A STUDY OF THE PREDICTIVE CONTROL OF THE ONDOL SYSTEM IN APARTMENTS

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ABSTRACT

The objective of this study is to improve the control performance of Ondol heating system in apartment buildings. For this purpose, prevalent control systems and relevant researches are evaluated. The control system of Ondol should easily be adapted to thermal mass characteristics and building loads variation without complication in real application.

In this study, predictive control using the ANN model is proposed and the possibility of this predictive control is investigated through experimental research. The results show that the performance of this predictive control is better than that of the current 2-position on/off control. And through the dynamic analysis of thermal mass model using a computer, the adaptability of the predictive control to several load variations and thermal characteristics are evaluated.

INTRODUCTION

In Korea, radiant floor heating is adopted as a domestic heating method that is originated from the Korean traditional heating method, Ondol. This is also adopted in apartment buildings. Owing to the remarkable progress of construction techniques, the current Ondol system is constructed with use of hot water running embedded tubes to heat floors.

There are two heating methods generally used in current radiant floor heating in Korea. One is intermittent heating control and the other is 2-position on/off control. Intermittent heating control is a method in which hot water of fixed flow rate and temperature is supplied intermittently according to a prescheduled time schedule. 2-position on/off control is one where hot water of a constant flow rate is supplied by on/off acting according to each room's set temperature.

It is recognized that due to the high peak load, intermittent heating control demands large system capacity compared to 2-position on/off control. With intermittent heating control, the room temperature variation range is so wide that it caused thermal discomfort. The basic 2-position on/off control system has thermal discomfort and energy waste problems of over-heating and under-heating caused by time lag.

The continuous control of supply water temperature reset proposed as an alternative method is good for maintaining room temperature. But the complicated system equipment prevents it from being used as a control mode for each room in apartment buildings.

In order to prevent over-heating, it is considered that the heating method should be able to determine the proper on/off position in advance to keep room temperature within set temperature range. Also, to prevent extra cost, piping and equipment should not be complicated compared to those of the current system.

In this study, a predictive control that determines the proper hot water supply on/off time by learning the thermal characteristics of a room is proposed considering the thermal characteristics of apartment buildings and the availability of control parameters. In the learning process, the Artificial Neural Network (ANN) model is used. To evaluate the applicability of the proposed control method, model experiments were performed.

CONCEPT OF PREDICTIVE CONTROL

In order to obtain a desirable solution using ANN, proper input and output parameters should be chosen. In the case of Ondol heating, control parameters generally could be split into three components: manipulated variable, input variable and controlled variable. Input variable is a measured value needed to output target values. Controlled variable is a set value to keep the controlled room comfortable. Manipulated variable is the quantity or condition regulated by the control system to keep controlled variables within a set value range.

For the predictive control of Ondol, the room temperature was selected as a controlled variable, as in the current 2-position on/off control. Other variables (supply water temperature, MRT, heat flux, etc.) are difficult to measure or need some expensive equipment or are unavailable to central heating systems.

In general, the factors affecting room temperature are as follows: convection and radiation at each surrounding surface, internal heat generations and infiltration. The heat transfer equation that governs room temperature with time is

$$\rho_{\text{air}} \cdot C_{\text{air}} \cdot V_{\text{room}} \cdot \frac{\partial T_{\text{room}}}{\partial t} = q_{\text{infil}} + q_{\text{gen}} + q_{\text{rad}} + q_{\text{conv}} \quad (1)$$

And the convection heat flows on the surrounding surfaces are expressed by the following equations according to Newton's law of cooling.

$$q_{\text{conv}} = \sum_{\text{i}} h_{\text{c}} A_{\text{i}} (T_{\text{room}} - T_{\text{surface}_\text{i}}) \quad (2)$$

Also, the radiant heat transfer to the surface is

$$q_{\text{rad}} = \sum_{\text{i}} h_{\text{r}} A_{\text{i}} (T_{\text{room}} - T_{\text{surface}_\text{i}}) \quad (3)$$

expressed in a manner similar to convection. The radiation heat transfer coefficient (h_{r}) in equation 3 is calculated as follows.

$$h_{\text{r}} \equiv \varepsilon\sigma (T_{\text{room}} + T_{\text{surface}_\text{i}})(T^2_{\text{room}} + T^2_{\text{surface}_\text{i}}) \quad (4)$$

If room temperature is replaced with outdoor temperature, equation 2 and 3 can be applied to outdoor surfaces. Indoor surface temperature is primarily affected by outdoor temperature through the wall layers. Making allowance for the time lag, variations in temperature for a period of time should also be considered. Thermal characteristics of constructed materials are the factors that can be learned by ANN. In conclusion, room temperature, outdoor temperature, variation of room temperature and variation of outdoor temperature with time are selected as input variables for the network model.

Manipulated variables are to prevent over-heating. To prevent over-heating and to keep room temperature within its set temperature range, the on/off action should be performed before the room temperature

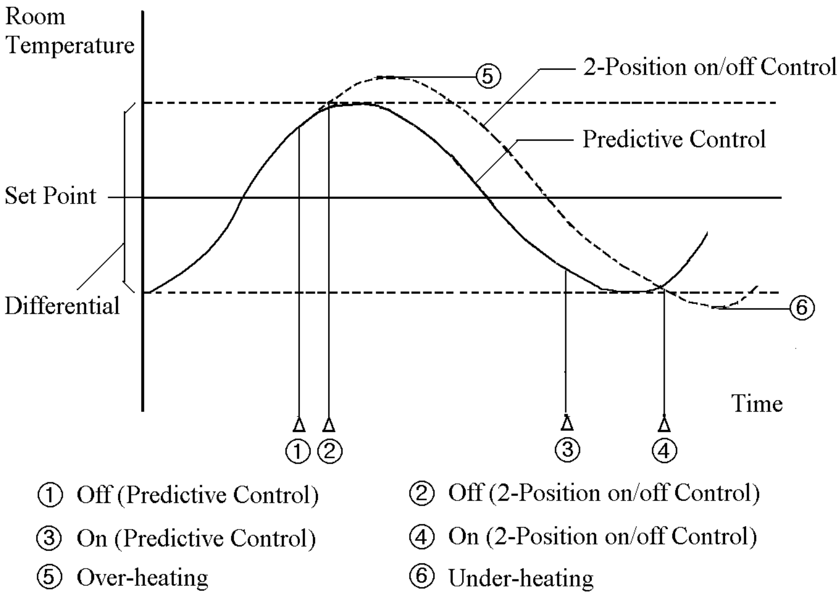

Figure 1. Comparison of Predictive Control and 2-Position on/off Control

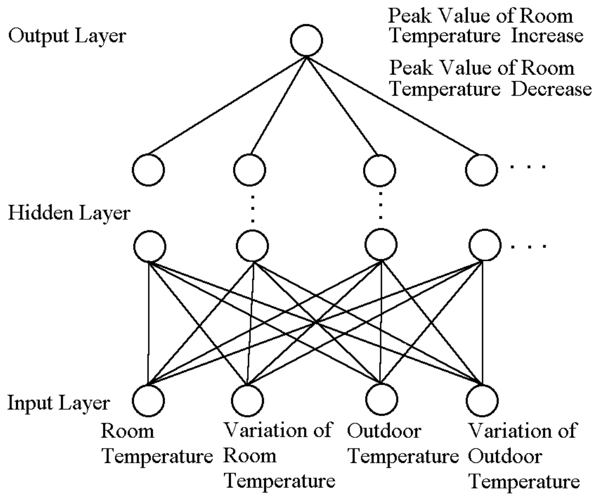

Figure 2. The ANN models for the Predictive Control of the Ondol System

reaches one of the two limits of the differential. So, the neural network used in this study is constructed to predict the peak value of room temperature increase when valve is open (on position) and the peak value of room temperature decrease when valve is closed (off position). Accordingly, the control algorithm is made to change the position of the control valve if the predicted value reaches the differential limits. Figure 1 shows the concept of predictive control compared to the current 2-position on/off control.

Two network models were constructed for the on and off terms. Figure 2 shows the ANN models constructed with their selected input and output variables.

EXPERIMENT TO EXAMINE THE APPLICABILITY OF PREDICTIVE CONTROL

As the basic research for the predictive control of Ondol system, the suggested control method was verified through experiments. The control algorithm of this predictive control was developed and a room temperature modulating program using this algorithm was realized (see Figure 3). In this study, an ANN emulator module was coded in a back-propagation method (Rumelhart and McClelland 1986). The control system is based on 2-position on/off control to make the system simple.

With two identical thermal chambers, the performance of predictive control (A model) and 2-position on/off control (B model) were evaluated under the same conditions. Two constant temperature baths were used to supply water of a constant temperature to each test chamber (see Figure 4). Pumps and the solenoid valve's on/off action circulated hot water. Table 1 shows the experimental conditions for comparing the performance of the two control methods. Measurement items and their locations are shown in table 2. The control apparatus

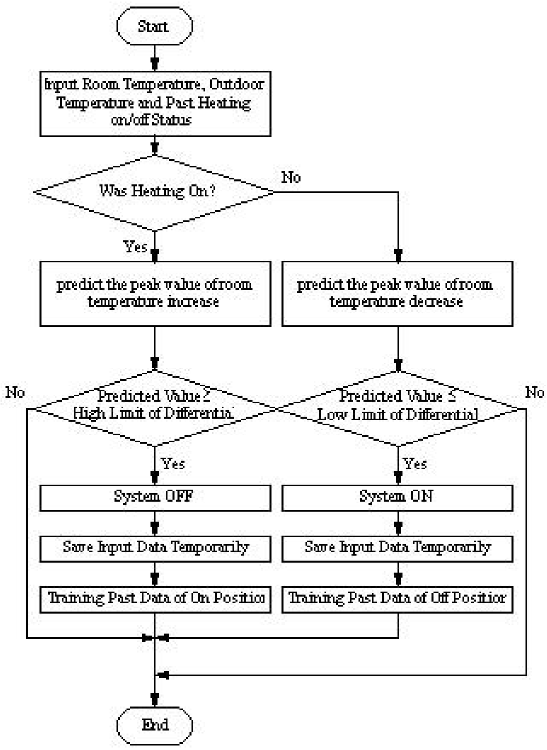

Figure 3. Flow Chart of the Predictive Control

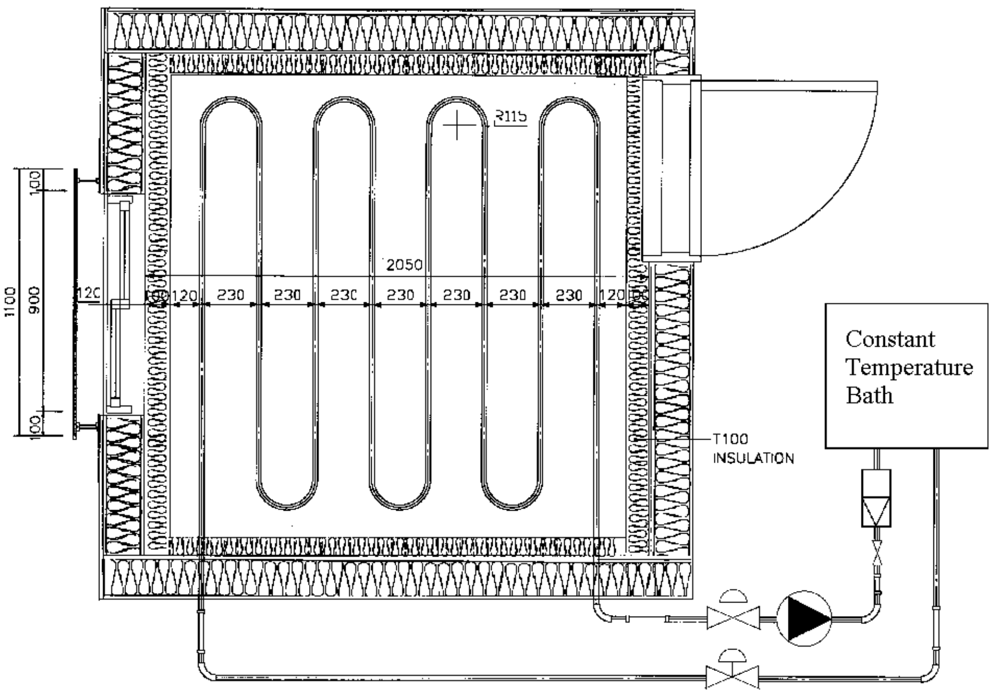

Figure 4. Plan of the Test Chamber

Table 1. Experimental Conditions

Period	Control method	Setpoint and differential	Supply water condition
6 hr	Model A: Predictive control Model B: 2-position on/off control	21°C ± 1.0	Water temperature: 50 °C Flow rate: 6 lpm

was composed of a data logger, solid-state relays and a PC with the control program (see Figure 5).

Table 2. Measurement items and locations

Measurement items	Measurement locations
Room temperature	The point 1.5m high from the floor surface
Floor surface temperature	Over pipe: 4 points Over 1/2 pitch: 4 points Over 1/4 pitch: 4 points
Supply/return Water temperature	In the supply/return pipe
Outdoor temperature	North outdoor area

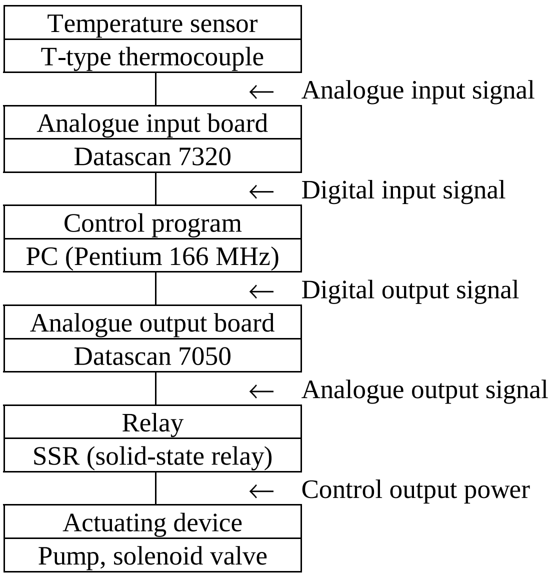

Figure 5. Control apparatus

First, to obtain the training data set for the ANN initialized, the A model was heated with the current 2-position on/off control for five days. Then, the obtained data was trained to the ANN. All the training data used in experiments were normalized to the range of 0 to 1 for some specific data not to govern the whole ANN's training process. Using this early-trained ANN, one chamber (A model) was heated with predictive control and the other chamber (B model) was heated with 2-position on/off control at the same time.

ANALYSIS OF EXPERIMENT

Figure 6 shows room temperature variations with outdoor temperature during the experimental period. As shown in figure 6, the room temperature of the A model to which predictive control was adopted was maintained within the differential, although the outdoor temperature varied over a wide temperature range of -3.3°C–15.5°C. Meanwhile, the over-heating condition occurred by 0.5°C–1°C in the B model with the current 2-position on/off control. Table 3 shows the errors between the peak values of the measured room temperature and the limits of the differential at each heating cycle. A comparison of these errors in the case of the predictive control and the 2-position on/off control is expressed in table 3.

Table 3. Errors of the limits of room temperature (°C)

Errors of low limit		Errors of high limit	
A model	B model	A model	B model
-0.12	-0.2	0.16	0.94
0.3	-0.07	-0.04	1.08
-0.07	-0.11	-0.04	0.96
-0.03	-0.17	0.01	0.67
-0.08	-0.09	0.03	0.92
0.03	-0.13	-0.03	0.59
0.06		0.15	
-0.12		-0.03	
0.07		-0.14	

Figure 7 shows the heating states and floor surface temperature variations of each chamber. The maximum floor surface temperature was 28.1°C in the A model with predictive control and 29.3°C in the B model with 2-position on/off control, and the minimum was 21.9°C in the A model and 21.7°C in the B model.

Table 4. Comparison of the total heating time

	A model	B model
Total heating time during experimental period	806 min	931 min

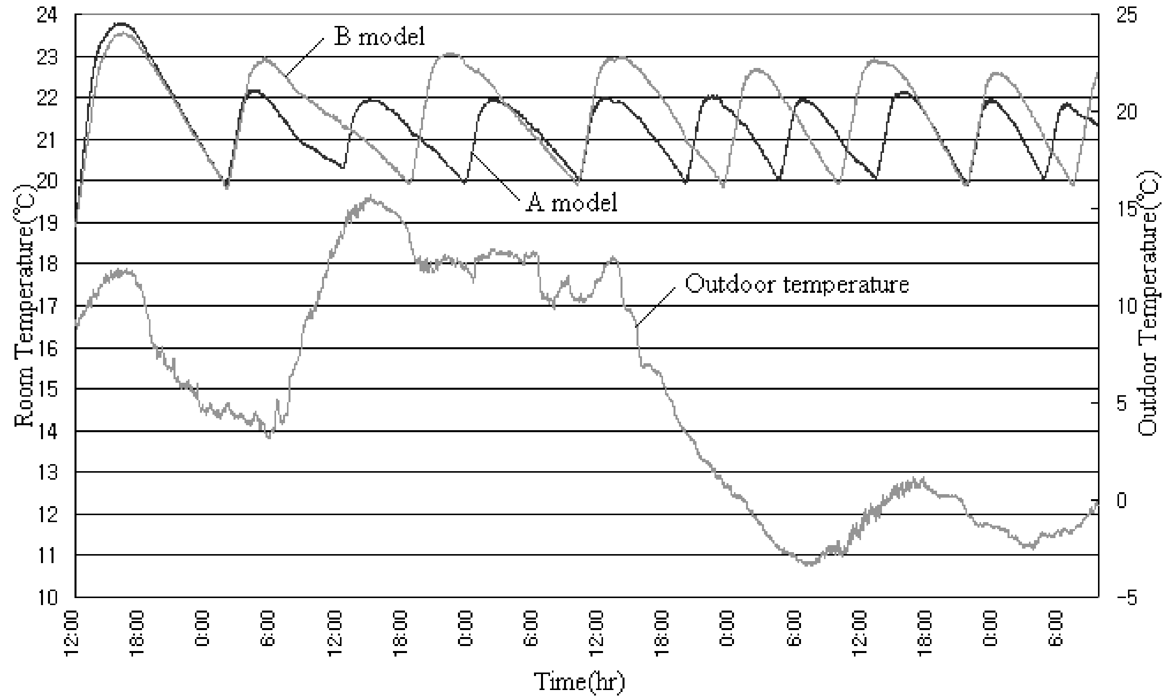

Figure 6. Experiment Result: Comparison of the Room Temperature of the A model and that of the B model

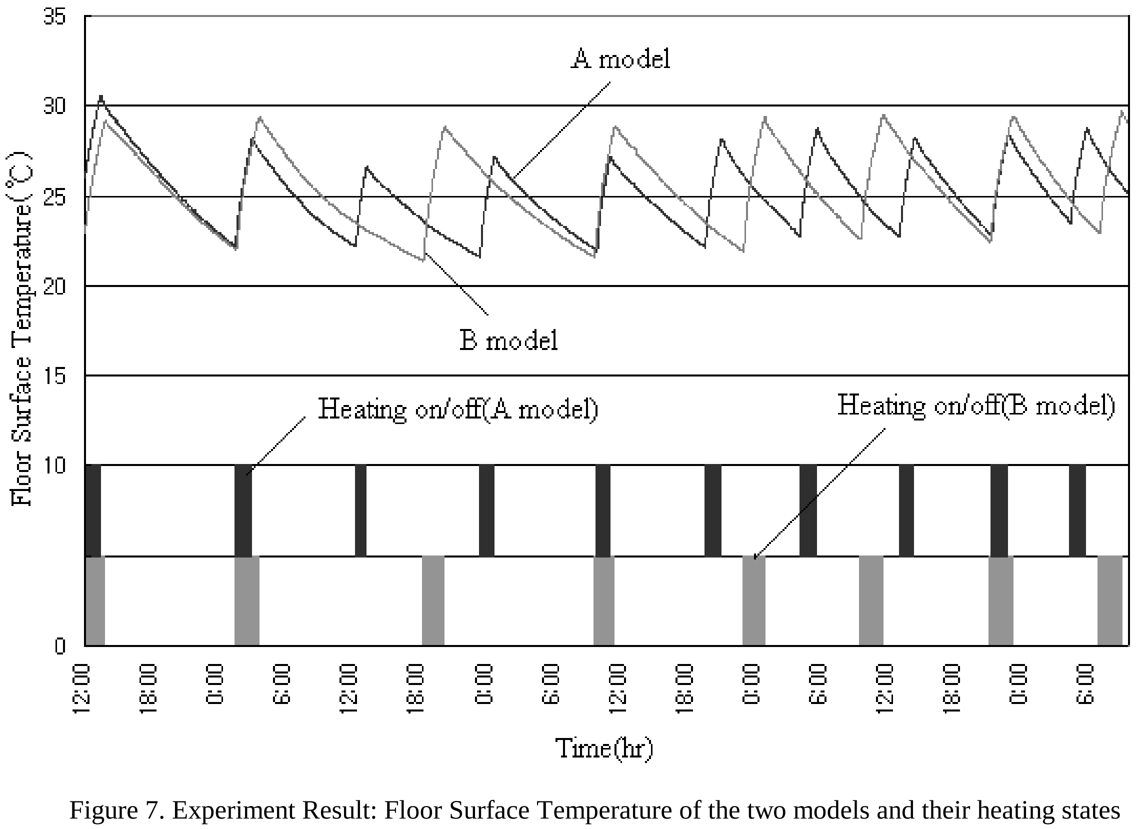

Figure 7. Experiment Result: Floor Surface Temperature of the two models and their heating states

From this result, it is known that the temperature range of the floor surface in the A model is less than that in the B model.

As shown in table 4, the total heating time during the experimental period was less in the A model than that in the B model. Also, from figure 6 and table 3, the results show that unnecessary heat was supplied to the B model.

From the experimental results, the performance of the predictive control proposed in this study is better than that of the current 2-position on/off control in terms of maintenance of room temperature and energy consumption. So, in an actual application, it may be possible for the predictive control to be adopted to electronic thermostats as the current 2-position on/off control.

SIMULATION WITH AN APARTMENT HOUSE MODEL

To determine whether the ANN can be adapted to the real scale of apartment houses, a dynamic thermal analysis was performed. For the accuracy of the results, an unsteady 2-dimensional analysis using the finite difference method (FDM) was adopted to calculate the temperatures of all the nodes in the wall layer. The effectiveness-NTU (number of transfer Unit) method was adopted to calculate the heat flow from the Ondol panel. For indoor spaces, radiant heat transfer as well as convection heat transfer is calculated. The surface heat transfer coefficients are calculated according to the heat flow's directions from all surfaces.

The unit rooms of an apartment building in Korea were selected as the simulation model. To compare the performance of the predictive control with the 2-position on/off control under identical conditions, three rooms facing north with little effects of direct solar radiation and located in the mid-floor of the building were selected. These three rooms are different in their dimensions and openings.

Under the same conditions, the predictive control and the 2-position on/off control were simulated using a week's weather data of Seoul. Before this, the current 2-position on/off control was simulated for pre-training of the ANN using another one week's weather data. The simulation conditions are shown in table 5. These were determined from the actual operation examples of Korean apartment buildings

Table 5. Simulation Conditions

Set point	Water temperature	Flow rate
21°C±1.0	60°C	3 lpm

RESULTS OF SIMULATION

Room temperature variations with the predictive control and with 2-position on/off control of three selected rooms are show in figure 8, figure 9 and figure 10. With the 2-position on/off control, the over-heating after off points is expressed irregularly by 0.2°C–0.7°C. But with the proposed predictive control, the room temperature of each room is kept within the differential range. The B room (used for kitchen) is open to the living room facing south. So, the effects of solar radiation to the living room were partially expressed.

Although three rooms are different in their physical characteristics, the ANN used in this simulation was adapted to each room. The ANN model is trained in real time. And the more training itself, the better performance will be expressed in its solutions. Therefore, as the ANN is used more time in real applications, the room temperature will be kept more exactly. Also, the operator does not need to adjust control parameters.

CONCLUSIONS

For the better performance of the current radiant panel heating method in Korea (Ondol), a predictive control using ANN was tested and simulated. The results of this study are summarized as follows.

1) Considering thermal characteristics of buildings and the availability of control parameters, room temperature, outdoor temperature, room temperature variation rate and outdoor temperature variation rate were selected as input parameters for predictive control. The control algorithm is based on 2-position on/off control to make the system simple.

2) The experimental results show that the performance of the proposed predictive control is better than that of the current 2-position on/off control in terms of maintenance of room set temperature and energy consumption.

3) The dynamic analysis using a computer shows that the neural network used in predictive control is adapted to each room of apartment building in Korea whose load variation and thermal characteristics are different from the others.

4) The evaluation of the experiments and the computer simulation proved that this predictive control system of Ondol is simple in real application and can easily be adapted to building load variation and different thermal mass characteristics.

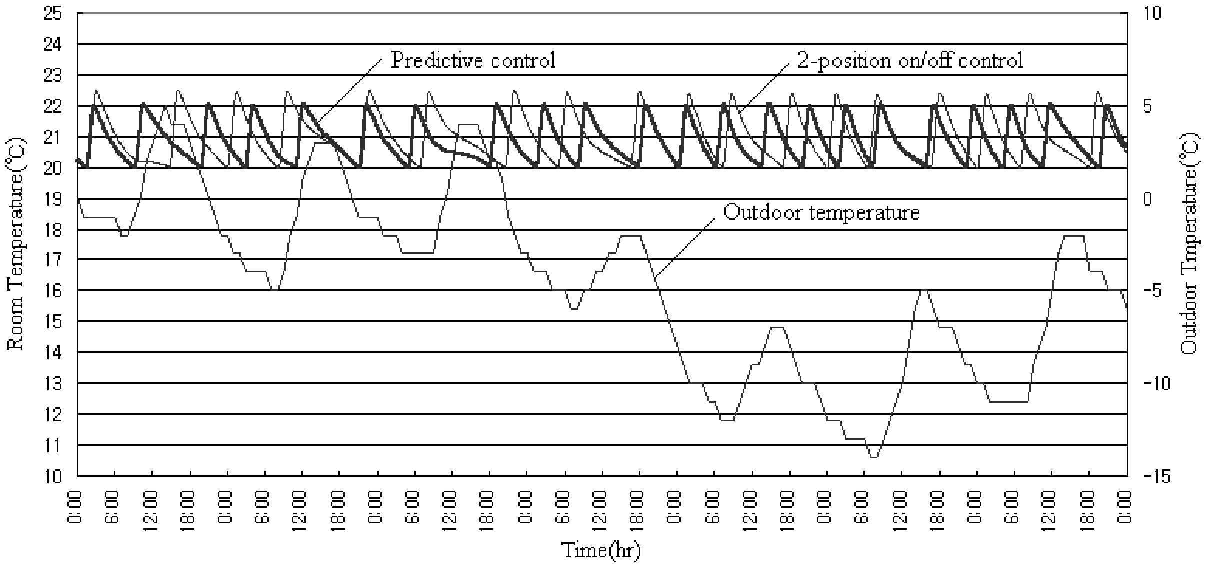

Figure 8. Simulation Result: Comparison of the Room Temperature (A room)

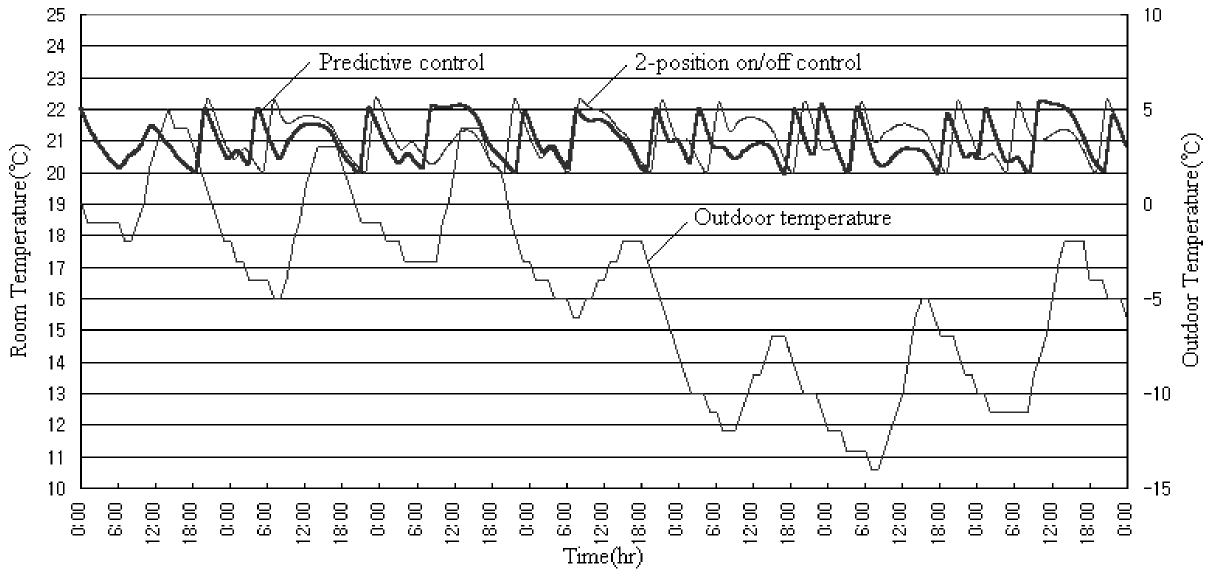

Figure 9. Simulation Result: Comparison of the Room Temperature (B room)

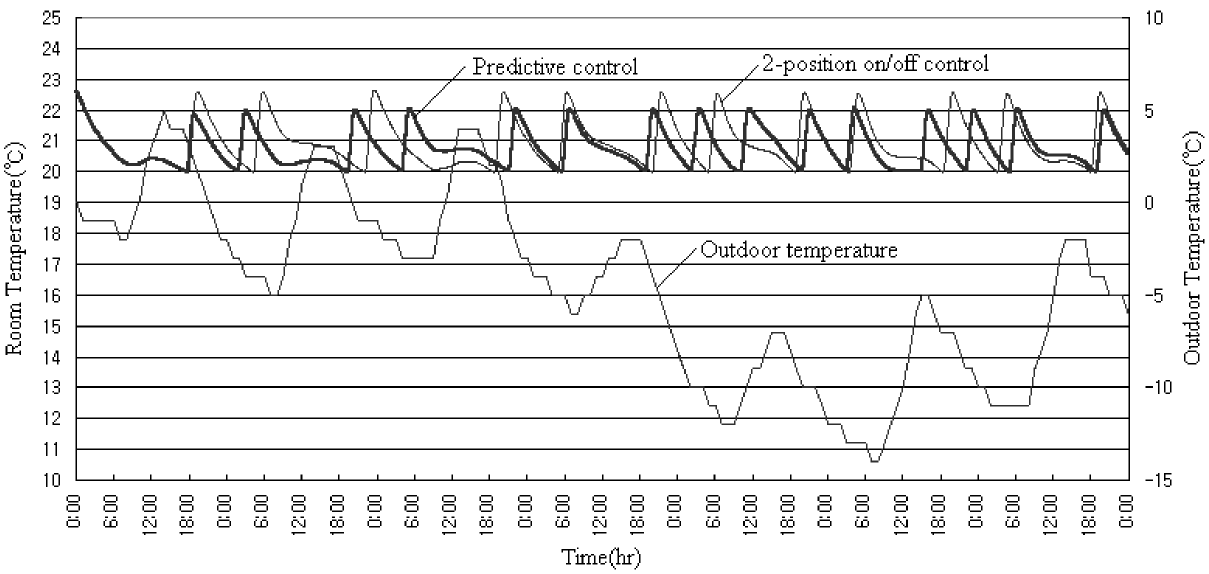

Figure 10. Simulation Result: Comparison of the Room Temperature (C room)

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NOMENCLATURE

ρ_{air} Density of air

C_{air} Specific heat of air

V_{room} Volume of a room

t Time

T_{room} Room temperature

q_{infil} Heat transfer with infiltration

q_{gen} Internal heat generation in a room

q_{rad} Radiant heat transfer

q_{conv} Convective heat transfer

A_i The surface area of the walls and the pannel

h_c Convection heat transfer coefficient

h_r Radiation heat transfer coefficient

$T_{surface_i}$ The surface temperature

ε Effective emissivity

σ Stefan-Boltzman constant