A Tutorial: Information and Communications-based Intelligent Building Energy Monitoring and Efficient Systems

Si-O Seo[1], Seung-Yong Baek[1], Doyeop Keum[1], Seungwan Ryu[2] and Choong-Ho Cho[1]
[1] Computer and Information Science, Korea University,
Seoul, Korea
[e-mail: sioseo@korea.ac.kr, chcho@korea.ac.kr]
[2] Information System, Chung-Ang University
Seoul, Korea
[e-mail: ryu@cau.ac.kr]
*Corresponding author: Choong-Ho Cho

Received February16, 2013; revised May 29, 2013; revised September 18, 2013; accepted October 23, 2013; published November 29, 2013

Abstract

Due to increased consumption of energy in the building environment, the building energy management systems (BEMS) solution has been developed to achieve energy saving and efficiency. However, because of the shortage of building energy management specialists and incompatibility among the energy management systems of different vendors, the BEMS solution can only be applied to limited buildings individually.

To solve these problems, we propose a building cluster based remote energy monitoring and management (EMM) system and its functionalities and roles of each sub-system to simultaneously manage the energy problems of several buildings. We also introduce a novel energy demand forecasting algorithm by using past energy consumption data. Extensive performance evaluation study shows that the proposed regression based energy demand forecasting model is well fitted to the actual energy consumption model, and it also outperforms the artificial neural network (ANN) based forecasting model.

Keywords: energy-saving, energy forecasting, building energy management, energy consumption, energy monitoring and management.

This work was supported by the Ministry of Knowledge Economy (MKE) of the Republic of Korea] and partially supported by BK21 plus. [20118510010040, Development of proactive energy management technologies for saving the energy cost of residential complex using cooperative sensing devices.

http://dx.doi.org/10.3837/tiis.2013.11.007

1. Introduction

In the last two decades, due to the rapid growth in world energy consumption, keen interest has been paid to energy conservation. There are various concerns over supply difficulties, exhaustion of energy resources and heavy environmental impacts such as global warming and climate change. According to the Energy Information Administration of the U.S. Department of Energy (DOE), in 2008 the portion of energy consumption by each end-user sector accounted to about 28% in transportation, 31% in industry, 19% in commercial, and 22% in residential sectors . respectively.

The commercial sector covers commercial and public buildings and it includes many types of buildings such as schools, office buildings, convention halls, hotels, and hospitals. In this sector, a variety of energy services such as heating, ventilation and air conditioning (HVAC), domestic hot water (DHW), lighting, refrigeration, and food preparation are provided. With the growth in population, building services and comfort levels have been enhanced, with the rise in the time spent inside buildings. Therefore, building energy consumption has risen rapidly compared to other sectors. 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%.

The increasing trends in energy consumption and CO2 emissions in the building environment have made energy saving and efficiency a prime subject for energy policies in most countries. As a result, the role of the BEMS has become more important in the achievement of energy saving and efficiency. The BEMS are the ICT-based on building an energy facility control system. The BEMS are generally applied to the control of active systems such as the building automation systems (BASs), the facility management systems (FMSs), HVAC, DHW, and lighting. Performance of the BEMS is closely related to the amount of energy consumed in the building and in the enhancement of the comfort levels. In particular, due to the requirements of indoor air quality and comfort levels, the HVAC systems present an important share of energy consumption (about 30%) in a building[2]. This implies that a large amount of energy and cost saving can be achieved through the improvement of efficiency of these systems.

In order to achieve energy saving and efficiency in a building environment, the ICT-based BEMS technologies should be applied with substantial energy saving efforts. One such substantial effort is the sophisticated energy consumption behavior which is based on a predetermined energy demand forecasting and supply plan. In other words, energy saving and efficiency can be achieved through the minimization of energy waste and/or shortage problem that stems from imbalance between the energy demand and supply. Therefore, for the optimization of energy consumption, it is crucial for the BEMS to be able to predict how the energy consumption varies hourly, daily. or monthly according to the various environmental parameters such as temperature, weather, humidity, and so on.

However, a heavy investment is required for the BEMS to be applied in a building environment. A vast number of remote sensors or sub-metering devices should be used in the active systems, i.e., BASs, FMSs, HVAC, DHW and lighting, to collect energy data and other energy related environmental and control data. It is also required to establish a central energy control and monitoring system to achieve energy efficiency while maintaining a comfortable building environment. In addition, many practical problems such as shortage of building energy management specialists and incompatibility among heterogeneous energy management systems have made the application of BEMS difficult to use in the building environment. Therefore, due to the above problems, the BEMS is currently being applied to a limited number of large sized buildings, and it cannot be applied to small or midsized buildings and multi-purpose buildings.

Our Contributions. In this paper, we propose an energy menagement system to solve the energy problems as mentioned above and our contributions can be summarized as follows:

- Firstly, we propose an ICT-based remote building EMM system to control and manage energy efficiency for a group of small or medium sized buildings and multi-purpose buildings.
- Secondly, we propose a builiding energy forecasting method that is a highly important part of operational phase of building energy management system. In addition, we provide an analysis results of two different forecasting methods.

Organization. This paper is organized as follows: In the next section, we review the building energy management technologies and present current problems. In section 3, to solve the problems of the current building energy management system, we propose the EMM system based on the ICT approach. In section 4, we propose the building energy demand forecasting algorithm which is crucial for the achievement of building energy saving and efficiency. Finally, we conclude this paper in the following section.

2. Building Energy Management Technologies

2.1 Building Energy Management Technologies

Energy control and management technologies for low energy buildings are classified into three groups. namely, the high-efficiency and low energy consuming technologies, the individual energy generation and storage system technologies, and the building energy control and management technologies. The high-efficiency and low energy consuming technologies include the eco-friendly and low energy construction materials utilization technologies and the constructive and mechanical energy efficient building design technologies. The individual energy generation and storage technologies include the eco-friendly energy generation from renewable energy sources such as solar power, wind power, geothermal energy and fuel cell based storage system technologies. The building energy control and management technologies contain building energy demand forecasting technologies; building energy design and management technologies; intelligent and automatic building management technologies; and energy monitoring and control system technologies. Table 1 presents three groups of low energy building technologies, and detailed energy technologies, systems and services of each group.

Table 1. Three groups of low energy building technologies.

Groups of low energy building technologies	Energy technologies, systems and services
High-efficiency and low energy consumption technologies	- energy-efficient outer wall system - high-efficiency heat source equipment and facilities - heat exchanger and ventilation system - natural lighting system - eco-friendly construction material design and production technologies

Individual energy generation and storage system technologies	- solar and wind power based energy generation system technologies - heat pump related geothermal energy generation system technologies - fuel cell system technologies - high-efficiency energy storage system technologies
Building energy control and management technologies	- building energy demand forecasting technologies - building energy design and management technologies - intelligent and automatic building management technologies - energy monitoring and control system technologies

According to the American Society of Heating, Refrigeration and Air-conditioning Engineers (ASHRAE), up to 77% of the total amount of energy saving can be achieved by building energy control and management technologies [3], and 83% of the building lifecycle cost originated from operation and maintenance processes. Therefore, among the three groups of low-energy building technologies, the building energy control and management technologies group is the essential one for building energy saving and efficiency.

2.2 Problems of Current Building Energy Management

However, a variety of heterogeneous energy management systems such as BASs, Intelligent Building Systems (IBSs), FMSs and Energy management systems (EMSs) have existed in the builidng environment, and those systems are incompatible with each other. Furthermore, even several control and management systems of the same type are incompatible with each other as they are manufactured by different vendors. Meanwhile, global energy equipment manufacturers and/or building energy management specialized companies such as Honeywell and Siemens try to keep their global leadership in this business area by the inclusion of their own non-standard proprietary-technologies in their energy facilities and equipment. Moreover, they try to expand their control power over the energy related business area by the development of various energy control and management solutions. They are mainly executable on their facilities and equipment. For instance, Honeywell manufactures many building energy and facility control systems such as BASs, IBSs, FMSs and EMSs. Honeywell also offers a building energy and systems control solution called the Enterprise Building Integrator (EBI). It is now expanding and diversifying its energy business area to other related business domains such as cost-effective building energy management, carbon emission reduction, and crime and disaster prevention.

On the other hand, the building manager is currently responsible for the monitoring, inspection, fault diagnostics, and energy consumption management of the building energy facilities and systems. However, due to the lack of expertise of the building manager in energy control and management, the objective of the building energy management cannot be sufficiently attained.

In order to tackle the current building energy management problems, in this paper, we propose an ICT-based remote building EMM system for a group of small and midsized buildings.

3. The Building Energy Monitoring and Management (EMM) System

The high-efficiency building EMM system is designed not only to solve the interoperability problems among the heterogeneous building energy facility and its control systems, but also to control groups of small and midsized buildings remotely by using TCP/IP based communication networking [4-7]. The proposed EMM system consists of two subsystems, namely, the EMM client subsystem that operates at the remote building sites and the EMM control center. Figure 1 shows a reference model of the proposed high-efficiency EMM system.

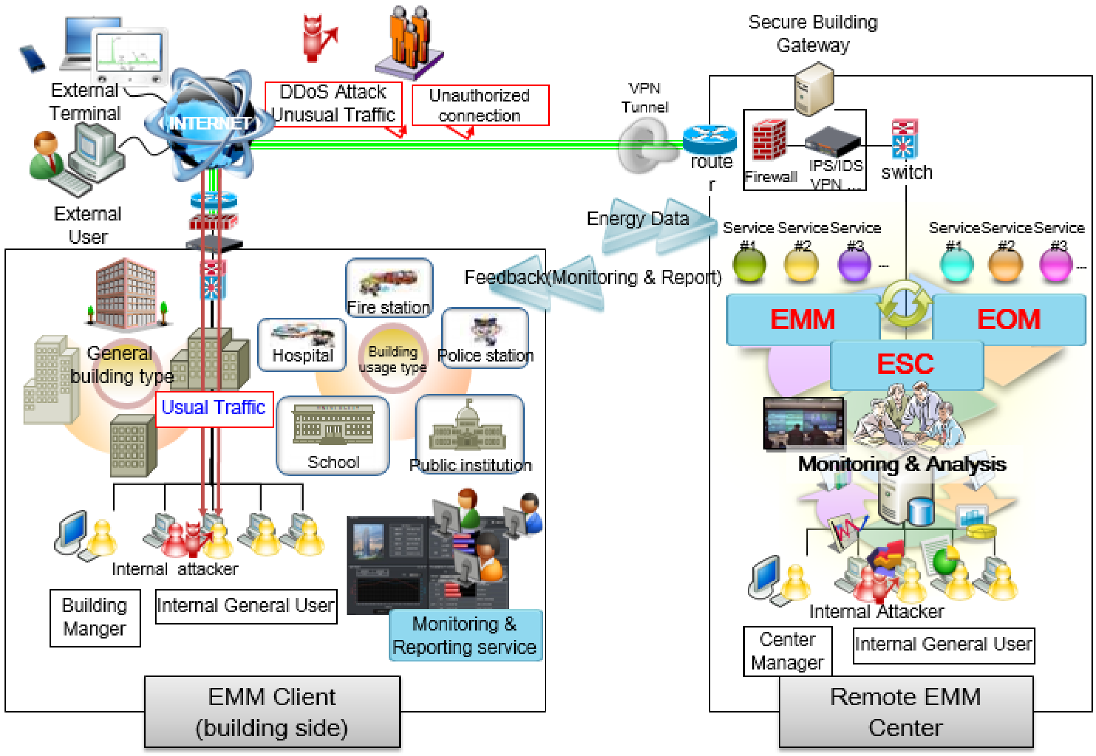

Fig. 1. A reference model of the high-efficiency EMM system

3.1 The EMM Client System

The EMM client subsystems are installed in each building for the collection of energy and environmental data. However, there are many heterogeneous incompatible building energy control and facility management systems and devices such as BASs, FMSs, EMSs and a variety of environmental sensors and energy metering devices [8-10]. Furthermore, these systems and devices are controlled individually via different incompatible networking protocols such as TCP/IP, BACnet, Modbus, Lonwoks, and Zigbee. In order to collect the building energy related data from heterogeneous systems and devices, and to send them to the remote EMM center effectively, it is required to integrate such heterogeneous data into a unified format [11-12]. Therefore, each EMM client adopts the multi-protocol/multi-network interface for the accommodation of such heterogeneous networks. In addition, the EMM client requires the BAS integration middleware to control and manage heterogeneous BAS systems and other systems in a unified manner. Then, the EMM client sends the unified data to the remote EMM center by using the TCP/IP networking. As a client system of the remote building control system, the EMM client carries out a remote control service framework by means of interworking with the EMM server system.

3.2 The EMM Control Center

The EMM control center consists of three subsystems, namely, 1) the EMM subsystem, 2) the EOM subsystem, and 3) the ESC subsystem. The EMM subsystem is responsible for the storage and monitoring of energy and environment monitoring data of each building. As an EMM server system, it is also responsible for the remote management and integrated control of each remote building. The EOM server is responsible for the implementation of the energy saving strategies for each building. In order to achieve this goal, the EOM subsystem analyzes the energy consumption pattern of each building to find out the key energy control factors. Then, it forecasts the future energy demand to save energy consumption optimally. It is also responsible for the maintenance of energy facilities and systems of each building. The ESC subsystem is responsible for the prevention of the EMM system from a variety of security threats [13] and this includes the EMM client. It is also responsible for the data integrity and real-time operation of the EMM system. Figure 2 shows the structure of the high-efficiency EMM system and roles of each sub-system, and figure 3 presents the functional sub-blocks of each subsystem.

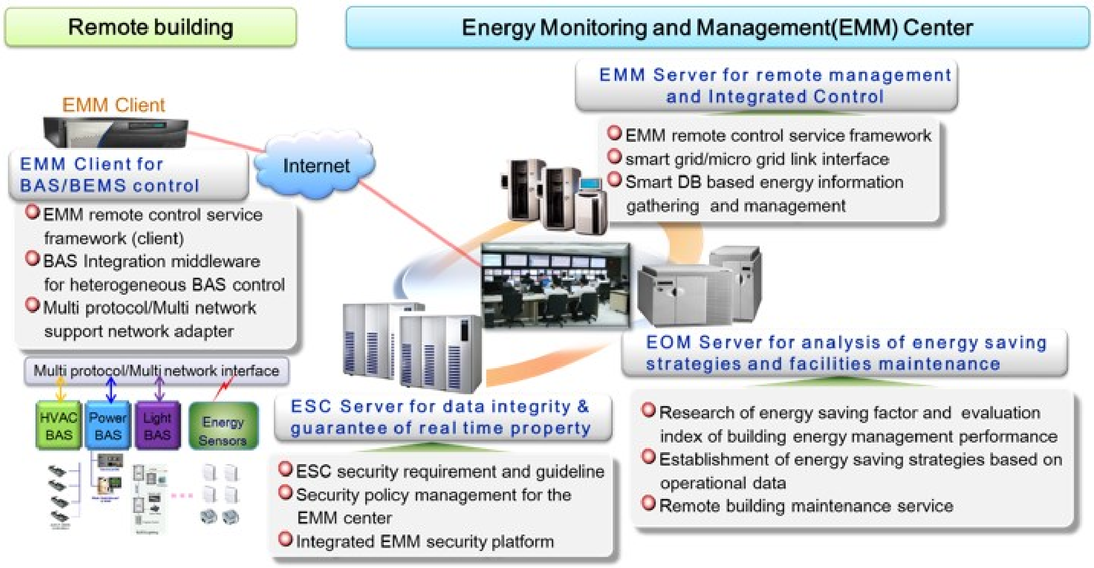

Fig. 2. Structure of the high-efficiency EMM system and roles of each sub-system

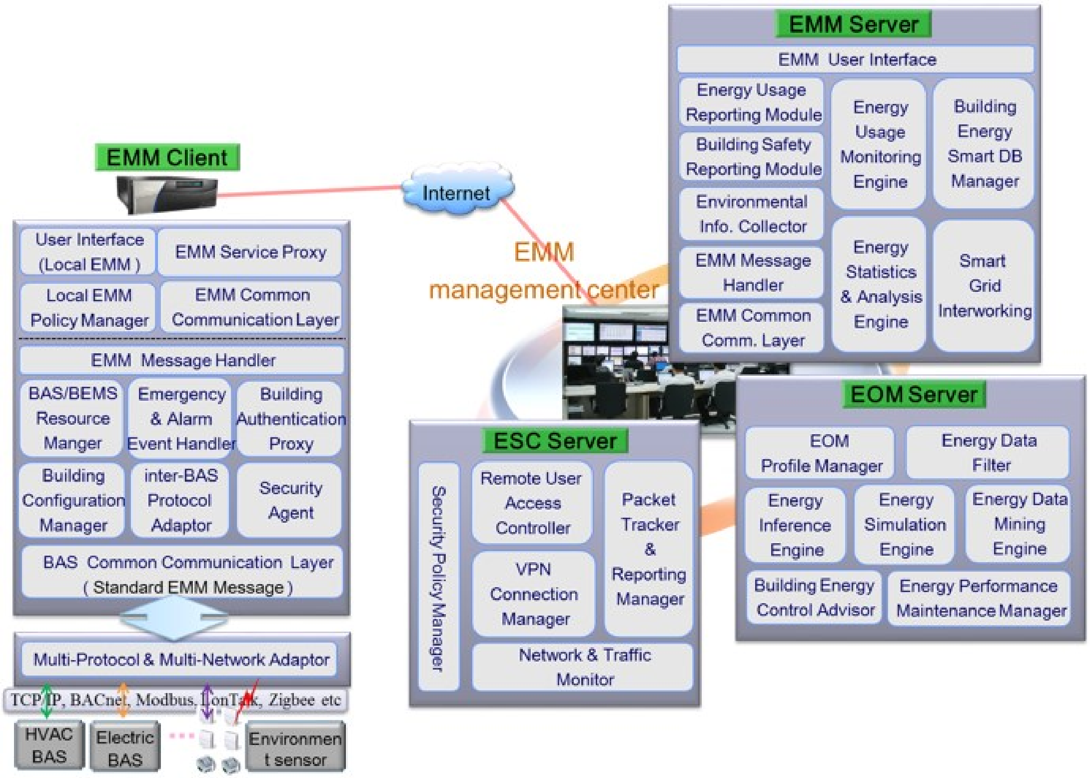

Fig. 3. Functional sub-blocks of each subsystem

4. Energy Demand Forecasting

The purpose of the EMM system is to control and manage energy saving and efficiency of a group of remote small and/or midsized buildings through ICT based integrated control while providing acceptable comfort level. In particular, as indoor air quality and the comfort levels are required, efficient energy control and management of the HVAC systems is crucial for the EMM system in the context of energy saving and efficiency. Therefore, as mentioned before, in order to achieve energy efficiency in the proposed system, it is indispensable to have a precise energy demand prediction with the consideration of various energy factors (or environmental parameters) such as temperature, weather, humidity, and so on.

Therefore, in this section, we briefly evaluate the existing energy demand forecasting algorithms for the building environment. Then, with a focus on the HVAC system, we derive essential energy factors, for example, key energy control parameters from various energy factors such as day, temperature, humidity, the discomfort-index, the solar irradiation index, the degree of cloudiness and the wind velocity. Then, we propose a building energy forecasting algorithm based on the derived key energy factors. Subsequently, we also evaluate the performance of the proposed algorithm with the neural network based forecasting algorithm.

4.1 A Review of Existing Energy Demand Forecasting Algorithms

In general, a building's energy consumption depends on how the building is to be used. Hence, after identifying the properties of a building's energy usage pattern, in order to precisely forecast its energy demand, we should apply a proper forecasting algorithm. Table 2 presents an example classification of buildings according to the purpose of use. It is obtained based on the Energy Performance of the Building Directive (EPBD) provided by EU as a building energy performance standard, the Commercial Buildings Energy Consumption Survey (CBECS) provided by the U.S. Energy information Administration, and the NS3032 provided by the Norwegian Government as an Energy and power budget planner for buildings.

Table 2. An example classification of buildings according to the purpose of usage

	classes	description
Purpose of use	Residential	detached houses, apartments
	Office	large(>4,200m2), midsized(>500m2), small(<500m2)
	Commercial	Shopping centers, Hotels, Restaurants
	Medical	Hospitals
	Education	Schools

Energy sources used in the building area can be classified into three groups, namely, heating, cooling. and electric power energies. In particular, cooling energy consists of air conditioning energy and air handling unit power energy. The HVAC energy implies the amount of energy consumed for the cooling and heating operations.

Among many forecasting algorithms, three types of approaches, namely,1) the statistical analysis, 2) the energy simulation program based approach, and 3) the intelligent computation based approach, are mainly used for the building energy demand [14]. Statistical analysis includes the ARX model, EModel, Energy-signature and Finish load model, and the energy simulation program based approach includes the DOE-2, TRNSYS, ESP-r and Energy-Plus based approaches. The intelligent computation based approach uses the feedback of the artificial neural networks, the feed forward neural networks, the probabilistic neural networks and the support vector machine.

4.2 The Proposed Building Energy Forecasting Algorithm

In this study, past HVAC based energy consumption data collected from the COEX Complex Mall located in Seoul, Korea is used not only to develop a precise energy demand forecasting algorithm, but is also used to evaluate the performance of the developed algorithm. As the COEX mall is a 1,200,000 square-meter large-scale multi-purpose complex center that consists of office towers, exhibition halls, and shopping centers, it can be an appropriate test-bed system for the evaluation of the EMM system's performance. The data used in this study is past HVAC operation data. Several types of weather information and other environmental data has also been collected from 2006 to 2009, especially for the four months of the summer season. The weather information includes the outside temperature, humidity, wind velocity, the solar irradiation index. and the degree of cloudiness. Furethermore, the environmental data includes the day and hour. The HVAC operation data includes the amount of the supplied air conditioning energy accumulated hourly in joules and the amount of electric power used to generate such air conditioning energy.

The proposed energy demand forecasting algorithm consists of two phases, namely, the energy demand forecasting model generation phase and the future energy demand forecasting phase. In the former phase, the data filtering process is executed first to increase the reliability by means of filtering out the abnormal data from the data set. Then, the essential energy factors are derived via correlation analysis from the refined sample data. Finally, the energy demand forecasting model is generated based on the essential energy factors. In the latter phase, the amount of future hourly energy demand is forecast based on the forecast weather information as well as on the generated energy demand forecasting model. Figure 4 describes the proposed energy demand forecasting algorithm and detailed processes of the algorithm.

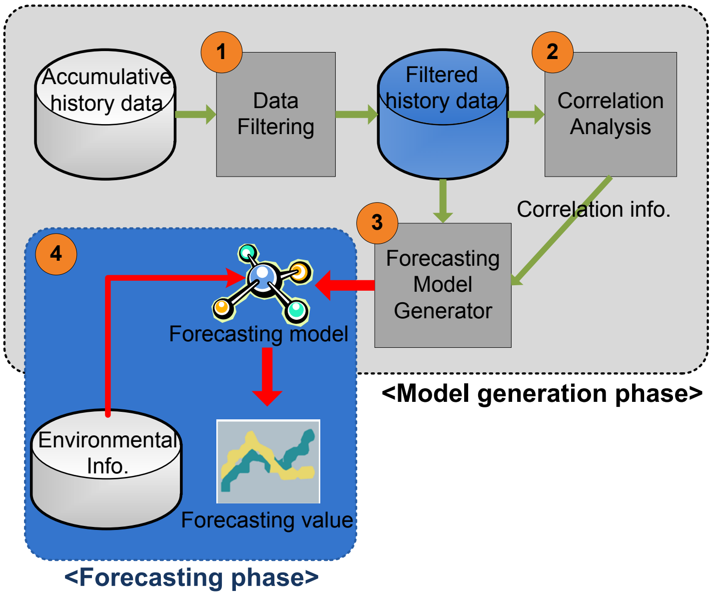

Fig. 4. Description of the proposed energy demand forecasting algorithm

4.2.1 The correlation Analysis

In the correlation analysis process, various environment parameters, except the energy consumption data, are used as an input variable. However, not all of the input parameters have positive correlation with the amount of energy consumption. Some parameters with weak correlation or negative correlation may increase the forecasting error. Therefore, derivation of the essential energy factors which have high correlation with the amount of energy consumption is crucial for performance of the forecasting model [15]. In this paper, we use the Pearson correlation coefficient to analyze the degree of correlation between the environment parameters and the amount of energy consumption [16, 17]. In general, for a paired sample data (X_i, Y_i), the Pearson correlation coefficient is obtained as follows,

$$r = \frac{1}{n-1} \sum_{i=1}^{n} \left(\frac{X_i - \bar{X}}{S_X} \right) \left(\frac{Y_i - \bar{Y}}{S_Y} \right), \tag{1}$$

where, $(X_i - \bar{X}) / S_X$ and $(Y_i - \bar{Y}) / S_Y$ are standard scores, $\bar{X}$ and $\bar{Y}$ are mean values, S_X and S_Y are the standard deviations and $-1 \le r \le 1$. Table 3 describes the Pearson correlation coefficient between each environment parameter and the amount of energy consumption.

Table 3. Pearson correlation coefficient between each environment parameter and the amount of energy consumption

Environment parameters	day	Temp.	Humidity	discomfort index	Solar irradiation index	degree of cloudiness	Wind velocity
Pearson correlation coefficient	0.015	0.477	0.121	0.592	-0.63	0.036	0.149

From the correlation analysis shown in table 3, temperature and the discomfort-index turned out to be the essential energy factors for the energy consumption, especially for air conditioning. As the discomfort-index is a combinatory index of temperature and humidity, we can deduce that humidity can be used as an essential energy factor instead of the discomfort-index. In order to identify this deduction, we analyzed the correlation of the temperature and humidity with the amount of energy consumption via partial correlation coefficient (PCC) analysis. PCC values of temperature and humidity were 0.698 and 0.589, respectively. As a result, in this paper, temperature and humidity are used as essential input parameters for the energy demand forecasting model generation..

4.2.2 Energy Demand Forecasting Model

In this paper, in order to establish the energy demand forecasting model, we use the ANN as a representative intelligent computational based approach and regression analysis as the statistical analysis. For the ANN based approach, the feed-forward neural network model is used for the energy forecasting modeling while the back-propagation model is used for the validation of the training (sample) data [18, 19]. Our ANN model is composed of four layers, and each layer has a feedforward connection. In this model, the number of input units is 2 or 6, first hidden units of 15, second hidden units of 10, and one output unit. On the other hand, two regression analysis based forecasting models are established, one with two essential energy factors as independent variables, and the other with all environmental parameters.

$$\begin{aligned} Q_{H\&T} &= -5523179.035 + 406705.479 * T + 69104.944 * H, \\ Q_{ALL} &= -5220105.242 + 474122.857 * \mathrm{T} + 65180.475 * \mathrm{H} - 34047.347 * \mathrm{U} \\ &\quad - 133077.323 * \mathrm{I} + 41756.828 * \mathrm{C} + 223626.738 * \mathrm{W}, \end{aligned} \tag{2}$$

where, $Q_{H\&T}$ and Q_{ALL} are the amount of the forecasted energy demand for each cases. T, H, U, I, C and W are also variables for temperature, humidity, the discomfort-index, the solar irradiation-index, the degree of cloudiness, and the wind velocity, respectively.

4.2.3 Forecasting Performance Evaluation

In order to evaluate the performance of the ANN based forecasting model and the regression based forecasting model, the Mean Absolute Percentage Error (MAPE) is used as a performance index [20]. The MAPE index is as follows,

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|, \tag{3}$$

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

The MAPE index is examined for the two forecasting models with two sets of input parameters. They are a set of all environment parameters and a set of only two essential energy factors. The MAPE index of the ANN algorithm and the regression model are 25.8% and 17.3% for the case of all parameters, whereas they are 19.7% and 13.1% for the case of two essential factors. From the performance evaluation study, the regression based forecasting model turns out to be more accurate than the ANN based model in terms of the MAPE index for the two cases of input parameter variable set. Moreover, for both the forecasting models, the MAPE index with two essential factors turns out to be better than that with all the parameters. This result implies that, as of some the parameters have weak correlation or negative correlation with the amount of energy consumption, it may increase the forecasting error. Therefore, it is crucial for the energy demand forecasting to find out the essential energy factor among the various parameters.

Figures 5, 6 and 7 comparatively diagram the differences between the amount of the forecast energy demand and the amount of actual energy consumption over a certain period of time. Figure 5 compares the amount of actual energy consumption with the amount of regression based forecast energy demand with all and two essential factors over a certain period of time. Figure 6 compares the amount of actual energy consumption with the amount of ANN based forecast energy demand with all and two essential factors over a certain period of time. From figures 5 and 6, the regression based energy demand forecasting model turns out to be more stable than the ANN based model over time. This means that energy supply planning along with the regression based forecasting model is easier than with the ANN model. Thus, the operation and maintenance of the energy facilities and equipment with the regression model will be easier than with the ANN model. Figure 7 compares the amount of actual energy consumption over time as shown by the two forecasting models with two essential factors. In this case, similar to the MAPE index based analysis, the regression based forecasting is more stable and it is a better fitted pattern over time than the ANN based model.

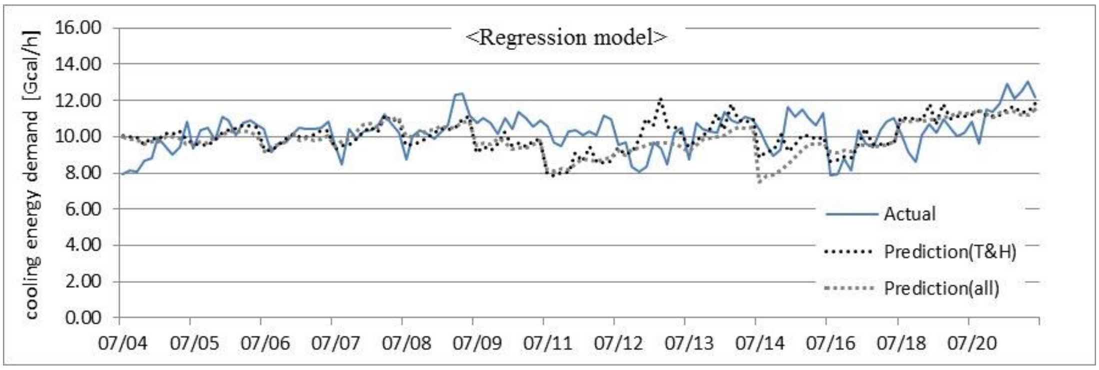

Fig. 5. Comparison of the amount of actual energy consumption with that of the regression based forecasting models (with two sets of parameters) over time.

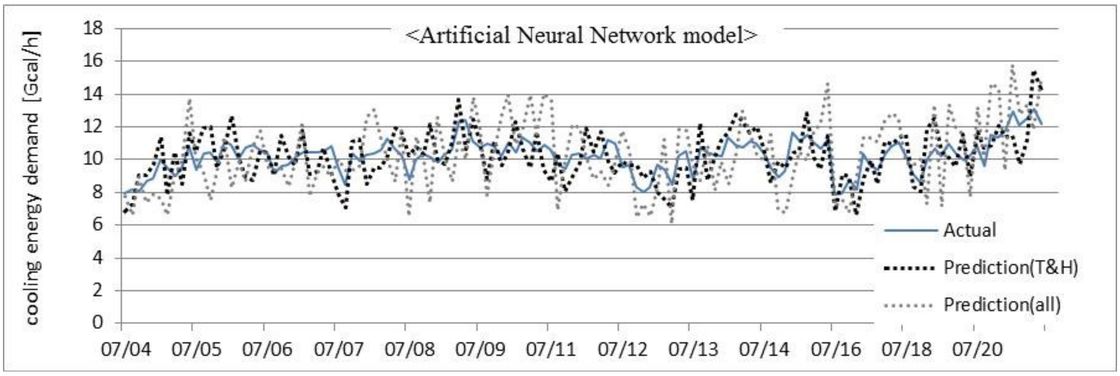

Fig. 6. Comparison of the amount of actual energy consumption with that of the ANN based forecasting models (with two sets of parameters) over time.

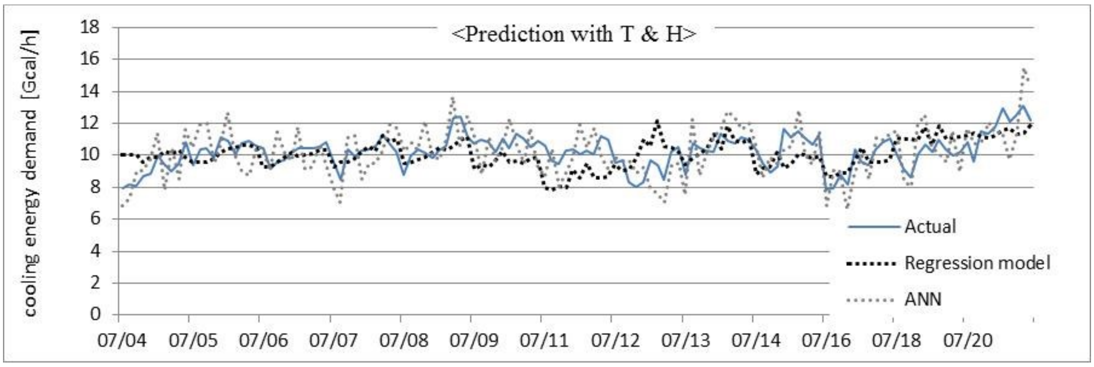

Fig. 7. Comparison of the amount of actual energy consumption over time with two forecasting models (with two essential factors).

5. Conclusion

Due to the worldwide increase in energy consumption, energy conservation has become an important issue. The increasing trends in the energy consumption and CO_2 emissions in the building environment has made energy saving and efficiency a prime subject for energy policies in most of the countries of the world. As a result, the role of the building BEMS has become more important for the achievement of energy saving and efficiency. The BEMS are able to control active systems such as HVAC systems. However, due to many causes such as shortage of building energy management specialists, and incompatibility among energy management systems of the different vendors, the BEMS can only be applied to a limited building environment. Moreover, they cannot be applied to small or medium sized buildings and multi-purpose buildings.

To tackle the above building energy problems, we propose an ICT-based remote building EMM system which consists of two subsystems, the EMM client subsystem and the EMM control center. We propose functionalities and roles of each sub-system which are designed to solve the current building energy control and management problems. We also propose a novel energy demand forecasting algorithm by using past energy consumption data. Extensive performance evaluation study shows that the proposed regression based energy demand forecasting model is well fitted to the actual energy consumption model, and it also outperforms the ANN based forecasting model.

The proposed EMM system is currently under development and will be installed on a multi-purpose complex building (the COEX center, Seoul, Korea, for instance) for field-test based performance evaluation.

References

[1] Energy Information Administration (EIA), "International Energy Outlook 2006," *U.S. Department of Energy*, June 2006. Article (CrossRef Link).
[2] Ellis, M. and Mathews, E. "Needs and trends in building and HVAC system design tools," *Building and Environment*, (37), 461-470, 2006. Article (CrossRef Link).
[3] American Society of Heating, "Refrigeration and Air-conditioning Engineers (ASHRAE)," Conference report. 2003. Article (CrossRef Link).
[4] Ancillotti E, Bruno R, Conti M, "The role of the RPL routing protocol for smart grid communications," *IEEE Communications Magazine*, Vol. 51, Issue 1, Jan 2013. Article (CrossRef Link).
[5] J. Gao et al., "A Survey of Communication/Networking in Smart Grids," *Future Generation Computer Systems*, vol. 28, pp. 391–404, 2012. Article (CrossRef Link).
[6] R. E. Castellanos, P. Millan, "Design of A Wireless Communications Network for Advanced Metering Infrastructure in A Utility in Colombia," *2012 IEEE Colombian Commun. Conf.*, pp. 1–6, May 2012. Article (CrossRef Link).
[7] M. Gharbaoui et al., "An Advanced Smart Management System for Electric Vehicle Recharge," in *Proc. of IEEE IEVC '12*, 2012. Article (CrossRef Link).
[8] Kwantae Cho et al, "Classification and Experimental Analysis for Clone Detection Approaches in Wireless Sensor Networks," *Systems Journal, IEEE*, Vol. 7, issue 1, March 2013. Article (CrossRef Link).
[9] J. Vasseur et al., "Routing Metrics used for Path Calculation in Low Power and Lossy Networks," IETF RFC 6551, Mar. 2012. Article (CrossRef Link).
[10] Abedelaziz Mohaisen et al, "Grid-Based Key Pre-Distribution in Wireless Sensor Networks," *Transactions on Internet and Information Systems,* VOL. 3, NO. 2, April 2009. Article (CrossRef Link).
[11] Insung Hong, Jisung Byun, Sehyun Park, "Cloud Computing-Based Building Energy Management System with ZigBee Sensor Network," in *Proc. of Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS), 2012 Sixth International Conference on*, 547-551, 2012. Article (CrossRef Link).
[12] Yueying Zhang et al, "User-Oriented Energy- and Spectral Efficiency Tradeoff for Wireless Networks," *Transactions on Internet and Information Systems*, Vol. 7, No. 2, Feb 2013. Article (CrossRef Link).
[13] Elias Bou-Harb et al, "Communication Security for Smart Grid Distribution Networks," *IEEE Communications Magazine*, Jan. 2013. Article (CrossRef Link).
[14] Pedersen, L." Load modelling of buildings in mixed energy distribution systems, Norwegian University of Science and Technology," 2007 Article (CrossRef Link).
[15] Cover, T. and Thomas, J."Elements of Information theory," WILEY, 1991. Article (CrossRef Link).
[16] Rodgers, J. and Nicewander, W. "Thirteen ways to look at the correlation coefficient," *The American Statistician*, 42(1), 59–66, 1988. Article (CrossRef Link).
[17] Stigler, S. "Francis Galton's Account of the Invention of Correlation," *Statistical Science,* 4 (2): 73–79, 1989. Article (CrossRef Link).
[18] Haykin, S. "Neural Networks and Learning Machines. (3rd Edition)," Prentice-Hall., 2009. Article (CrossRef Link).
[19] Jing Xu, Xiu Li Wang, "A Structural Identification Method Based on Recurrent Neural Network and Auto-Regressive and Moving Average Model," *Applied Mechanics and Materials*, volumes 256-259, 2012. Article (CrossRef Link).

[20] Armstrong, J. and Collopy, F. “Error measures for generalizing about forecasting methods: Emprical comparisons,” *International Journal of Forecasting*, 8, 69-80, 1992. Article (CrossRef Link).

Si-O Seo received the B.S and M.S degrees in Computer and Information Science in 2007 and 2009, respectively, from Korea University, Korea, where he is currently working toward the Ph.D. degree in computer science at Korea University. His research interests include building energy management system, demand response, electric vehicle charging system, load balancing and design and analysis of energy management systems.

Seung-Yong Baek received the B.S degrees in Computer Engineering in 2003 and 2008, from Kyungnam University, and received the M.S degrees Management and Information in 2009 and 2011, respectively from Korea University, Korea, where he is currently working toward the Ph.D. degree with the Department of electronics & information engineering. His research interests include building energy management system, analysis of energy management system, Enterprise Resource Planning system.

Doyeop Keum received the B.S. in degrees in Computer and Information Science in 2013, from Korea University, Korea, where he is currently working toward the Master’s course. His research interests study on electric vehicle charging scheduling.

Seungwan Ryu is the corresponding author of this paper received the B.S. and the M.S. degrees from Korea University, Seoul, Korea, in 1988 and 1991, respectively, and Ph.D. from University at Buffalo (SUNY at Buffalo), buffalo, NY, USA, in 2003, all in Operations Research. From 1993 to 2004, he has been with Electronics and Telecommunications Research Institute (ETRI) where he has participated in various research projects including CDMA mobile system, IMT-2000 system, and the next generation mobile systems at Mobile Telecommunications Research Division (MTRD). In 2004 he joined the Department of Information Systems at Chung-Ang University, Anseong, Korea, where he is a professor. His research interests include wireless MAC protocols, wireless packet scheduling, and next generation wireless systems design and analysis.

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. From 1990 to 1993, he was an invited researcher at Electronics and Telecommunications Research Institute (ETRI). His research interests include IT convergence technology, Building Energy Management System, 4G/5G mobile/wireless networks, D2D communication, small cell and SDN.