International Journal of Multimedia and Ubiquitous Engineering
Vol.11, No.8 (2016), pp.213-224
http://dx.doi.org/10.14257/ijmue.2016.11.8.23

Implementation of an Efficient Electricity Saving Scheme Using Mobile Cloud Computing and SARIMA Model

Jun Heo[1] and Moon-Sik Kang[2]

[1]Dept. of Information & Communication, Kyungmin College
Uijeongbu, South Korea
[2]Dept. of Electronic Engineering, GangneungWonju National University
Gangneung&Wonju, South Korea
E-mail: heojun@kyungmin.ac.kr, mskang@gwnu.ac.kr

Abstract

In recent years, lots of studies have been in progress around the world to solve the problem of global warming. The reduction of CO_2 would be important to solve the global warming problem. Probably the production and conservation of energy might be thought to be highly crucial. Also it would be important to produce new energy with high efficiency. In addition, the efficient use of the current energy might be also an important issue. Therefore, this paper focused on the development of devices for reducing electricity as a primary energy source for mobile cloud computing, which can be utilized in homes, shops, buildings, factories and so on. Moreover, we should further emphasize to develop the inference engine as core component. As a result, this paper proposes an efficient electricity saving system for reducing the electricity consumption using the mobile cloud computing technique and SARIMA model. Performance evaluation is carried out for showing the effectiveness of the proposed system.

Keywords: *inference engine, SARIMA model, reducing electricity consumption, mobile cloud computing, global warming problem*

1. Introduction

Currently, the energy management system for buildings and factories, namely, the electricity saving device is a system that reduces the electrical energy by providing the operating information of energy devices in a building. It collects or analyses energy usage and facility operating history through various sensor devices. The electricity saving device is mostly introduced when constructing new buildings as well as when being installed additionally in existing buildings. In both cases, introducing the electricity saving devices needs a number of facilities. Due to the number of additional facilities, when comparing the costs and investments, managing energy efficiently is a very difficult situation.

In order to devise a high-efficiency electric economizer, it is essential to develop the efficient algorithm for the electric energy reduction. An electric economizer consists of both a predictive engine and a predictive control engine. The former on a server is designed to activate the predictive algorithm for the management of power usage. This model is operated by big data based on cloud system such as fixed data, external data and internal data. The predictive control engine at the client is designed to activate the algorithm for reducing energy consumption. We have studied to obtain the optimal solution to make precise prediction possible by using both mobile cloud computing and SARIMA model based upon the estimated data at a server. In this paper, an efficient electricity saving system is proposed for reducing the electricity consumption.

The rest of this paper is organized as follows: the next section describes demand estimation and SARIMA model, the proposed inference algorithm will follow, the

ISSN: 1975-0080 IJMUE

proposed inference algorithm is described in Section 3, the performance evaluation section which includes performance evaluations and discussion of the effect of the proposed scheme, and finally, we conclude this paper in the last section.

2. Demand Estimation and SARIMA Model

The various industrial or social sectors have been using the ARIMA model to estimate user's demand. However, since it is impractical to apply ARIMA model to periodic and seasonal condition, we will try to deal with SARIMA (Seasonal Auto-Regressive Integrated Moving Average) model shown in Figure 1, which is the supplemented model for ARIMA model. The following equations (1) and (2) are the basic form of ARIMA model.

$$(1-\Phi_1 L - \Phi_2 L^2 - \cdots - \Phi_p L^p) Z_t = \delta + (1 - \Theta_1 L - \Theta_2 L^2 - \cdots - \Theta_p L^p)\epsilon_t \quad (1)$$

AR: $\Phi_p(\mathrm{L}) = 1 - \Phi_1 L - \Phi_2 L^2 - \cdots - \Phi_p L^p$

$$\text{MA: } \Theta_q(\mathrm{L}) = 1 - \Theta_1 L - \Theta_2 L^2 - \cdots - \Theta_q L^q \quad (2)$$

The SARIMA model shown in Figure 1 is divided into three steps such as identification, estimation, and forecasting ones. In identification phase, the required model is set through analyzing the input data by taking conversion, differences, and seasonal variations. In estimation phase, by calculating a statistic representing the accuracy of the parameter estimation and checking that the model is adequate and it determines whether there is any forecasting.

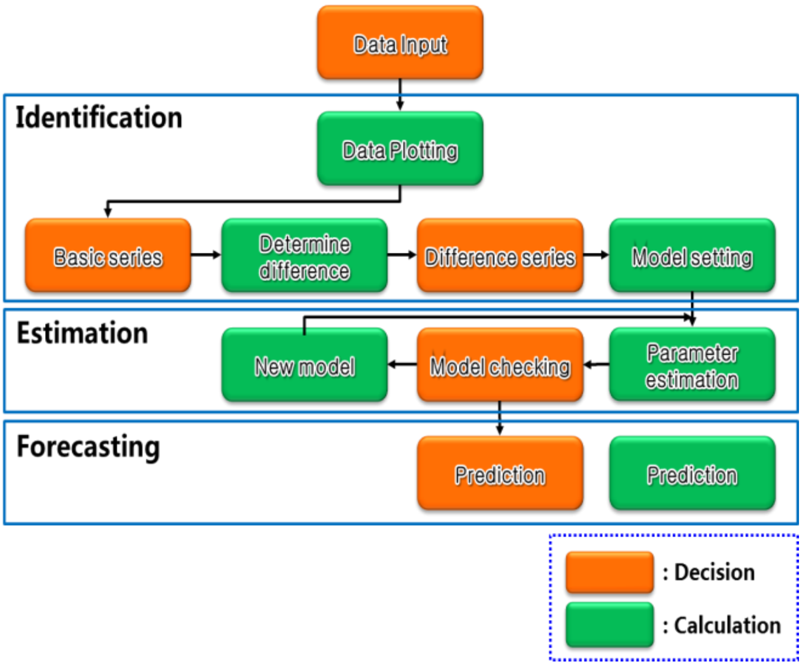

Figure 1. SARIMA Model

If we simplify ARIMA(p, d, q) model, the equation (3) below will be obtained.

$$\Phi_p(\mathrm{L})(1-\mathrm{L})^d Z_t = \delta + \theta_p(L)\epsilon_t \quad (3)$$

Here, Z_t, t, ϵ_t mean the row series data, time operator, and the error term due, respectively. Also L, p, q, d, δ mean the operation followed by, the degree of autoregressive term, the degree of moving average term, the degree of difference, and constant value, respectively. SARIMA model will be the suitable technique for the seasonal and periodic procedure. The equation (4) below is related to the model of SARIMA(p,d,q) (P,D,Q)s.

$$\Phi_P(\mathrm{L})\Phi_Q(\mathrm{L})(1-\mathrm{L})^d\left(1-\mathrm{L}^d\right)^D Z_t = \delta + \theta_p(L)\theta_Q(L^d)\epsilon_t \quad (4)$$

Here, P, Q, D mean the degree of seasonal AR terms, the degree of seasonal MA terms, and the degree of seasonal difference respectively.

3. The Proposed Inference Algorithm

The predicted algorithm is designed and evaluated based on SARIMA model. Table 1 shows the sample data collected by the data represented, which provides a one-year period of historical data that is collected for five years from the mobile cloud server. The collected data consists of a month and a year, parking, day, time, temperature, weather, and the number of visitors *etc*. The predictive data for predicting the time (weather, temperature, month and year) will be compared with the collected historical data for 5 years, in order to predict the number of visitors on "October 24, 2014 the third week Friday at 15:00".

Table 1. Predicted Number of Visitors from Historical Data

Suppose that the current time is "October 24, 2014 the third week Friday 14:00", what is the number of the expected visitors one hour later from now?

rank	year month	Week	day	time	temp	Weather	visiting
3	2009/10	3^{rd}	Fri	15:00	15	Sunny	5
4	2010/10	3^{rd}	Fri	15:00	16	Sunny	7
1	2011/10	3^{rd}	Fri	15:00	14	Rain	2
2	2012/10	3^{rd}	Fri	15:00	15	Cloud	5
5	2013/10	3^{rd}	Fri	15:00	18	sunny	10
Now	2014/10	3^{rd}	Fri	15:00	15	rain	**4**

The comparison of the priority placed on the properties that show the highest rate of relevancy with the visitors. If the compared value is the same, compare the second highest relevant property. Next step is to add the weighted value to the high correlated attribute with the compared one, and do the same to the second correlated property. Then finally the calculated data means the expected visitors who would visit the store on "October 24, 2014 the third week Friday at 15:00".

Let's find the prediction value by using the predicted visitor historical data. Current weather condition value is "rain" and the first value has the same weather condition. Since the data of October of 2011 is the closest value, we multiply 0.4 to 2, the number of visitors (0.4*2). The data of October of 2012 is 'cloudy' which is close to the current weather, so we add the weighted value 0.3 to the value(5*03). The third, fourth, and fifth value shows equal weather of 'sunny'. Because the third value is the same as the current one, we add the weighted value 0.2 to the data of October of 2009(5*0,2). Finally we add 0.1 and 0.05 respectively to the fourth(7*0.1) and fifth value(10*0.05). The expected number of visitors = 0.4*2 + 0.3*5 + 0.2*5 + 0.05*7 + 0.05*10 = 4.15 (persons). Consequently, the expected number of visitors on "October 24, 2014 the third week Friday at 15:00" is 4. We have predicted the number of expected visitors on "October 24, 2014 the third week Friday at 15:00". Next we will predict the amount of usage in cold / heating operation temperature and illumination data on "October 24, 2014, the third week

Friday, at 15:00" using the predicted number of visitors, the fixed data, the external and internal data. In prediction engine, various simulations can be added under the various environments. However, we will only deal with the illumination simulation and the temperature in this paper. Here, Figure 2 shows the behavior of the proposed prediction algorithm.

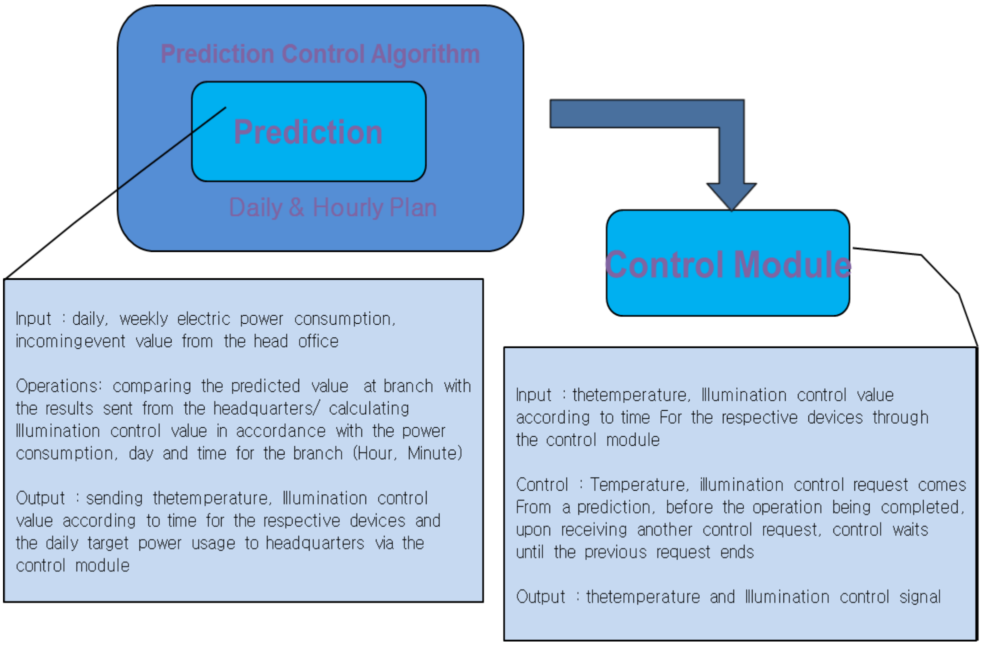

Figure 2. The Proposed Predicted Scheme

3.1. Illumination Simulation

In the initial process, we have predicted the number of visitors on "October 24, 2014, the third week Friday, at 15:00". In illumination simulation, we will predict illumination value on the same condition by using all the data that we have gathered up as the procedure proceeded so far. Associated attributes of the illumination simulation will vary from sunset, sunrise, prediction, the number of predicted visitors, fixed contract electrical power. Table 2 shows the data values which need predicted illumination on "October 24, 2014, the third week Friday, at 15:00". To calculate prediction illumination, we should set the illumination in accordance with the sunset and sunrise times by comparing those times and checking current illumination value. Also illumination value should be set by the number of visitors. With the difference between the contract and currently using electric power, we can calculate margin electric power per hour. With the difference between the internal cumulative power and the target power, we will calculate the monthly average margin power and divide your monthly power margin back to 24 the number of shares remaining days, and finally calculate the hourly average margin progressive power. Prediction illumination extracts the predicted illumination value by adjusting illumination value based upon sunset, sunrise, and the number of visitors.

Table 2. Predicted Illumination from Historical Data

Est _sunrise	Est _sunset	Est _visiting	Fix_contract Power	Int_Cum Power	Int_target_Pwr
06:48	17:44	1.1	20KW	6,650	9,000KW

3.2. Temperature Simulation

Along with illumination simulation, temperature simulation extracts the prediction value of the coolers / heaters for 1 hour at a point after the current time by using the predicted number of visitors, the fixed data, external data, and internal data. Temperature simulation is an environment property in which the properties for usage management are in a month, the highest external temperature. The lowest external temperature, fixed contract electric power, internal electric power, the internal cumulative power and the target power. Table 3 shows the attributes necessary to predict the standard temperature of coolers and heaters on "October 24, 2014, the third week Friday at 15:00". After we calculate the prediction of standard temperature, we check the months which we operate coolers and heaters. We choose cooling or heating according to the month. The internal temperature is checked in the chosen cooler/heater. In the winter a heater is operated under the 15 °C, and in the summer, a cooler is operated over the 24°C. In terms of cooling and heating, if the temperature value is adjusted when the temperature is increasing or decreasing by 1°C, the electric consumption is reduced by 7%. We calculate the margin electric power per hour by differencing between the contract power and the usage of current power. Similar to the illumination simulation, the electric power consumption is managed. Temperature simulation affects the power usage depending on which season the month is.

Table 3. Predicted Temperature from Historical Data

Month	Ext _High temp	Ext _Optmal Temp	Int_temp	Int_cumm power	Int_target power	Fix_contr power
Oct	21℃	10℃	20Kw	6,650	9,000KW	20KW

Here, let's consider the entire process of the proposed algorithm both at BEMS server and at BEMS client. Details of the algorithm are described step by step as shown in Figure 3.

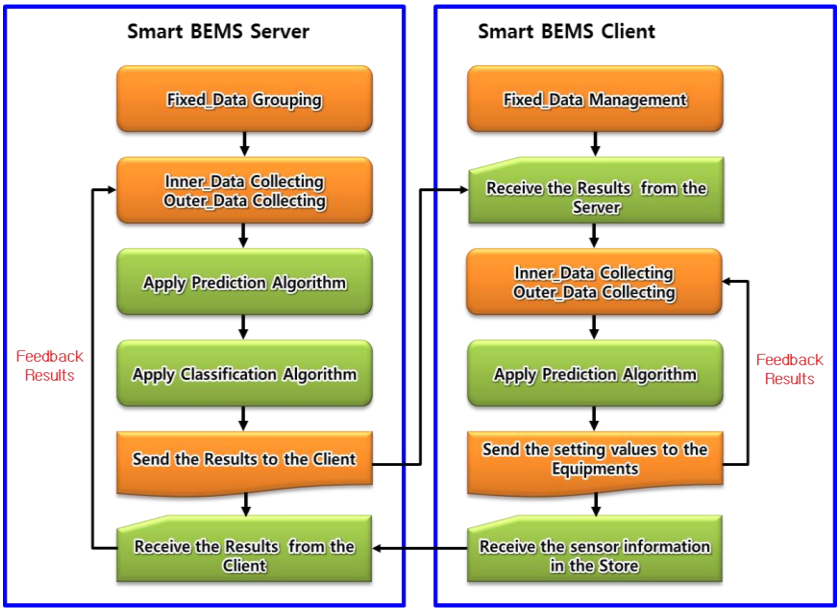

Figure 3. The Entire Process of the Proposed Algorithm

Here, we assume the following steps for simulations.

Step 1. Retail stores are operated as franchises form. (for example, 24-hour convenience store)

Step 2. The head office manages all data for a retail store. (big data & DBMS)

Step 3. Among the data managed from the head office, the number of customers, weather, and energy data are used to hold up to the maximum 3-5 years old data.

Step 4. The area of the retail store is 49.5 square meters.

Step 5. The operating mode is the power-saving mode.

Maximum power saving mode is used to save the power consumption up to the maximum value, and the optimal mode is used to save the power consumption to an optimal value. Figure 4 represents the service system model for simulation.

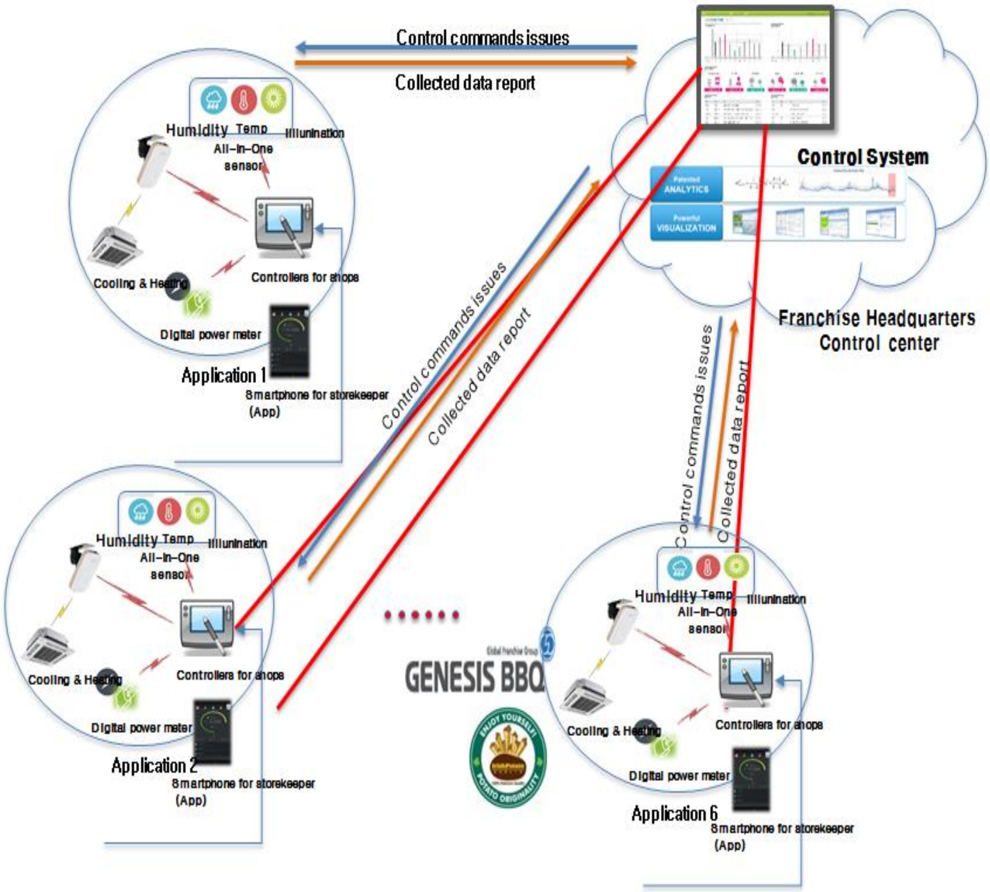

Figure 4. Service Model

4. Performance Evaluation

In this chapter, we confirmed that space division intelligent BEMS has energy savings effect by using the environment suggested earlier. The experimental environment was selected by a convenience store as it can be found everywhere. In the setting phase of SARIMA model, we use the measured value of the same time zone. The measured values consist of fixed data, external data and internal data. Location is a 24-hour convenience stores located in 15-pyeong, Songpa-gu, Seoul. The contract power is 20Kw. External and internal data include the data values of the 15-pyeong 24-hour convenience store from 2008 to 2012. A meteorology weather web site provided minimum temperature, maximum temperature, sunrise time, and sunset time. The number of visitors was converted into the POS data which is generated from usage of convenience store. Power consumption was set depending on the size of a convenience store refrigerator, freezer, open-chilled fruit and vegetables, vegetables in refrigerator, air conditioning, refrigerator, and fluorescent lights. The contract power consumption was determined by the electricity use per hour, the first contract one, between KEPCO and convenience store.

Figure 5, 6, and 7 show the results obtained by using the illumination and cooling / heating based on the temperature that came up with extraction using a predictive control algorithm of prediction and prediction value obtained by using the prediction engine control algorithm of the intelligent BEMS server. In this experiment, the use of power savings for a year was compared to data predicted from the data of five years based on the data 2013. From Figure 7, we can estimate the trend of electric power usage. While the electric power usage tends to increase in summer and winter, it tends to decrease in spring and winter. In case of using the space division intelligent BEMS, the same results are shown. Besides, reduction effect in the existing environment were attained by 7~8%. The results suggest that the properties of the test data have been simplified, and it cannot be obtained a large reduction. However, if you use a lot of data attributes and the Self-Learning, many savings are expected.

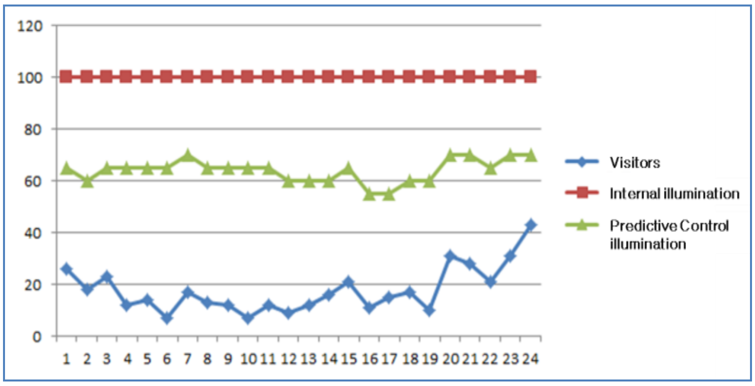

Figure 5. The Predicted Control Illumination Results

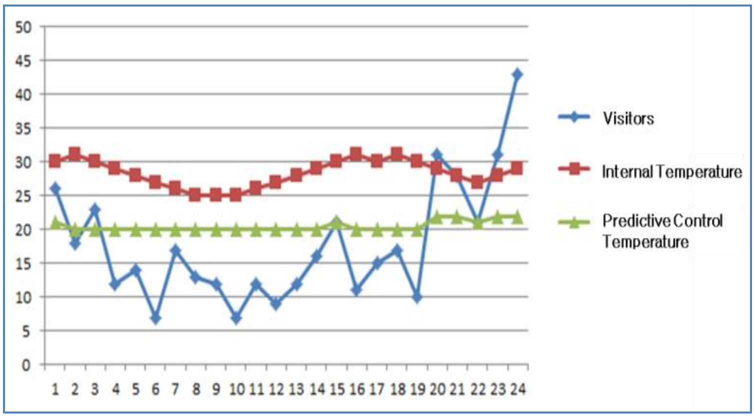

Figure 6. The Predicted Control Temperature Results

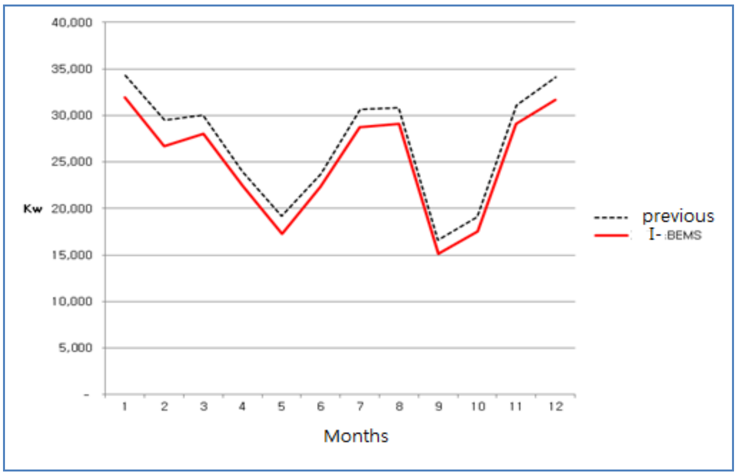

Figure 7. Savings Compared to None of Intelligent BEMS and Intelligent BEMS

Table 4 and Figure 8 show the results for power consumption by applying the proposed algorithm to the actual store. These are test results for the air-conditioning in August 2014 and the results for heating in December of the same year, respectively. The comfort level of the proposed system is improved while reducing energy usage compared to the conventional air conditioning system.

Table 4. Analysis of Results for the Power Usage

Test results (August)	Test results (January)
Original: High energy consumption and low comfort level E/S: 12.5% increase compared to existing comfort level Energy consumption decreased by 24.1% Comfort: 17.2% increase compared to existing comfort level, Energy consumption decreased by 11.1%	Original: similar results in summer. Limit the manual controls by that E/S:7.1%increasecompared to existing comfort enough, Energy consumption decreased by 26.8% Comfort:12.7%increasecompared to existing comfort enough, 23.2%reduction in energy consumption

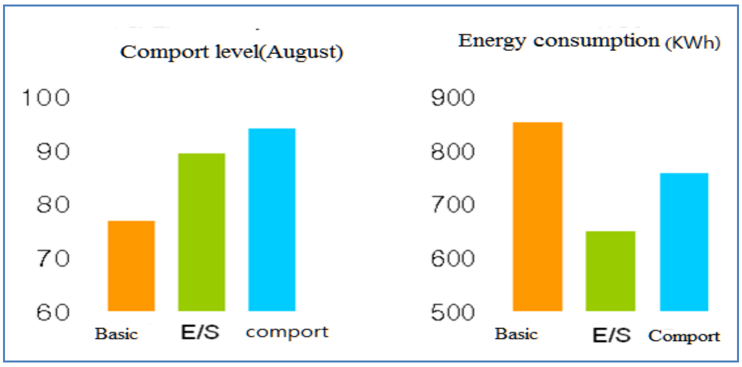

Figure 8. Comport Level and Energy Consumption (August)

Figure 9 shows the console for the system administrator. This console has a function of monitoring and controlling the system. Also, it shows the usage of energy and electricity.

It is possible to check the execution status for dynamic statistical data, including the mode changes if necessary.

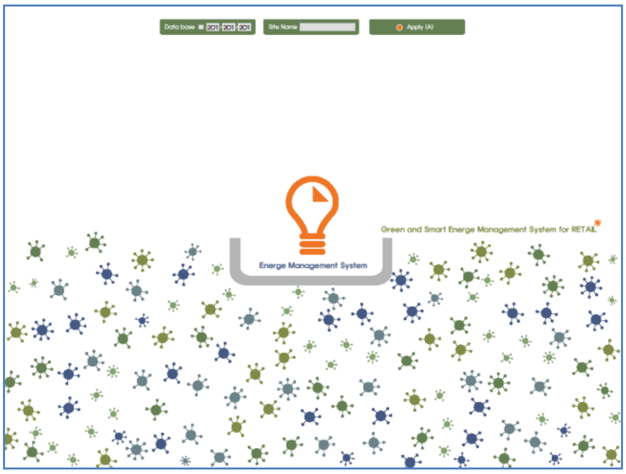

Figure 9. The Console for the System Administrator

The controller provides basic information about the store by a manager and administrator. This provides a target power usage, power consumption, and demand forecasting. It implements the functions of the real-time confirmation of operation status for the current, air conditioners. Mobile terminals of both managers and operators can control cooling and heating of the store. There is currently operational status monitoring and control functions. It provides an On/Off function for some devices if necessary.

5. Conclusion and Future Works

The energy related research may be a national agenda in a society where energy management system is a national policy subsidized by federal funds, even though as research area of human history. In general, most people consider that energy reduction can be attained by saving tiny stuff rather than saving big stuff. In the true sense the energy reduction has to be achieved without harming the quality of human life. By taking advantage of the electricity saving inference algorithm as proposed in this paper, the energy can be reduced by analyzing data. This algorithm makes it possible to the efficient use of SARIMA model by predicting the forecasting data after 1 hour of 10 minutes based on the existing data. The predicted results can be applied to control electric devices. This paper suggests that the function of prediction algorithm will be reasonable enough for normal utilization. Possible future projects include the development of the electric power reduction device equipped with the proposed algorithm as well as the EMS device for various applications.

Acknowledgments

This paper is a revised and expanded version of a paper entitled “A Study on An Efficient Electricity Saving Scheme for Mobile Cloud Computing” presented at ICGHIT (International Conference on Green and Human Information Technology) 2016, Clark, Philippines.

References

[1] W. Y. K. Jeong and I. W. Lee, "Energy Management Technology for High Energy-Efficient Building", ETRI, Electronics and Telecommunications Trends, vol. 26, no. 6, **(2011)**.
[2] Y. K. Jeong, W. K. Park, J. S. Han, C. S. Choi, H. J. Yoon and I. W. Lee, "An architecture of the remote building management and control platform for high-efficient low-cost building energy management", ETRI, **(2010)**.
[3] A. Y. Kim, H. J. Yoon, Y. K. Jeong and I. W. Lee, "A Study on the Problems in Adopting Building Management Systems to Korea and the Suggestions for Improvement", The Korean Institute of Communications and Information Sciences Summer Conference, **(2011)**.
[4] H. J. Lee, J. S. Han, Y. K. Jeong, I. W. Lee and S. H. Lee, "A Technology of Context-aware based Building Management for Energy Efficiency", Journal of IT Convergence Society for SMB, vol. 2, no. 1, **(2012)**, pp. 69-75.
[5] D. S. Kong, Y. H. Kwak and J. H. Huh, "Artificial Neural Network based Energy Demand Prediction for the Urban District Energy Planning", Journal of Architectural Institute of Korea, vol. 29, no. 1, **(2013)**.
[6] G. J. Levermore, "Building Energy Management Systems", E&FN Spoon, **(2000)**.
[7] Honeywell, "Engineering Manual of Automatic Control", Honeywell, **(1988)**.
[8] R. W. Haines and D. C. Hittle, "Control Systems for Heading", Ventilating and Air Conditioning, Springer, **(2006)**.
[9] Z. Yu., F. Haghighat, C. Benjamin, M. Fung and H. Yoshino, "A decision tree method for building energy demand modeling", Energy and Building, **(2010)**.
[10] X. Li, C. P. Bowers and T. Schnier, "Classification of Energy Consumption in Building with Outlier Detection", IEEE 2009, **(2009)**.
[11] B. Dong, C. Cao and S. E. Lee, "Applying support vector machines to predict building energy consumption in tropical region", Energy and Building, **(2005)**.
[12] S. T. Kim, "Management System of USN-based Collaborative Lighting Energy", The Journal of The Institute of Webcasting, Internet and Telecommunication, vol. 13, no. 4, **(2013)**, pp. 47-53.
[13] Y. G. Kim, G. C. Sin and S. K. Kim, "Collaboration Interface for Hadoop-based Bigdata Processing Platform", Proceedings of KIIT Conference, **(2013)**, pp. 511-516.
[14] H. J. Moon, K. A. An and M. S. Choi, "A simulation-based control approach in a mechanical ventilation system", Proceedings of ASim, Shanghai, China, **(2012)**.
[15] H. J. Moon and M. S. Choi, "The effect of weather data in an integrated real-time building simulation connected to a monitoring system", Proceedings of ISOEN, **(2013)**.
[16] M. Wetter, "Building control virtual test bed user manual version 1.1.0", Lawrence Berkeley National Laboratory, **(2012)**.
[17] X. Pang, M. Wetter, P. Bhattacharya and P. Haves, "A framework for simulation-based real-time whole building performance assessment", Building and Environment, vol. 54, **(2012)**, pp. 100-108.
[18] Z, O'Neill, M. Shashanka, X. Pang, P. Bhattacharya, T. Bailey and P. Haves, "Real-time model based energy diagnostics in buildings", Proceedings of Building Simulation, Sydney, Australia, **(2011)**.
[19] A. K. Dey, "Providing Architectural Support for Building Context-Aware Applications", PhD thesis, Georgia Institute of Technology, **(2000)**.
[20] S. Sigg, S. L. Lau and S. Haseloff, "Approaching a definition of context prediction", Proceedings of the Third Workshop on Context Awareness for Proactive Systems, **(2007)**.

Authors

Jun Heo, received his B.S., M.S. degrees and Ph.D. Candidate in Computer Science and Engineering from Sogang University, Seoul, Korea in 2000, 2002, and at present respectively. And he received Ph.D. degree in Information and Control Engineering, Kwangwoon University, Seoul, Korea in 2013. He joined Telecommunication R&D Center of LG Electronics as a senior engineer in 2002, where he was in charge of the research on the CDMA2000 system Radio Access Network Software R&D. He also served universities and colleges as an instructor from 2006 until now. In 2010, he joined the Communication R&D Center of Addwin Company, Seoul, Korea, as a senior specialist who was in charge of the Modeling and Simulation of Military Communication Network. In 2013, he joined the faculty of the Department of Information and Communication, Kyungmin College, Uijeongbu, Kyunggi, Korea, as an assistant professor. His research interests include wired and wireless network protocol,

military communication network, ubiquitous computing, energy management system and ad hoc network.

Moonsik Kang, is a professor of Department of Electronic Engineering at College of Engineering, GangneungWonju National University (GWNU), South Korea. He is the director of the Institute of Engineering Research at GWNU. He received his B.S. and M.E. degrees in Electronic Engineering from Yonsei University, South Korea, in 1985 and 1988, respectively and his Ph.D. in Electronic Engineering from the same University in 1993. He was a post doctorate research associate at department of Electrical and Electronic Engineering, University of Pennsylvania, PA, USA. Also he worked as a research associate at Department of Electronic and Computer Engineering, Illinois Institute of Technology, IL, USA. In addition, he had worked as a Researcher with Samsung Electronics, South Korea. He also served or currently serving as a reviewer and Technical Program Committee for many important Journals, Conferences, Symposiums, Workshop in Computer Networks area. His research interests include wired/wireless communication protocols, convergence technology for next generation networks, QoS traffic control techniques, and mobile multimedia traffic modeling and applications.