Applied Thermal Engineering 103 (2016) 1135–1144

Contents lists available at ScienceDirect

Applied Thermal Engineering

journal homepage: www.elsevier.com/locate/apthermeng

Research Paper

Development of a thermal control algorithm using artificial neural network models for improved thermal comfort and energy efficiency in accommodation buildings

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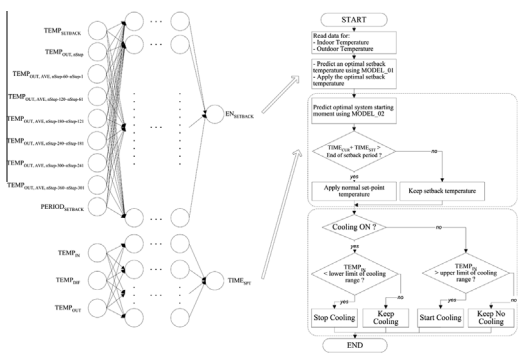
HIGHLIGHTS

- An ANN model for predicting optimal start moment of the cooling system was developed.
- An ANN model for predicting the amount of cooling energy consumption was developed.
- An optimal control algorithm was developed employing two ANN models.
- The algorithm showed the advanced thermal comfort and energy efficiency.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 20 October 2015
Revised 15 February 2016
Accepted 1 May 2016
Available online 2 May 2016

Keywords:
Setback temperature
Restoration period
Artificial neural network
Predictive and adaptive controls
Thermal comfort
Energy efficiency

ABSTRACT

The aim of this study was to develop a control algorithm to demonstrate the improved thermal comfort and building energy efficiency of accommodation buildings in the cooling season. For this, two artificial neural network (ANN)-based predictive and adaptive models were developed and employed in the algorithm. One model predicted the cooling energy consumption during the unoccupied period for different setback temperatures and the other predicted the time required for restoring current indoor temperature to the normal set-point temperature. Using numerical simulation methods, the prediction accuracy of the two ANN models and the performance of the algorithm were tested. Through the test result analysis, the two ANN models showed their prediction accuracy with an acceptable error rate when applied in the control algorithm. In addition, the two ANN models based algorithm can be used to provide a more comfortable and energy efficient indoor thermal environment than the two conventional control methods, which respectively employed a fixed set-point temperature for the entire day and a setback temperature during the unoccupied period. Therefore, the operating range was 23–26 °C during the occupied period and 25–28 °C during the unoccupied period. Based on the analysis, it can be concluded that the optimal algorithm with two predictive and adaptive ANN models can be used to design a more comfortable and energy efficient indoor thermal environment for accommodation buildings in a comprehensive manner.

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http://dx.doi.org/10.1016/j.applthermaleng.2016.05.002
1359-4311/

Nomenclature

$TEMP_{SETBACK}$ setback temperature, °C
$TEMP_{OUT,\ nStep}$ outdoor air temperature in the current control cycle, °C
$TEMP_{OUT,\ AVE,\ nStep\text{-}60\sim nStep\text{-}1}$ average outdoor air temperature from nStep-60 to nStep-1, °C
$TEMP_{OUT,\ AVE,\ nStep\text{-}120\sim nStep\text{-}61}$ average outdoor air temperature from nStep-120 to nStep-61, °C
$TEMP_{OUT,\ AVE,\ nStep\text{-}180\sim nStep\text{-}121}$ average outdoor air temperature from nStep-180 to nStep-121, °C
$TEMP_{OUT,\ AVE,\ nStep\text{-}240\sim nStep\text{-}181}$ average outdoor air temperature from nStep-240 to nStep-181, °C
$TEMP_{OUT,\ AVE,\ nStep\text{-}300\sim nStep\text{-}241}$ average outdoor air temperature from nStep-300 to nStep-241, °C
$TEMP_{OUT,\ AVE,\ nStep\text{-}360\sim nStep\text{-}301}$ average outdoor air temperature from nStep-360 to nStep-301, °C
$PERIOD_{SETBACK}$ setback period during the daytime, min
$EN_{SETBACK}$ predicted cooling energy consumption during the setback period, kW h
$TEMP_{IN}$ indoor air temperature, °C
$TEMP_{DIF}$ temperature difference from the set-point temperature, °C
$TEMP_{OUT}$ outdoor air temperature, °C
$TIMP_{SPT}$ predicted time required for restoring current indoor temperature to the normal set-point temperature, min
S_i predicted value by ANN model
M_i numerically simulated value

1. Introduction

Thermal quality (TQ) in indoor space is one of the principal components for creating comfortable indoor environmental quality (IEQ). IEQ is affected by diverse components such as lighting quality, acoustic quality, and air quality as well as thermal quality. The indoor thermal quality is strongly related to the occupants' satisfaction with the thermal environment, health, productivity, and building energy efficiency. The significance of the thermal quality has recently become increasingly apparent as the period that occupants stay indoors has increased to up to 90% of their life.

Studies on methods for providing improved thermal quality have been widely conducted, while many standards and guidelines for proposing the range of comfortable thermal conditions [1] have been published. Based on these studies and standards, control strategies for maintaining the thermal conditions within the comfortable ranges by using a proper system application and control have been suggested.

For example, artificial intelligence (AI) is newly being studied for the improved control of the indoor thermal environment of buildings. Various theories have been presented on how to maximize the success of AIs by using intelligent agents that can perceive the surrounding environments and take actions based on their perception. Applying AI to intelligent machines increases the opportunity for the systems and control algorithms to work optimally and to satisfy their designed purposes [2].

Among the diverse AI theories, the artificial neural network (ANN), which is one of the various types of artificial intelligence, is a computational model that artificially mimics the biological processes of the human nerve system [3]. ANN can successfully operate non-linear systems or systems with unclear dynamics without the need for the operator to understand the complicated knowledge of the system's dynamics [2]. Two major processes are conducted in the ANN models: (1) a back-propagation process for iterative self-training, and (2) a feed-forward process for calculating output using a series of input neurons and hidden neurons, transfer functions, and connectivity between neurons. Based on these two processes, the predictive and adaptive control of the systems is feasible.

The ANN-based control strategies have shown their applicability as the building thermal control method. Table 1 summarizes the recent ANN-based studies which were applied for the building thermal controls. Previous studies proved that the ANN-based strategies provided more comfortable thermal conditions with reduced overcooling and overheating. In addition, building energy efficiency has been significantly improved by the reduction of heating and cooling energy consumption.

Similar to other types of buildings, the indoor thermal conditions and controls in accommodation buildings are carefully considered in order to create a thermally comfortable environment and to improve building energy efficiency. In addition to these associated features, thermal controls in hotel rooms have two distinctive features. Firstly, most of the rooms are generally unoccupied during the day. Thus, thermal comfort during the unoccupied period does not need to be specifically treated. Secondly, the energy efficiency for thermal conditioning of each room may not be the occupants' concern. Occupants pay their designated lodging charge without any extra payment for thermal conditioning such as electricity bills for heating and cooling. They may sometimes operate the heating and cooling systems more than necessary. For example, general hotel users do not understand the setback application or proper setback temperature during the unoccupied period. In addition, the optimal moment to switch to the normal set-point temperature cannot be determined by the occupants.

Thus, active management by the building manager or expert system is required for the proper operation of the heating and cooling systems in accommodation buildings. For example, the optimal setback temperature during the unoccupied period needs to be applied to improve energy efficiency. In addition, the optimal moment to employ the normal set-point temperature during the setback period needs to be determined to provide comfortable thermal conditions when the occupants return.

From this aspect, the aim of this study is to propose a control algorithm and test its performance for demonstrating improved thermal comfort and building energy efficiency during the cooling season. This algorithm employs two ANN models for predictive and adaptive controls. The first ANN model will calculate the cooling energy consumption during the setback period for different setback temperatures. By comparing the amount of cooling energy required for the different setback temperatures, the optimal setback temperature in which the least amount of energy is consumed can be applied to the control algorithm.

The second ANN model will calculate the time required for restoring the current indoor temperature to the normal set-point temperature. By applying the calculated time to the control algorithm, the predetermined operation of the cooling system will be performed during the setback period to condition the indoor temperature comfortably when the normal set-point period begins. Based on the two ANN model applications, thermal controls that

Table 1
Previous studies using the ANN models for building thermal controls.

Reference number	Author(s)	Outcomes
[4,5]	Yeo, M.S.; Kim, K.W.; Yang, I.H.	• Two An ANN models were developed for calculating the optimal start and stop moments of the heating system at the beginning and closing periods of the office building • The suggested model accurately predicted optimal start and stop moments respectively using the length of times for ascending and descending the indoor temperature to the designated set-point temperatures
[6]	Ben-Nakhi, A.E.; Mahmoud, M.A.	• An ANN model was suggested for predicting the optimal end of setback moment of the cooling system for the begging period of the business hours • The prediction results presented strong correlation coefficient with the simulated results
[7]	Morel, N. and et al.	• Three ANN models were developed for predicting outdoor temperature, solar radiation, and future indoor temperature • Using predicted values, a domestic radiant heating system provided more comfortable thermal condition with improved energy-efficiency
[8,9]	Lee, J.Y. and et al.	• An ANN model was developed for controlling a radiant under-floor heating system • Using the ANN model, heating system worked predictively for the significant reduction of overshoots and undershoots of indoor temperature
[2,10,11]	Moon, J.W.	• Three ANN models were developed for conditioning indoor air temperature, humidity, and PMV of the detached home through the controls of the heating, cooling, humidifying, and dehumidifying systems • ANN-based methods provided more comfortable and stable thermal environment
[12,13]	Argiriou, A.A. and et al.	• An ANN model was developed for calculating the optimal supply of the hydronic heating systems in the solar buildings • The proposed ANN-based method reduced energy consumption by 15%
[14]	Abbassi, A.; Bahar, L.	• An ANN model was proposed for controlling an evaporative condenser • The ANN-based method presented the reduction of process errors compared to the PID controller
[15–17]	Esen, H. and et al.	• ANN-based prediction models were developed for operating ground coupled heat pump system • ANN models proved applicability with accurate calculation results for the coefficient of performance of ground coupled heat pump system
[18]	Chow, T.T. and et al.	• ANN and Genetic algorithm was suggested in an incorporative manner for the optimal use of electricity and fuel by an absorption chiller system • ANN model accurately calculated the coefficient of performance of the system, the mass flow rated of diesel oil, and electric power of the cooling water pump and chilled water pump

are more comfortable and energy efficient will be feasible for accommodation buildings.

2. Development of the control algorithm

2.1. Framework of the thermal control algorithm

A framework of a thermal control algorithm was previously proposed by Moon and Kim as shown in Fig. 1. The thermal comfort and energy efficiency of the building were considered synthetically [2]. The control algorithm proposed in this study was based on the flow of this framework.

The framework is composed of five steps. The first step, physical conditions, involves monitoring climatic data such as indoor and outdoor air temperatures and transferring these to the control panel in which the control algorithm is embedded. The climatic data is used in the control algorithm to determine the operation of the thermal control systems such as heating and cooling systems. In the second step, the thermal comfort range, the operation range of the thermal control systems is determined. In this step, a set-point temperature can be set by the occupants or recommended by the building manager or expert system. In the third step, energy, the setback values and periods of the thermal control system are determined for the non-occupied period. Similar to the second step, these values and periods can be determined either by the occupants or by the building manager or expert system for improving the building energy efficiency. The fourth step, decision of system operation, involves determining the operation of the thermal control systems based on the information from the previous steps. The climatic data, set-point temperature, and the setback temperature and period are used in this step. Finally in the fifth step, the operation of the control system, the thermal control systems follow the output signal from the fourth step to provide a comfortable and energy efficient thermal environment.

The ANN models used in this study will be applied in the third and fourth steps. In the third step, the first ANN model, which predicts the optimal setback temperature in terms of energy efficiency, can recommend the setback temperature during the setback period. In the fourth step, the second ANN model, which determines the optimal start moment of the thermal control system during the setback period, will recommend the best starting moment for restoring the indoor temperature to the normal set-point temperature.

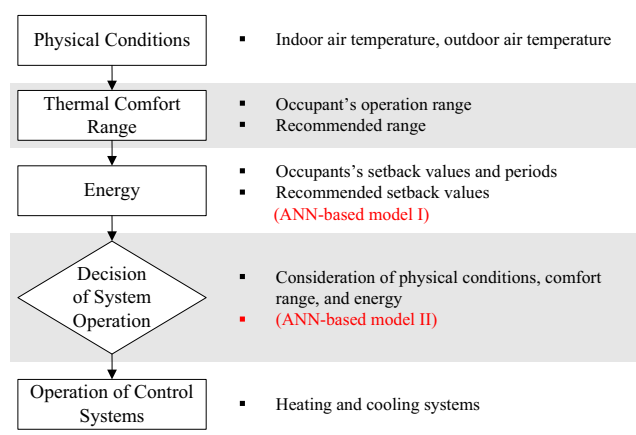


Fig. 1. Framework of thermal control algorithm for the indoor thermal controls.

2.2. Applied prediction models

Two ANN models were preliminarily developed by Moon and et al. [19,20] to be applied in the control algorithm proposed in this study. The first ANN model was developed for predicting the amount of cooling energy consumption ($EN_{SETBACK}$) during the setback period for the different setback temperatures. The cooling energy consumption refers to the total cooling energy during the setback period and the cooling energy needed to restore the indoor temperature to the normal set-point temperature. Since the cooling energy for restoring indoor temperature to the normal set-point

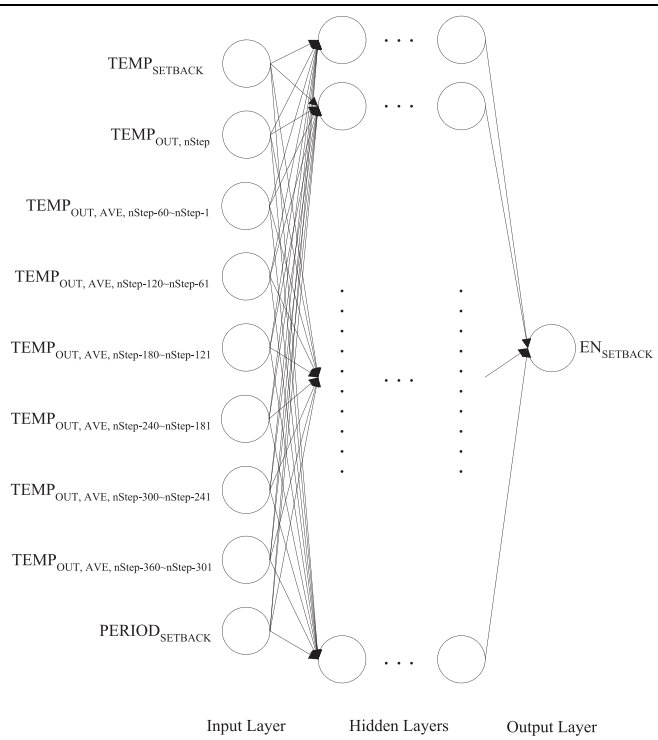
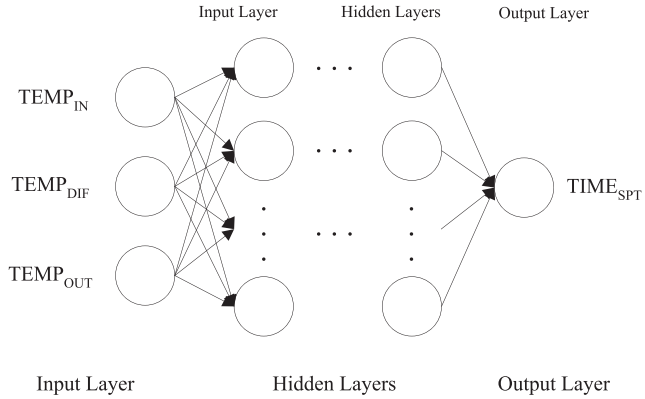
temperature condition will be increased as the setback temperature during the setback period increases, the optimal setback temperature needs to be found in order to reduce the overall cooling energy consumption. For this, the amounts of cooling energy from the ANN model for the different setback temperatures are compared, and the optimal setback temperature that consumes the least amount of energy can then be determined and applied to the control algorithm for improving the building energy efficiency [19].

The second ANN model was developed for predicting the length of the operating time ($TIME_{SPT}$) required for restoring the current indoor temperature under the setback condition in hotel rooms to the normal set-point condition during the cooling season. For example, if the summation result of the current time of the day (e.g. 5:30 P.M.) and the predicted time (e.g. 30 min) from the ANN model reaches the starting moment of the normal set-point moment (e.g. 6:00 P.M.), the algorithm is predetermined to turn on the cooling system to cool down the indoor space for restoring comfort when the normal set-point begins to be applied. As this ANN model is applied in the control algorithm, more comfortable temperature conditions can be provided when the normal set-point period begins. In addition, the unnecessary energy consumption for the cooling during the setback period can be prevented because the cooling system will not start working before it is actually required [20].

The optimal structure and composition of the proposed ANN models are summarized in Table 2. The number of hidden layers and hidden neurons, learning rate, and moment were optimized through parametrical performance tests, in which the optimal values for each component were determined to reduce calculation errors. Parametrical performance tests for model optimization were conducted in two previous studies [19,20] using the numerical simulation method employing Transient Systems Simulation (TRNSYS) [21] incorporated with Matrix Laboratory (MATLAB) [22].

The 196 and 45 training data sets, which were acquired from the computer simulation using TRNSYS and MATLAB, were prepared for each ANN model. The sliding-window method was applied for the data management, thus the new data set was added to the training data sets replacing the oldest data set. The iterative training process was conducted when the new data set was added for adapting the ANN models to the new environment.

Table 2
Structure and composition of the two developed ANN models.

Purpose	Structure	Composition
Prediction of the cooling energy consumption during the setback period (Model 1)		– Input neurons • $TEMP_{SETBACK}$ • $TEMP_{OUT, nStep}$ • $TEMP_{OUT, AVE, nStep-60\sim nStep-1}$ • $TEMP_{OUT, AVE, nStep-120\sim nStep-61}$ • $TEMP_{OUT, AVE, nStep-180\sim nStep-121}$ • $TEMP_{OUT, AVE, nStep-240\sim nStep-181}$ • $TEMP_{OUT, AVE, nStep-300\sim nStep-241}$ • $TEMP_{OUT, AVE, nStep-360\sim nStep-301}$ • $PERIOD_{SETBACK}$ – Output neuron • $EN_{SETBACK}$ – Number of hidden layers and neurons • hidden layers: 3 • hidden neurons: 19 – Transfer functions • hidden neurons: tangent-sigmoid • output neuron: pure-linear – Training methods • learning rate: 0.6 • moment: 0.2 – Number of training data sets: 196 [19]
Prediction of the optimal starting moment (Model 2)		– Input neurons • $TEMP_{IN}$ • $TEMP_{DIF}$ • $TEMP_{OUT}$ – Output neuron • $TIME_{STT}$ – Number of hidden layers and neurons • hidden layers: 3 • hidden neurons: 4 – Transfer functions • hidden neurons: tangent-sigmoid • output neuron: pure-linear – Training methods • learning rate: 0.6 • moment: 0.2 – Number of training data sets: 45 [20]

2.3. Control algorithm

A thermal control algorithm, which was developed using MATLAB, is shown in Fig. 2. The algorithm employed two predictive ANN models for providing improved building energy efficiency and thermal comfort. During the normal set-point period, the cooling system works based on the normal set-point temperature. When the setback period begins, the first ANN model predicts the optimal setback temperature in which the least amount of cooling energy is consumed, and this temperature is applied as the setback temperature during the unoccupied period.

At each control cycle that was assigned 1 min in this study for performance tests, the second ANN model predicts the time required for restoring the current indoor temperature to the set-point temperature. When the total current time and required time reach the end of the setback period, the cooling system follows the normal set-point temperature to provide the comfortable indoor temperature condition at the beginning moment of the occupied period. For the entire period, the cooling system works following the operating range determined by the optimal setback temperature or the normal set-point temperature.

The proposed algorithm was designed to be applied to every single room of the hotel building. The ANN models and algorithm can be embedded in the micro-controller which is a core component of a thermostat. Using the thermostat with the proposed algorithm, the cooling system can be optimally controlled for satisfying the thermal requirement and for saving energy of each room.

In addition, when the algorithm is applied to the real building, the algorithm needs to have a specific function for preventing improper system operation. When data is missed or erroneous as well as the calculation results from the ANN models are erroneous (e.g., negative number or too big), the system operation will be identical to the previous day. In addition, no iterative training process occurs.

Fig. 3 shows the workflow of the controller when it is applied in building. The indoor and outdoor temperature conditions are monitored using sensors and transferred to the control algorithm through the data acquisition device in the thermostat. The developed control algorithm determines the optimal operation of the cooling system based on the values from sensors, normal set-point temperature, setback period, optimal setback temperature by the ANN model 1, and optimal cooling system operation by the ANN model 2. The cooling system follows the optimal system operating signal from the algorithm for providing thermal comfort and for improving building energy efficiency.

3. Performance tests of the models and control algorithm

For the performance tests of the two ANN models and the control algorithm, TRNSYS and MATLAB software were incorporated and employed, as shown in Fig. 4. Type155 components linked the MATLAB based control algorithm to the TRNSYS model.

The tests were conducted for the test module presented in Fig. 5. The test building was located in Seoul, South Korea (latitude:

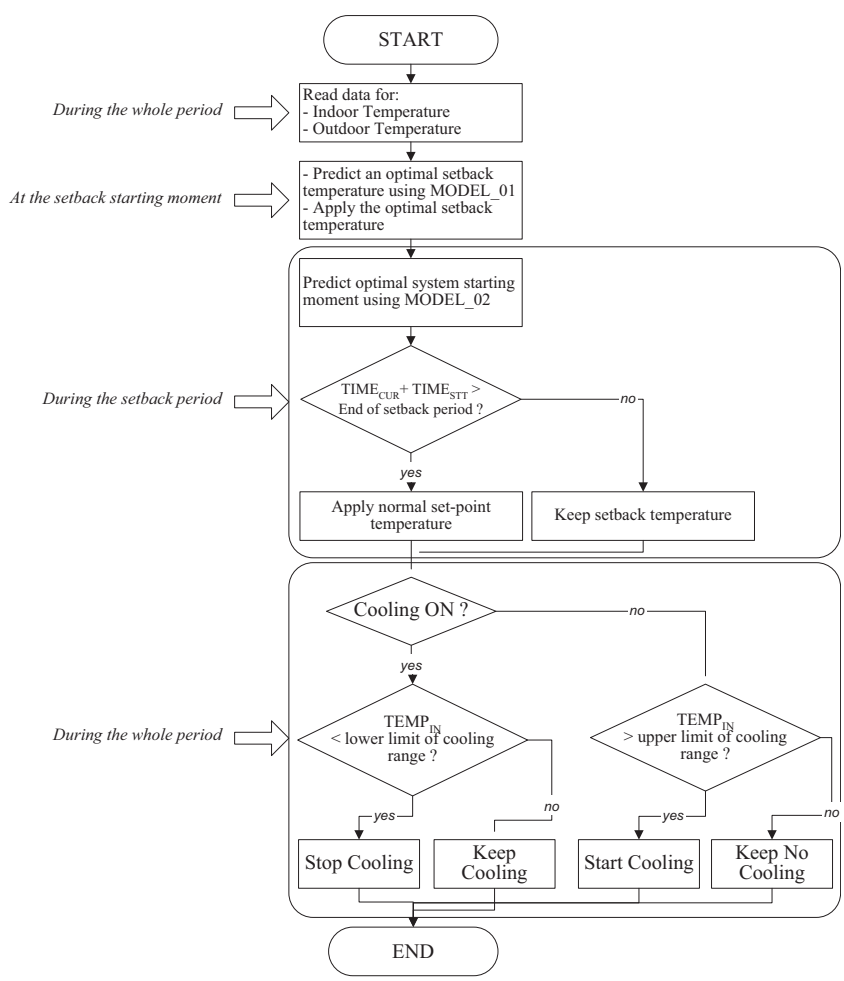


Fig. 2. Control algorithm for the cooling system.

37.56°N, longitude: 126.98°E), which is hot and humid in summer and cold in winter. The test module was situated at the center of nine identical modules with the dimensions of 3.6 m width, 7.4 m depth, and 2.7 m height. At the center of each module, a window of 1.8 m^2 was installed. The insulating level of the envelope components was 2.801 m^2 K/W for exterior walls, 0.492 m^2 K/W for interior walls, roof, and floor, and 0.353 m^2 K/W for windows. The infiltration rate was assumed to be 0.7 air change ratio per room and the internal heat gain was based on 1 occupant with seated and light work, 1 computer, and printer, and 5 W/m^2 lighting fixtures. For space cooling, a convective cooling with 8901 kJ/h heat removal capacity was installed in each module.

For the performance tests of the two ANN models, 100 checking data sets were collected during the cooling season from June 1st to September 30th. The output data of the checking data sets were compared with the predicted output data from the ANN model. The prediction accuracy of each ANN model was statistically analyzed using the Mean Biased Error (MBE) between the simulated results and the predicted results (Eq. (1)).

$$\mathrm{MBE} = \frac{\sum_{i=1}^{n} |S_i - M_i|}{\sum_{i=1}^{n} M_i} \times 100 \tag{1}$$

The performance tests of the control algorithm were comparatively conducted with two conventional algorithms as summarized in Table 3. The first conventional algorithm employed a fixed setpoint temperature of 23 °C with a dead-band of 3 °C for the entire day, thus the cooling system worked within a 23–26 °C operating range. The second conventional algorithm applied the setback temperature of 25 °C during the unoccupied period. Therefore, the operating range was 23–26 °C during the occupied period and

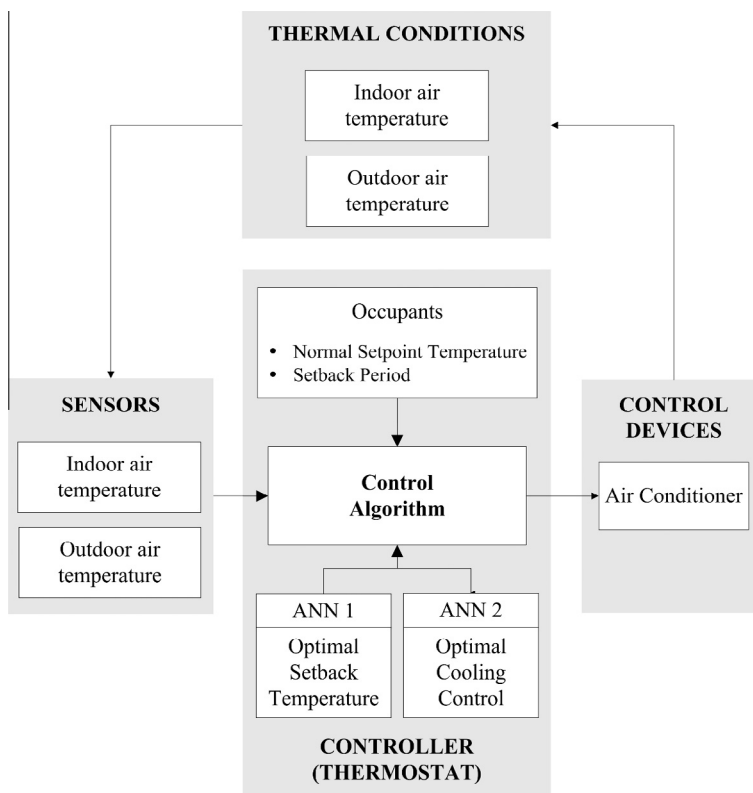


Fig. 3. Workflow of the controller.

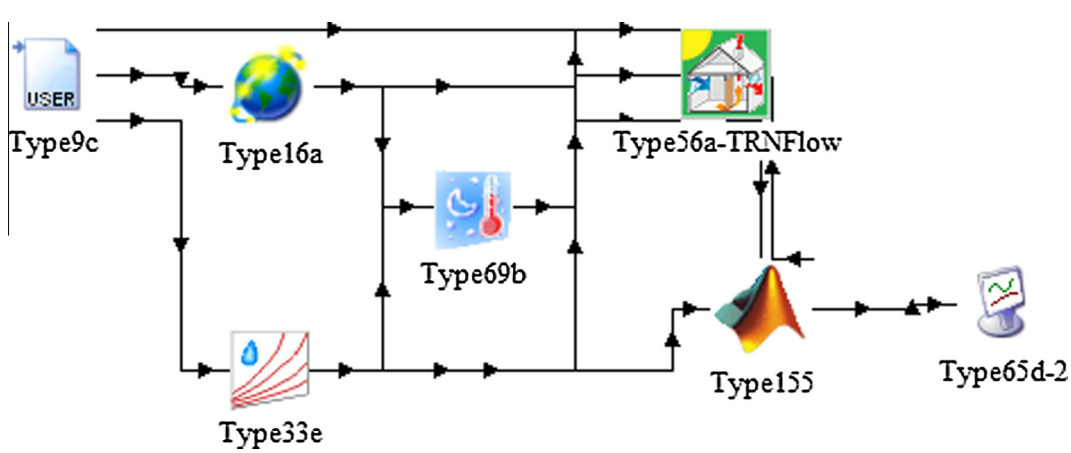


Fig. 4. Simulation modeling results.

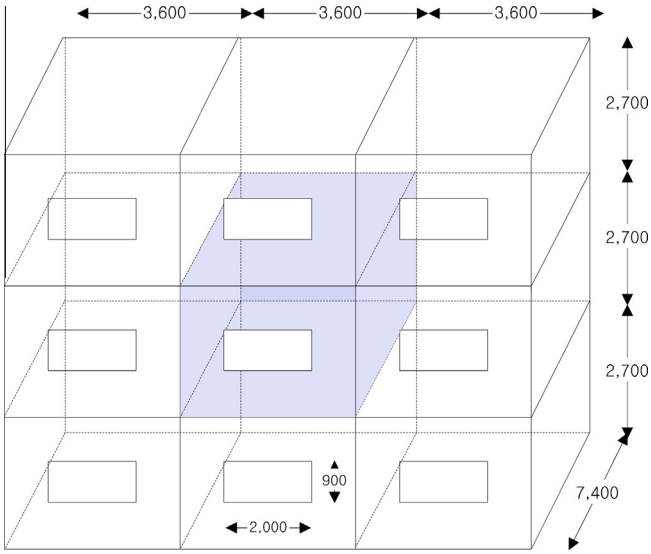


Fig. 5. Test model (unit: mm) [19].

25–28 °C during the unoccupied period. The setback temperature during the unoccupied period followed the value used in a previous study which investigated the impact of thermostat strategies on the residential energy consumption [23].

On the other hand, the optimal algorithm developed in this study employed a 23 °C set-point temperature during the occupied period and the predicted optimal setback temperature obtained by model 1 was employed during the unoccupied period. In addition, the optimal starting moment from model 2 was used during the unoccupied period to provide improved thermal comfort. Performance tests were conducted for two weeks from August 5th to 18th 2014, when the cooling load was at its peak.

4. Result analysis

4.1. Prediction performance of the ANN models

The prediction performance of the first ANN model, which calculated the amount of cooling energy during the unoccupied period, was evaluated using the comparison with the simulated results (Fig. 6). The predicted amounts from the ANN model showed similar results to those of the numerically simulated amount. For the 100 cases, the amount of cooling energy used ranged between 0.03 and 4.06 kW h by ANN prediction and between 0.00 and 5.05 kW h by simulation. The difference between the ANN prediction and simulation ranged between 2.47 kW h and 0.01 kW h in absolute values and their average was 0.57 kW h, which was 17.07% of the average of the simulated results. In addition, the MBE between the ANN prediction and numerical simulation was 17.66% for the 100 cases. In the previous study, the statistically meaningful value for proving the validity of the model was proposed to be around 25% [24]. Thus, the average difference of 17.07% and MBE of 17.66 supported the applicability of the developed ANN model to the control algorithm for improving building energy efficiency.

The prediction performance of the second ANN model, which calculated the number of minutes required for restoring the current indoor temperature to the set-point temperature, was also evaluated using the comparison with the simulated results. For this, 100 data sets were collected from the simulation model. As shown in Fig. 7, the predicted results from the ANN model showed a similar pattern to that of the numerically simulated results. The amount of time required ranged between 2.09 and 141.09 min by ANN prediction and between 2.00 and 164.00 min by simulation. The difference between the ANN prediction and simulation ranged between 0.00 and 42.48 min in absolute values and their average was 7.06 min, which was 20.87% of the average of the simulated results. The MBE between the ANN prediction and numerical simulation was 21.90% for the 100 cases. Similar to the first model, the validity of the second ANN model was proven with a lower average of difference and MBE of less than 25%; thus, the applicability of the developed ANN model to the control algorithm was proved for supplying improved thermal comfort when the normal set-point temperature would be applied at the beginning moment of the occupied period.

4.2. Performance analysis of the control algorithms

The comparative test results of the optimal algorithm and the two conventional algorithms are shown in Figs. 8–10 for a sample day. The first conventional algorithm, which did not apply the setback temperature for the unoccupied period, operated the cooling system between 23 and 26 °C all day (Fig. 8); thus, the indoor temperature was maintained within this range. On the other hand, the second conventional algorithm applied the setback temperature during the unoccupied period for improving energy efficiency (Fig. 9). The indoor temperature during the unoccupied period therefore increased to a level where air-conditioning was needed between 25 and 28 °C.

The temperature profile obtained by the optimal algorithm is shown in Fig. 10. Since the first ANN model predicted the cooling energy consumption for different setback temperatures during the unoccupied period and proposed the most energy-efficient temperature, the algorithm employed the proposed temperature as a setback temperature. The setback temperature was 40 °C for this sample day. The cooling system did not work during the unoccupied period because the indoor temperature did not reach the setback temperature.

Fig. 11 shows the amount of cooling energy consumption during the setback period according to the change of the setback temperature. The amount of cooling energy was calculated for the evaluation period using the TRNSYS and MATLAB simulation methods. The cooling energy increased as the higher setback temperature was applied for the whole evaluation period. In particular, the consuming pattern was identical for the cases that the setback

Table 3
Comparatively tested algorithms.

Operating method of the cooling system		Conventional algorithm without setback	Conventional algorithm with setback	Optimal algorithm
Set-point temperature (°C)	00:00–08:00 (occupied)	23	23	23
	08:00–18:00 (unoccupied)	23	25	Optimal setback temperature by Model 1
	18:00–24:00 (occupied)	23	23	23
Operation during the unoccupied period		Operation by designated setback temperature		Operation by optimal setback temperature by Model 1 and optimal starting moment by Model 2

temperature was set to 32 °C and higher. Thus, the propriety of ANN model and algorithm, which determined 40 °C as the most energy efficient method, was proved.

The cooling system started before 18:00 by the optimal algorithm when the normal set-point temperature was applied. As shown in Fig. 12 in detail, the second ANN model predicted the required time as 11 min to restore the indoor temperature to the normal set-point temperature. Therefore, the cooling system started working at 17:49, resulting in comfortable temperature conditions when the normal set-point temperature began at 18:00. In contrast, the second conventional algorithm provided uncomfortable temperature conditions over 26.0 °C for a certain period after 18:00 as shown in Fig. 12.

Table 4 summarizes the performance results of the three control algorithms for the entire test period. The average indoor temperature was conditioned to be lower when the first conventional algorithm was applied since the setback temperature was not considered during the unoccupied period. On the other hand, the second algorithm and optimal algorithm provide higher indoor temperature by applying the setback temperatures.

The total period of discomfort for the first control cycles after 18:00 when the normal set-point temperature began to be applied showed different results according to the control algorithms. The conventional algorithm without the setback application did not present a period of discomfort. This was because the set-point

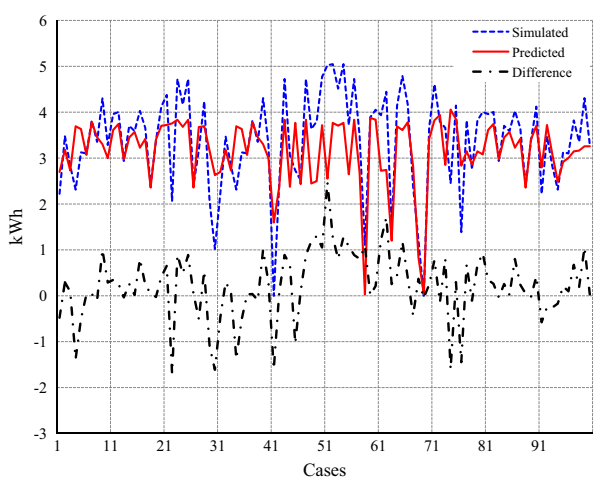


Fig. 6. Cooling energy consumption by ANN prediction and numerical simulation.

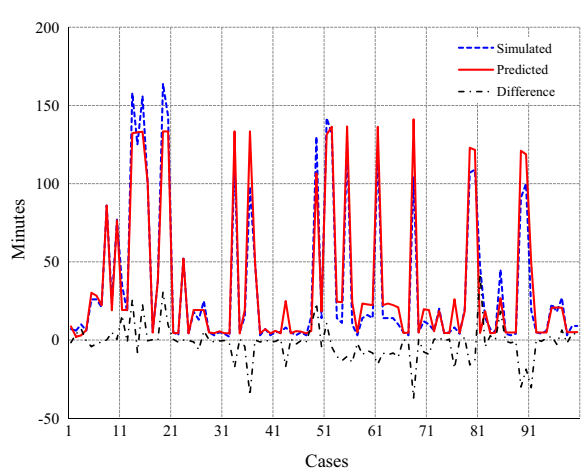


Fig. 7. Number of minutes required for restoring current indoor temperature to the normal set-point temperature by ANN prediction and numerical simulation.

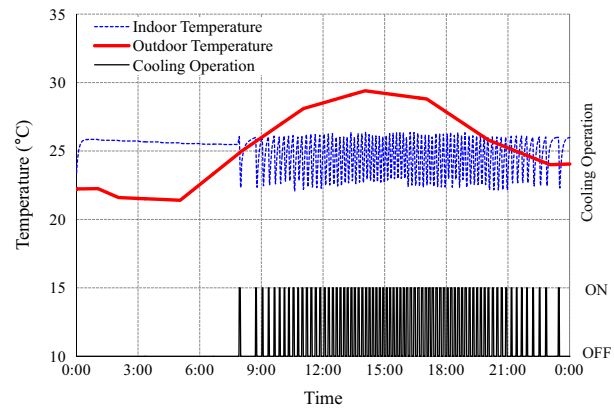


Fig. 8. Temperature conditions and cooling operation by the conventional algorithm without setback (August 9th 2014).

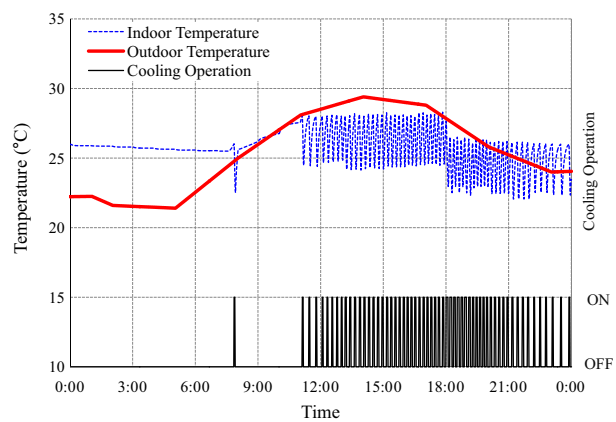


Fig. 9. Temperature conditions and cooling operation by the conventional algorithm with setback (August 9th 2014).

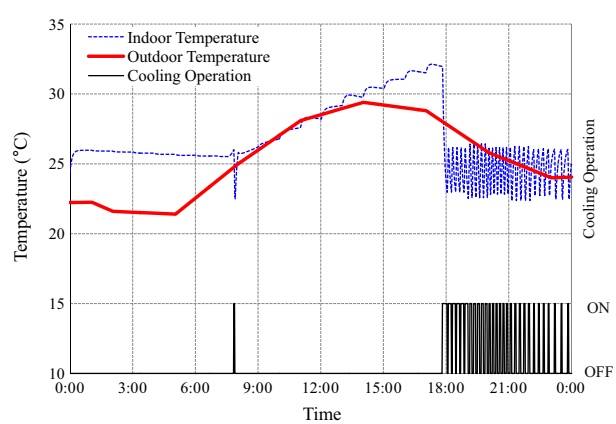


Fig. 10. Temperature conditions and cooling operation by the optimal algorithm (August 9th 2014).

remained unchanged for the entire day. However, the conventional algorithm with setback and the optimal algorithm provided a certain period of discomfort since they employed the setback temperature during the unoccupied period. The lengths of these periods were 63 min and 26 min, for the conventional algorithm with setback temperature and the optimal algorithm, respectively. Since the optimal algorithm employed the ANN model for predetermining the cooling system operation before the normal set-point temperature was applied, the period of discomfort was

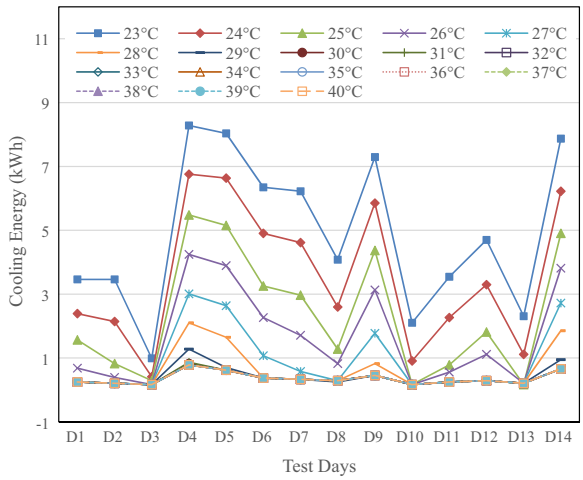


Fig. 11. Cooling energy consumption during the unoccupied period according to the different setback temperatures.

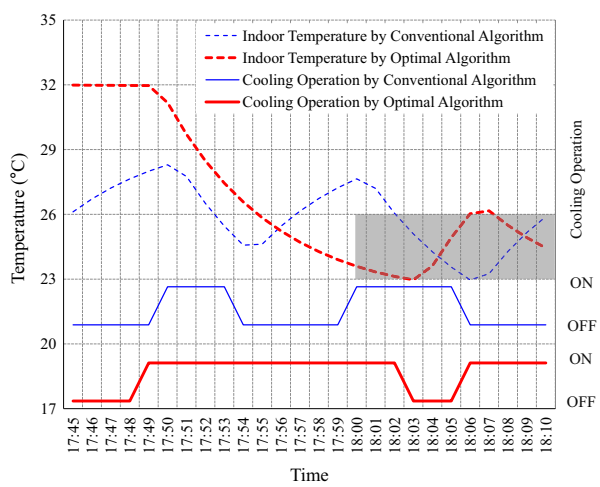


Fig. 12. Temperature conditions and cooling operation in detail when the normal set-point period began (August 9th 2014).

reduced compared to the conventional algorithm with the setback temperature.

The total number of operating minutes of the cooling system and the amount of energy were largest by as much as 2516 min and 103.68 kW h, respectively, when the conventional algorithm without setback was applied because the cooling system worked due to the identical set-point temperature during the unoccupied period. The conventional algorithm with the setback worked for a reduced period of as much as 1875 min and thus less energy was used with 77.27 kW h because the setback temperature was applied during the unoccupied period. In addition, the optimal algorithm showed the most energy efficient results with 1537 min of system operation and 63.34 kW h energy consumption since the highest optimal setback temperature was applied based on the prediction by the ANN model. The reduced amounts by the optimal algorithm were 38.91% and 18.03% compared to the first and second conventional algorithms, respectively.

From the analysis of the results, it can be concluded that the optimal algorithm provided a more comfortable thermal condition by the predictive cooling system operation than the conventionally applied control method with setback temperature during the unoccupied period. In addition, building energy efficiency can also be improved when the ANN-based optimal setback temperature is applied in the control algorithm.

In spite of the advantages found in the analysis, there are intrinsic disadvantageous features in the ANN-based algorithm. First of them is to require the proper and sufficient training data sets for the ANN models. Even though the model can adapt itself to the surrounding environment, proper initial input data sets which are significantly related to the output need to be considered and their number of sets should be sufficient in order to stably calculate the output.

The next of them is to require supportive functions in the algorithm for the more proper operation of the cooling system. The ANN models have probability to produce erroneous output values. Thus, functions in the algorithm should be able to discriminate the incorrect output for preventing malfunctions of the cooling system and iterative training with incorrect data set. Before the actual application to the buildings, the more thorough verification is required.

5. Conclusion

The aim of this study was to develop a control algorithm for proving improved thermal comfort and building energy efficiency during the cooling season. For this, two ANN-based predictive and adaptive models were proposed and employed in the algorithm. One model was used for predicting the cooling energy consumption during the unoccupied period for the different setback temperature and the other model was used for predicting the time required for restoring the current indoor temperature to the normal set-point temperature. The prediction accuracy of the two ANN models was tested and the performance of the algorithm was analyzed using the numerical simulation method. The findings in the tests are summarized as follows:

(1) The first ANN model, which calculated the amount of cooling energy during the unoccupied period, showed accurate prediction results by the acceptable difference with the simulation results. The average difference and MBE were 17.07% and 17.66%, respectively, for 100 cases, which was the statistically meaningful value for proving the validity of the model. Thus, the applicability of the developed ANN model to the control algorithm was proven for improving building energy efficiency.

(2) The second ANN model, which calculated the number of minutes required for restoring the current indoor temperature to the normal set-point temperature, also presented accurate prediction results. The average difference and

Table 4
Performance summary of three algorithms.

Performance components	Conventional algorithm without setback	Conventional algorithm with setback	Optimal algorithm
Average indoor temperature (°C)	25.12	26.00	26.11
Uncomfortable minutes after normal set-point period began	0	63	26
Total operating minutes of the cooling system	2516	1875	1537
Amount of energy (kW h)	103.68	77.27	63.34

MBE with the simulation results were 20.87% and 21.90%, respectively, for 100 cases. Similar to the first model, the second ANN model proved its validity as it was successfully applied to the control algorithm for advancing thermal comfort when the normal set-point temperature would be applied.

(3) The performance of the two ANN model based optimal algorithms was tested using comparative analysis with the two conventional control algorithms. The optimal algorithm provided a more comfortable thermal condition by the predictive cooling system operation than the conventionally applied control method with setback temperature during the unoccupied period. In addition, the building energy efficiency can also be improved when the ANN-based optimal setback temperature is applied in the control algorithm. From the analysis, it can be concluded that the optimal algorithm can supply a more comfortable and energy efficient indoor thermal environment in a comprehensive manner.

The two ANN models and the control algorithm showed their potential to improve the indoor temperature conditions and building energy efficiency of accommodation buildings during the cooling season. Further study is warranted to test the performance of the thermal control algorithm in a real building situation. For this, the developed algorithm and control systems are being equipped in an existing building. The performance analysis with the actual data will support the applicability of the suggested algorithm.

ANN models and an algorithm for the heating season will also be developed in a future study. In addition, the integrated thermal control algorithm needs to be developed for providing the overall thermal comfort of the indoor space. A PMV-based control strategy can be a solution for providing overall thermal comfort based on the proper controls of the humidity as well as temperature. Based on a comprehensively developed control algorithm, the indoor thermal environment of the accommodation buildings will be better conditioned with improved comfort and energy efficiency.

Acknowledgements

This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (Grant number: 2015R1A1A1A05001142) and by Chung-Ang University Research Grants in 2015.

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