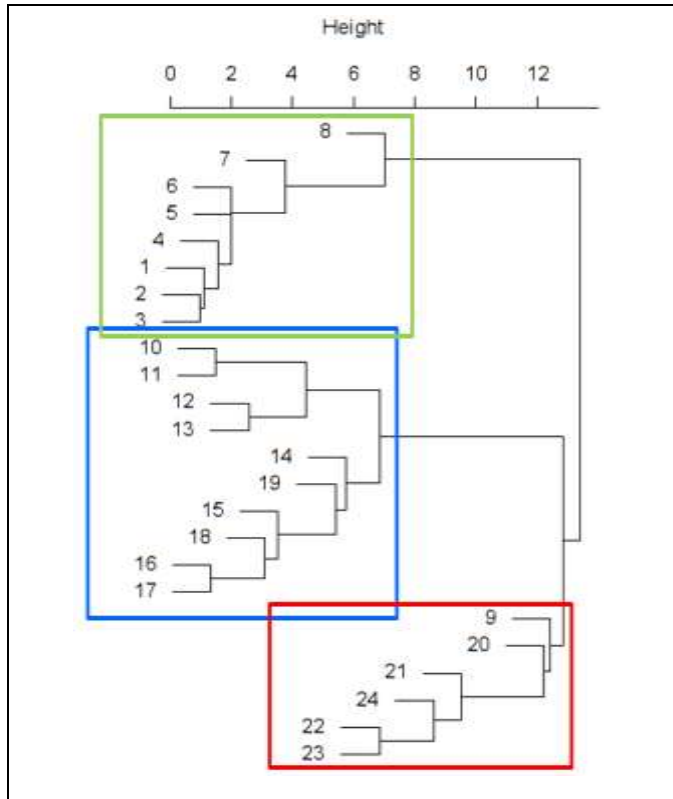

Figure 2.   Hourly energy usage pattern in N building on March 25, 2013

Figure 2 shows the time-specific clustering results for the total power data in N Building for March 25, 2013. The results from this figure show that the hourly power usage is divided into three types as non-business hours, Type 1 business hours and Type 2 business hours in working days.

In Figure 2, the energy usage is divided into three patterns: - between 8:00 am to 1 (non-business hours) and between 10:00 to 19 (normal business hours, job type 1), 20-24 and finally 9:00 24 (2 types of business services preparation and overtime).

After clustering the actual power usage by time, energy consumption can be observed for different time intervals. Thus, electricity consumption tendencies appear differently following the given time intervals. Accordingly, this suggests that the energy prediction should be performed hourly to obtain more accurate predictions.

III. AECP(Adaptive Energy Consumption Prediction) scheme for prediction of building energy consumption

In Chapter 2, it has seen that electricity consumption tendencies appears differently as the hours. In this section, considering the energy use characteristics, we modified the RLS algorithm[4-7] as AECP (Adaptive Energy Consumption Prediction) scheme. In AECP, like in RLS algorithm, the output vector is determined by multiplying the Input vector and weight vector, in which the Input vector has the value of actual data. Unlike conventional RLS, in AECP, the feedback of the predicted value replaces the input vector. The more the prediction is performed by adjusting the value of the error from the actual data the more the accurate is the result.

AECP proceeds by feeding back the predicted value to the Input vector tape. The process keeps repeating so that to reduce the error rate of the predicted value until the input-vector converges to zero.
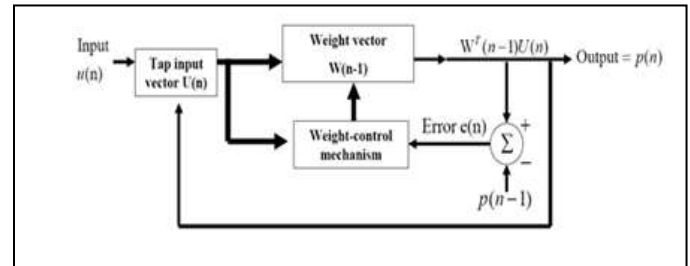

Figure 3.   AECP scheme

IV. Performance evaluation of proposed AECP scheme

In this chapter, we analyzed the error rates of the actual data and the forecast data with the total power usage data in building N in the year 2015. The performance was verified by comparing the Moving-Average scheme, which is a widely used in the energy prediction, and a predicted value generated by AECP.

For an accurate verification of the results, the prediction was performed by varying the data categories in units of time, 15 minutes, and the Mean Absolute Percentage Error(MAPE) is used as a performance index[8-9]. The MAPE index is as follows,

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \qquad (1)$$

where, A_t is the actual value and F_t is forecast value.
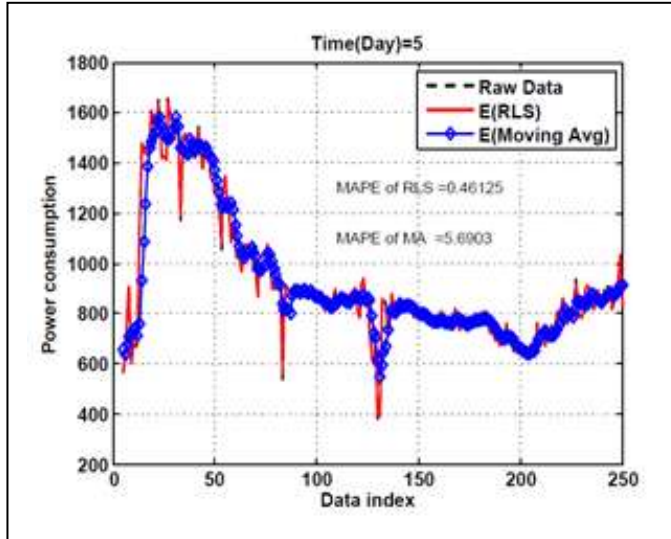

Figure 4.   Comparison of MAPE between measured and prediction data in hourly

Figure 4 shows the comparison of the prediction data using the MA algorithm, proposed AECP scheme and the actual measured data. From the figure, the black dotted line, the blue line and the red line represent the measured data, the prediction data using MA algorithm, and the predicted data using the AECP scheme, respectively. The accuracy of the prediction is determined by how closely the black dotted line follows. The calculation showed a MAPE value of 5.69 for the predicted value using MA algorithm whereas the MAPE value of 0.46 was observed for the AECP scheme.
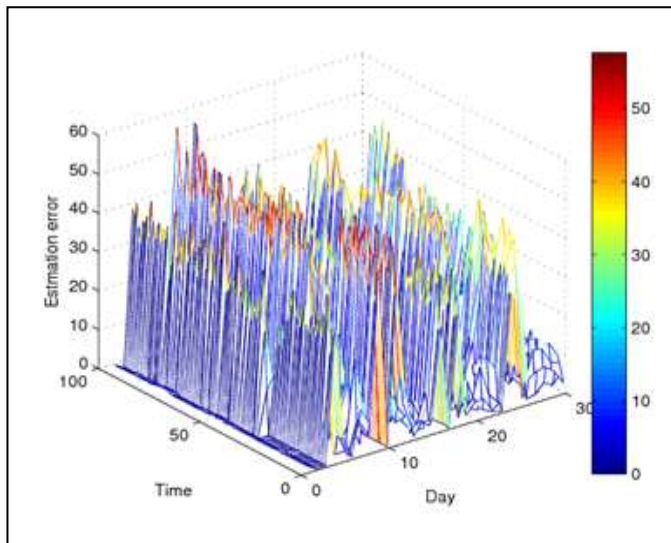

Figure 5.   MAPE using MA in 15-minute intervals

Figure 5 and Figure 6 show the results of the prediction using MA and AECP schemes in 15-minute intervals. AECP scheme showed a significantly much better performance with a MAPE of 2.7 compared to AM scheme. The analysis of the predicted value in different time intervals showed the same

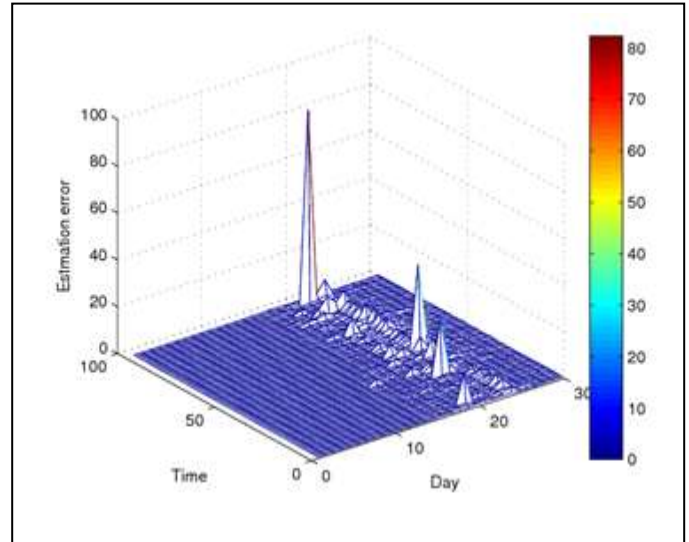results. This verifies the validity and the accuracy of the energy usage prediction method using AECP.

Figure 6.   MAPE using AECP in 15-minute intervals.

v. Conclusion

In this paper, we performed energy use pattern analysis using power usage data of the office building and proposed the AECP scheme as the modified RLS algorithm in order to accurately predict the energy consumption in office buildings. The similarity of electricity usage data in office building showed a different tendencies on weekdays, holidays, during working time. Based on this, we proposed an AECP energy forecasting scheme as a modified RLS algorithm.

In addition, we verified the validity and accuracy of the proposed model. With the AECP prediction model proposed in this study, we may use an efficient energy management and perform an effective demand-response management in office buildings.

Acknowledgment

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About Author (s):

Seok-Ho Yoon received the B.S and M.S degrees in Computer and Information Science in 2009 and 2011, respectively, from Korea University, Korea, where he is currently working toward the Ph.D. degree in the Laboratory for Data Communication Networks, Korea University. He has participated in various research projects involving a BEMS(building energy management system), demand response, design and analysis of energy management systems.

Seung-Yeon Kim received the Ph.D. degree in electronics and information engineering in 2012 from Korea University, Korea. He is currently an assistant professor in the Department of Computer and Information Science. He has participated in various research projects involving an IMT-Advanced system, cognitive radio, and interference management. His research interests include performance evaluation of communication networks.

Choong-Ho Cho received B.S. and M.S. degrees in industrial engineering from Korea University in 1981 and 1983, respectively. He received M.S. and Ph.D. degrees in computer science from the Institute National des Sciences Appliques, Lyon, France, in 1986 and 1989, respectively. He was an assistant professor at Sooncheunhyang University from 1990 to 1994, and is currently a professor at Korea University. He was a visiting professor at university of Washington from 2001 to 2002. His research interests include IT convergence technology, Building Energy Management System, 4G/5G mobile/wireless networks, D2D communication, small cell and SDN.