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Development of Intelligent Electricity Saving System Using SARIMA Algorithm

Jun Heo[1*], Kyung-Shin Kim[2]

[1*]*Dept. of Information & Communication, Kyungmin College, Korea*
heojun@kyungmin.ac.kr

[2]*School of Mobile Communications, ChungKang College, Korea*
kskim@ck.ac.kr

Abstract

Many people all over the world have been conducting a great deal of research to solve the problem of global warming since the great majority consider reduction of CO2 as the only solution for that. That is why the production and conservation of energy is thought to be highly crucial. while it is important to produce energy with the high efficiency, the efficient use of the energy is also important. This paper focused on the development of devices for the reducing electricity which is a primary energy source used in homes, shops, buildings, factories and so on. Also the objective of this paper is to develop the inference mechanism as the core component of the devices. Therefore, in this paper, we propose the inference algorithm for reducing the electricity consumption using SARIMA mode and present the feasibility of the procedure.

Keywords: *Inference algorithm, SARIMA mode, Reducing electricity consumption, Global warming*

1. Introduction

Currently, the energy management system for buildings and factories, namely, the electricity saving device is a system that collects or analyzes energy usage and facility operating history through various sensor devices, and reduces electrical energy by providing driving information as to building energy devices. The electricity saving device is mostly introduced when constructing new buildings but at times it is installed additionally in existing buildings. In both cases, introducing electricity device requires a number of facilities. Due to these additional facilities, it is challenging to manage energy efficiently comparing to the investment costs.

In order to devise a high-efficiency electric economizer, it is essential to develop algorithm for electric reduction. An electric economizer consists of both a predictive engine and a predictive control engine. The predictive engine on a server is designed to activate predictive algorithm in which management of power usage is possible. This model is operated by Big Data based on cloud system such as fixed data, external data and internal data. The predictive control engine from the client is composed to activate the predictive control algorithm for reducing the energy consumption. It is designed to make precise prediction by using SARIMA model based upon predicted data at server.

2. Inference algorithm using SARIMA model

A. SARIMA model

The various industrial or social sectors have been using the ARIMA model to estimate its demand. However, since it is impractical to apply ARIMA model to periodic and seasonal condition, we will try to

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Corresponding Author: heojun@kyungmin.ac.kr
Tel:+82-31-828-7180,Fax:+82-31-828-7947
Dept. of Information & Communication, Kyungmin College, Korea

deal with SARIMA (Seasonal Autoregressive Integrated Moving Average) model, which is the supplemented model for ARIMA model.

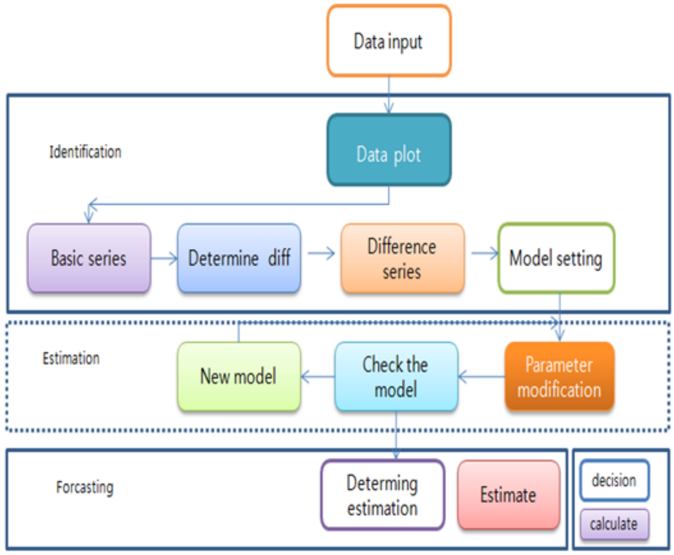

Figure 1. SARIMA model

The following equation (1) is a basic form of ARIMA model.

$$
\begin{aligned}
&(1-\Phi_1 L-\Phi_2 L^2-\cdots-\Phi_p L^p)(1-L)^d Z_t \\
&\qquad =\delta+(1-\Theta_1 L-\Theta_2 L^2-\cdots-\Theta_q L^q)\epsilon_t \\
&AR:\ \Phi_p(L)=1-\Phi_1 L-\Phi_2 L^2-\cdots-\Phi_p L^p \\
&MA:\ \Theta_q(L)=1-\Theta_1 L-\Theta_2 L^2-\cdots-\Theta_q L^q
\end{aligned} \tag{1}
$$

If we simplify ARIMA(p, d, q) model, the following equation is obtained.

$$\Phi_p(L)(1-L)^d Z_t=\delta+\Theta_q(L)\epsilon_t$$

Z_t : raw series data
t : time operator
ϵ_t : error term due
L : operation followed by
p : the degree of Autoregressive term
q : the degree of Moving Average term
d : the degree of differential
δ : constant

SARIMA model will be the suitable technique for the seasonal and periodic procedure. The equation (2) is related to the model of SARIMA (p,d,q)(P,D,Q)s.

$$\Phi_p(L)\Phi_P(L^s)(1-L)^d(1-L^s)^D Z_t=\delta+\theta_q(L)\Theta_Q(L^s)\epsilon_t \tag{2}$$

P : the degree of seasonal AR terms
Q : the degree of seasonal MA terms
D : the degree of seasonal difference

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 estimates and check that the model is adequate and determines whether any forecasting.

Suppose 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 “October 24, 2014, the third week Friday at 15:00”?

Table 1. Predictive Visitors Sample Data

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**

Based on SARIMA model, the predictive algorithm is simulated. Table 1 shows the sample data collected by the data presented, which provides a one-year period of historical data collected for five years. The property of the collected data shows that it comprised of month and year, parking, day, time, temperature, weather, and the number of visitors. After preparing the historical data of the annual, we compared the predictable data for predicting the time (weather, temperature, month and year) 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".

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 the finally 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 predicted value by using the predicted visitor sample 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 number of expected visitors = 0.4*2 + 0.3*5 + 0.2*5 + 0.05*7 + 0.05*10 = 4.15 (persons)

Finally, the number of expected visitors on "October 24, 2014 the third week Friday at 15:00" is predicted as 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" based on the predicted number of visitors, the fixed data, external data and internal data. In predictive engine, various simulations can be added under the varied environment. However, we will only treat the illumination simulation and the temperature one in this paper.

B. Illumination Simulation

The 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 the all 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. Predictive Illumination Sample Data

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

C. 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 month, the highest external temperature. The lowest external temperature, fixed contract electric power, internal electric power, the internal cumulative power and the target power. Figure shows the necessary property in order 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℃, and in the summer, a cooler is operated over the 24℃. In terms of cooling and heating, if the temperature value is adjusted when the temperature is increasing or decreasing by 1℃, 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. Predictive Temperature Sample Data

Month	Ext _High temp	Ext _Optmal temp	Int _temp	Int_cumm pow	Int_target pow	Fix_contr pow
Oct	21℃	10℃	20Kw	6,650	9,000Kw	20Kw

3. Performance evaluation

In this chapter, we have 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 in everywhere. In the setting phase of SARIMA model, we use the measured value of the same time zone. The measured value is comprised 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 2.3.4 shows the results obtained by using the illumination and cooling / heating based on the temperature 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 the figure 2, we can estimate the trend of electric power usage. While 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 is shown. Besides, reduction effect in the existing environment were attained by 7~8%. The results suggest that it does not take an effect of reduction in a way that it simplified the property of exterminated data, but with various data property and self-learning there is a possibility of considerable reduction.

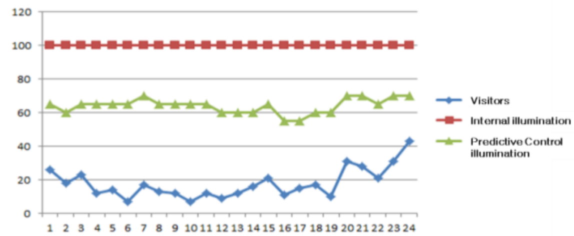

Figure 2. The Predictive Control illumination results

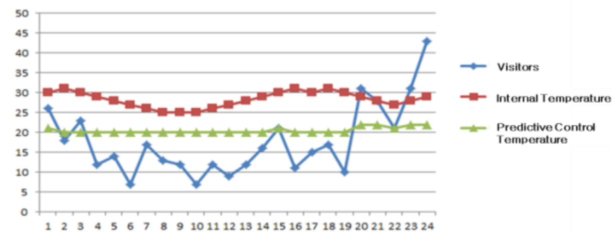

Figure 3. The Predictive Control Temperature results

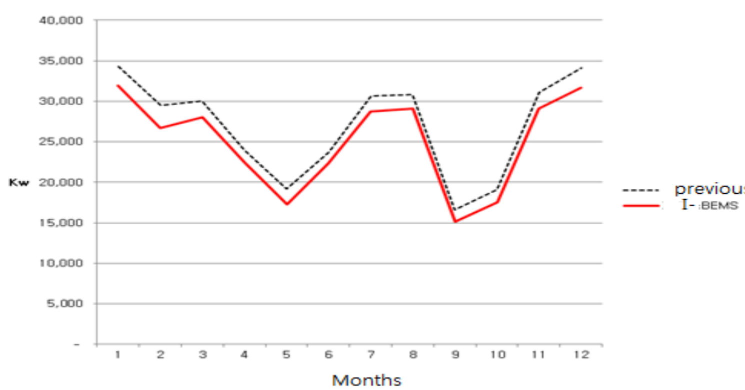

Figure 4. The saving effect comparison of the previous with the intelligent BEMS

4. Conclusion and future work

In a society where energy management system is a national policy subsidized by federal funds, energy related research may be a national agenda even as a research of human history. In general, most people consider that energy reduction can be attained by saving tiny stuff rather than saving big stuffs. It is only said to be true energy reduction when it saves energy without harming the quality of human life. By taking advantage of electricity saving inference algorithm proposed in this paper, the energy can be reduced by analyzing data. This algorithm makes the best use of SARIMA model to predict the estimating data after 1 hour of 10minutes based on the existing data. The predicted results can be applied to control electric devices. In the paper it is suggested that the function of prediction algorithm is reasonable. Possible future projects include the development of the electric power reduction device equipped with the proposed algorithm as well as the EMS devise that can be applied to various fields.

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