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Prediction of optimum heating timing based on artificial neural network by utilizing BEMS data

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ABSTRACT

As the energy consumption in buildings accounts for about 30% of the total energy consumption, there is a growing need for people to pay attention to energy saving in buildings. From the perspective of building life cycle, buildings consume 70–90% of energy for their operation, and therefore it is very important to reduce the energy consumed for building operation. In this regard, we developed an Artificial Neural Network (ANN) model, which predicts when the heating system should run in order to reduce energy usage on winter mornings when the energy consumption is high. Especially, existing research about heating timing uses typical variables as input data of the ANN model. But in this study, accuracy of prediction is improved by adding time variable to the ANN model. Consequently, the predictive data of the ANN model were found to be significantly similar to the empirical data of BEMS, and the prediction performance of the ANN model was approximately 13.13% of CvRMSE and 0.197% of MBE, thus satisfying ASHERAE guideline 14. Therefore, the ANN model proposed in this study would help not only in reducing the energy consumed in buildings but also in providing pleasant thermal comfort by predicting the optimal heating timing.

1. Introduction

Recently, there has been a steady increase in greenhouse gas emissions across the globe, and climate change leads to environmental issues. In order to reduce the impact of climate change, various countries signed the Paris Agreement in 2016 under the leadership of the Intergovernmental Panel on Climate Change (IPCC), and Korea stated its goal of reducing greenhouse gas emissions by 37% from business-as-usual (BAU) levels by 2030 in the United Nations Framework Convention on Climate Change (UNFCCC). [1]

As of 2015, the energy consumption in Korea was as follows: 48% for industries, 19% for transportation, and 33% for buildings. This means that the energy consumed in buildings accounts for about 30% of the total energy use. [2] In particular, as people are giving more importance to the thermal comfort of occupants owing to the growing domestic incomes and increasing standards of living, energy consumption tends to increase [3], and the figure has been on the rise since 2000. [4] Therefore, the government is searching for various measures to reduce energy consumption in buildings, and various projects are underway.

When it comes to the life cycle of buildings, buildings use 70–90% of its total energy for their operation [5,6]. Of this, about 30–50% is consumed by HVAC systems. [7] The energy consumption distribution of commercial buildings during winter is shown in Fig. 1, which shows that heating energy accounts for 14% of the total energy consumption in buildings. [8] Thus, it can be seen that heating consumes much energy during winter, and in particular, higher energy are used in commercial buildings in order to warm up the buildings during morning hours when people start coming in. It is necessary to propose a plan to reduce the energy consumed for heating during morning hours.

1.1. Purpose of the study

Many measures have been suggested to reduce the energy required for building operation, including the Building Automation System (BAS) or the Building Energy Management System (BEMS). The BEMS technology has reached a stable stage in terms of hardware, but not so much in terms of the operation technology and software for analyzing the collected energy data. [9] In addition, even if the BEMS is installed in a building, there are many cases where the BEMS is used only for simple data storage or comparison due to the lack of experts. Therefore, it is necessary to come up with measures to overcome the limitations of the current BEMS. To that end, this study was designed to develop a prediction model, which can reduce energy consumption by using the empirical data collected by the BEMS. It especially focuses on energy reduction during the morning hours in commercial buildings where

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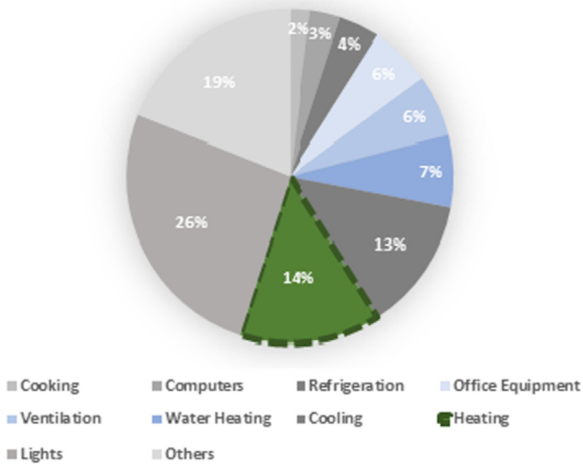

Fig. 1. Energy Consumption Distribution of Commercial Buildings.

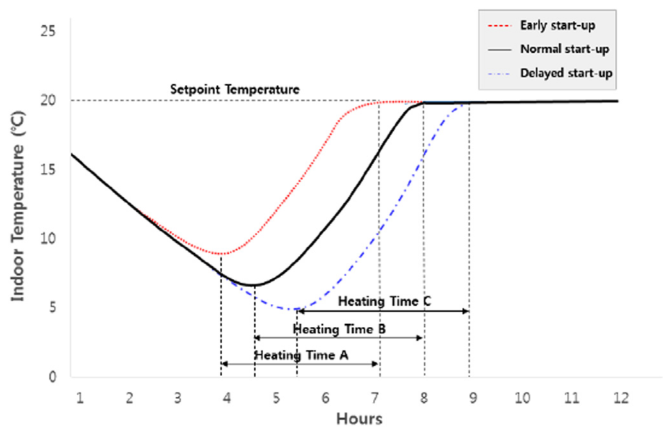

Fig. 2. Changes in Indoor Temperature according to Buildings' Heating Timing during Winter.

there is significant energy consumption. In general, commercial buildings operate heating facilities before their operation time for the thermal comfort of occupants and for preheating the buildings. When doing so, it is very important to set the heating time. For this reason, office buildings typically use HVAC start-up algorithms to control the system. As shown in Fig. 2, if the heating facilities are started too early and the indoor temperature reaches the set-point temperature before the operation time, the temperature would remain the same in the early morning hours when people do not stay inside, leading to a waste of energy. However, if the heating facilities in the building are activated too late, the indoor temperature would reach the set-point temperature much later than the building's operation time, adversely affecting the thermal comfort of occupants.

It is necessary to consider buildings' heating timing in the morning hours during winter for the sake of energy management and comfort of occupants. In previous research, mathematical methods were often used to predict the heating timing. [10] However, the predictive model using mathematical methods is mainly based on the use of rule-based algorithms [11], and real-time data of the buildings is rarely used. Particularly, in terms of a building facility manager, it is not possible to understand all the data of building; thus, the heating timing of the HVAC was manually selected by manager's experience. Recent developments of IoT based sensors have created an environment that can solve such problems. Big data is gathered by IoT based sensors, and many studies are working on optimizing building operation by studying how to use this big data. [12] Existing mathematical rule-based methods have limitations in handling a lot of data. And the data on the HVAC control and response of building load to predict the heating timing have many types and non-linear characteristics. [13] Therefore, this study predicted the heating timing with the ANN model which has a high prediction accuracy for non-linear and high-dimensional data. Also, the accuracy of the ANN model's prediction depends on the type of input data and how to convert it. In this study, we have developed the model which can derive predicted heating timing by selecting suitable input data for a real-time ANN model. If this ANN model achieves high accuracy of heating timing in office buildings, then it follows that heat operation timing would reduce energy consumption and improve the thermal comfort of building occupants.

1.2. Heating timing prediction method

In general, there are three ways to predict the starting time of heating facilities in a building, as shown in Table 1. [14]

Statistical analysis is a method that can make the most realistic prediction by using the empirical data. Although it is possible to make very precise prediction, it consumes a large amount of time and labor to collect the data. In addition, there is a limitation to the process variables due to the enormous amount of data.

Prediction using a simulation program is one of the most widely used methods. The higher the accuracy of the modeling, the more reliable the prediction and the program can be used to design various energy saving measures. However, for using such simulation programs, professional workers who can deal with the program are needed. The program is highly dependent on the engineers' work experience. [15] In addition, there is a high probability of human error in the process of inputting data and setting various hypotheses, adding significant uncertainty [16].

In order to overcome such limitations of statistical analyses and simulation programs, recently there has been a growing interest in intelligent computer systems. [17] As an intelligent computer system can easily process a huge amount of data comprehensively, it is suitable for buildings with BAS and BEMS installed as they can store enormous amount of data. In addition, unlike the simulation program, it is not necessary for people to input data; thus, it can prevent human error and can be an alternative to resolve hypothetic scenarios and their uncertainties, which could have occurred when using a simulation program. [18] Therefore, as it learns based on a vast amount of data, it is easy to process a large number of variables and make precise prediction.

Therefore, this study focused on the development of a model to predict the optimal heating timing of office buildings using ANN from among the various intelligent computer systems suitable for utilizing the BEMS data of the subject building. In addition, this research aims to train the ANN by using the actual data collected through BEMS and provides measures to overcome the limitations of statistical analyses, which consume much time and energy, or simulation programs, which

Table 1
Prediction Method.

Method	Statistical Analyses	Simulation Program	Intelligent Computer System
Features	- Predict very accurately - Need enormous data - Consume much time and workforce	- Most frequently used - Engineers' experience decides accuracy - Human error can occur when putting data in	- Easy to process enormous data comprehensively - Learn based on lots of data - Make precise prediction

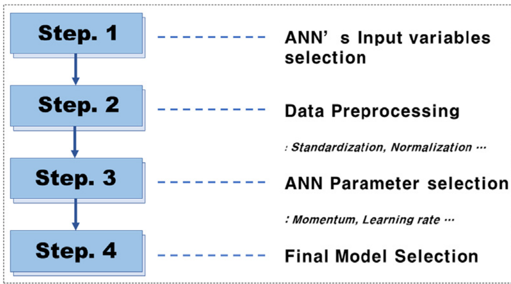

Fig. 3. Process flow chart for the ANN Model.

require a large amount of input data. To develop the ANN model for predicting the optimal heating timing, the study was conducted according to the following steps as shown in Fig. 3. In Step 1, the variables that are necessary or influential for the ANN are selected. In Step 2, the data is preprocessed in order to use the empirical data collected from BEMS in the ANN model. In Step 3, the parameter values for momentum and learning rates that are necessary for the ANN are selected. In Step 4, the hidden layer and hidden node of the ANN with the highest accuracy are selected.

Evaluation of the predicted values was based on Coefficient of Variation of Root Mean Square Error (CvRMSE) and Mean Bias Error (MBE). In addition, the standard for the results used the ASHRAE Guideline 14. [19]

1.2.1. ANN (Artificial Neural Network)

The ANN (Artificial Neural Network) model is used to predict heating timing in the early morning. ANN is learning algorithms developed by Warren S. McCulloch and Walter H. Pitt [20] in 1943 as a method inspired by biological neural networks of the human central nervous system. ANN is a method corresponding to the supervised learning method along the lines of the machine learning method and has a strong point when dealing with non-linear data with a lot of input variables. Especially, in this paper, ANN using Backpropagation and gradient-descent algorithms are used and, the latter of which is a method to minimize the error between the predictive value and the empirical value.

1.2.2. Data preprocessing

In the ANN model method, data-preprocessing is required for standardization of input variable data. Especially in buildings using BEMS, data is collected through various sensors. Therefore, preprocessing of data must be performed to evaluate each data equally. There are two kinds of data-preprocessing methods used in the ANN model:(1) Normalization, (2) Standardization. This study learns the ANN model using empirical data. Empirical data may have outlier data, but normalization is very sensitive to outliers. Therefore, standardization is used as a method of preprocessing input variables in this study. The formula is as follows:

$$\mathrm{x}_{\mathrm{standard}} = \frac{x-\mu}{\sigma}$$

(μ = Mean of empirical data, σ = Standard deviation of empirical data)

1.2.3. Evaluation

In order to evaluate the prediction results from the ANN model, the criteria of ASHRAE guideline 14 was used. The evaluation criteria are shown in Table 2. The Root Mean Squared Error (RMSE) is a measure of the difference between the predictive value and the actual measured value. CvRMSE is a percentage of RMSE. The Mean Bias Error (MBE) is a measure of how much the predictive value of the ANN model is biased. The formula of evaluation standard is as follows

Table 2
Prediction evaluation standard of ASHRAE guideline 14.

	CvRMSE	MBE
Prediction evaluation standard	30%	± 10%

$$\mathrm{RMSE} = \sqrt{\frac{\sum(P-X)^2}{N}}$$

$$\mathrm{CvRMSE} = \frac{RMSE}{\mu} \times 100 \quad (\%)$$

$$\mathrm{MBE} = \frac{\sum(P-X)}{\sum X} \times 100 \quad (\%)$$

(P = predictive result, N = The number of data, μ = Mean of empirical data)

1.3. Analysis of previous studies

With the increasing effort to reduce energy consumption in buildings, various measures are being designed to save energy. Especially in building operation, there are many cases that use the ANN model to reduce energy consumption.

The study conducted by Sooyoun Cho et al. [21] pointed out that engineering analysis techniques such as simulation programs have issues such as the results being changed by users, large time consumption, high cost, and uncertainties, and argued that the data-driven method would realize better energy saving than the engineering method with regard to the actual subject building. For efficient use of energy, the study by In-Ho Yang et al. [22] designed an ANN model to find out the stop time for the buildings' HVAC system when there are no occupants and there is no need to maintain the set-point temperature. The authors used the simulation data to train the ANN model, and through that, they suggested the optimal measurement intervals and allowable errors during the down time by date. In the study of Adbdullatif E. Ben-Nakhi et al. [23], the authors used the ANN model to predict the ending time of buildings' setback based on the simulation results of ESP-r as its ANN model learning data. As a result, the authors found out that the simulation predictive data were similar to that of the ANN model. In the study of In-Ho Yang et al. [24], the authors used the ANN model to predict the optimal heating operation timing of buildings. In their study, they mentioned that it was difficult to obtain empirical operation data, and instead they used simulation data. In addition, they used indoor temperature, outdoor temperature, indoor temperature variation, and outdoor temperature variation as the input variables. However, it is considered that the recent buildings with BEMS can use the empirical data as they are equipped with various sensors and data storage and that there can be other important variables affecting the heating timing when using the empirical data. Jin Woo Moon et al. [25] designed an ANN model that can control the thermal comfort, simulated houses located in the U.S., and used it for their learning data. As a result, the researchers suggested a thermal comfort strategy that can make the room more comfortable. Yong kyu baik et al. [26] used an ANN model to determine the optimal temperature for setting the buildings' setback temperature. In their research, they used simulation results as the data, and the value of the correlation coefficient, R^2, was 0.9999, which indicates a high accuracy.

The prediction methods using ANN in the previous studies mostly utilized simulation results as their learning data for the ANN model, and empirical data was rarely used. Buildings with BEMS store their empirical data each hour, and such data need to be utilized. In addition, in the previous studies, the variables put in the input layer of the ANN model were mostly typical input variables related to temperature, such as outdoor or indoor temperatures, as shown in Table 3. However,

Table 3
ANN Input Variables of Advanced Studies.

Author	Type of ANN Input Variables
Kang et al.	Indoor Temperature, Outdoor Temperature, Outdoor Humidity, Air Temperature, Steamed Heat, Warm Water Temperature
In-Ho Yang et al.	Indoor Temperature, Outdoor Temperature, Indoor Temperature Variation, Outdoor Temperature Variation
Jin Woo Moon et al.	Indoor Temperature, Outdoor Temperature, Indoor Temperature Variation, Outdoor Temperature Variation, Outdoor Humidity, Indoor Humidity, Outdoor Humidity Variation, Indoor Humidity Variation
Yong kyu baik et al.	Indoor Temperature, Outdoor Temperature, Indoor Temperature Variation, Outdoor Temperature Variation, Temperature Gap between Indoor and Outdoor

Fig. 4. Front View of Subject Building.

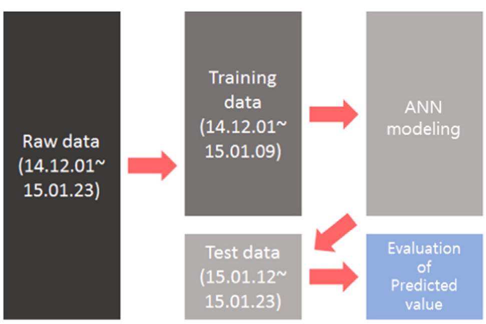

Fig. 5. Process of Applying the BEMS data of the subject building.

Table 4
Building Information.

Static Data	Dynamic Data
● Building envelope performance ● U-value ● Capacity of systems ● Shading devices ● Climate	● Indoor Temperature ● Outdoor Temperature ● Relative humidity ● Air velocity ● Direction of the wind ● Occupant ● HVAC schedule

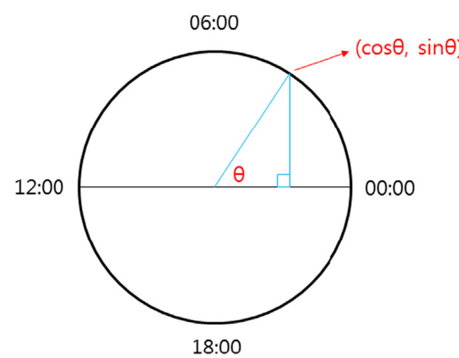

Fig. 7. Conversion of the time data.

when using the empirical data, there could be more variables having a new relationship with the output. Therefore, it is considered necessary to take a new approach on the input variables of the ANN model.

2. Subject building

In this study, the test-bed building located on the International

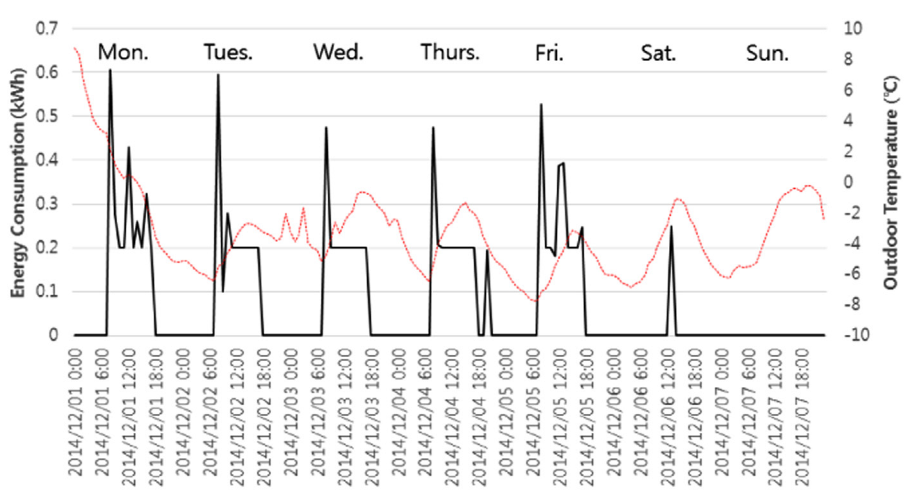

Fig. 6. Energy Consumption of Subject Building Compared to Outdoor Temperature.

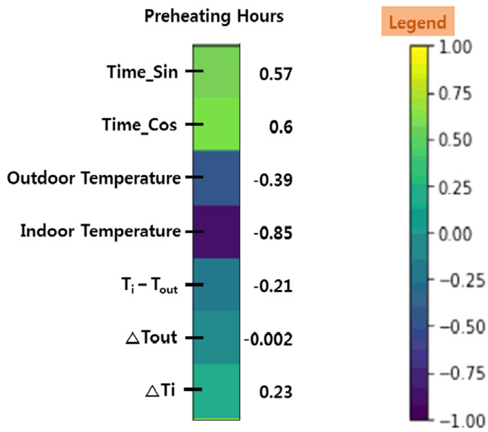

Fig. 8. Correlation coefficient of Input Variables.

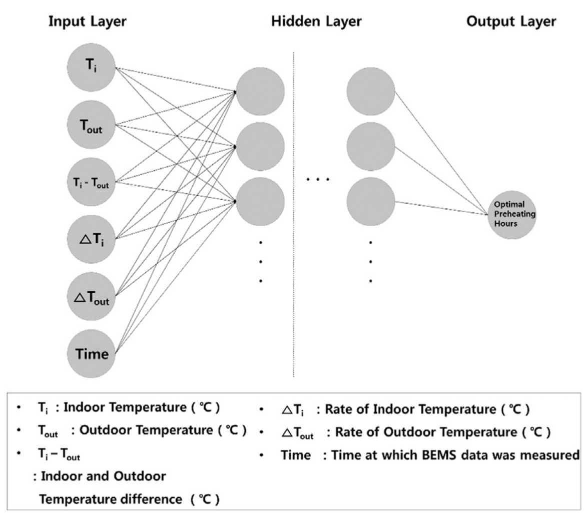

Fig. 9. Input Variables of ANN Model.

Table 5
Initial Parameter Value of ANN.

Classification	Parameter Values
Learning Rate	0.001
Momentum	0.9
The Number of Hidden Layers	2–5
The number of Hidden Nodes	6–20
Max iteration	50,000
Solver	Stochastic gradient descent
Activation Function	ReLU (Rectified Linear Unit)

Campus of Yonsei University at Yeonsu-gu, Incheon Metropolitan City, was selected as the subject building. Fig. 4 shows the front view of the subject building, which is an office building for the education and research facility. The subject building can automatically operate and control its facilities as it has BAS and BEMS, and can collect and store data for every 15 min with approximately 1600 sensors. The building is open from 8 a.m. to 6 p.m. on weekdays. As shown in Fig. 5, the empirical data collected from 1 December 2014–23 January 2015 in the building were used as the learning data in this research.

Fig. 6 illustrates the energy consumption empirical data of AHU for one week during the actual surveying period. It confirms that the building consumes a significant amount of energy in the morning when it starts operation. This is because during winter, a large amount of energy is needed for heating in order to warm up the building structure, which has already cooled down at dawn. In addition, it takes considerable time and energy to warm up the building especially in the morning on Monday as the building is closed during the weekends.

Therefore, it is considered important to come up with measures to save energy in the office building as it consumes a large amount of energy in the morning during winter.

3. Overview of ANN model

In this study, Scikit-learn, which is a library of Python for machine learning, was used to predict the heating timing. In particular, the study was conducted by using the Multi-Layer Perceptron (MLP) regressor to realize the ANN.

In order to prevent the overfitting of the ANN model, the following three issues were considered.: i) Data-shuffling was performed to eliminate the tendency of raw data.; ii) Raw data were split at a ratio of 7:3, where 70% of the data was used as a training data, and the remaining 30% of the data was used for validation.; iii) Early-stopping algorithm was used to prevent too much learning from the training data.

3.1. Input variables selection of ANN model

Table 4 shows the general information that can be obtained from the building. In order to predict the heating operation timing under rapidly changing conditions, we developed a prediction model using the dynamic data collected from BEMS. In previous studies, the following parameters were mainly used for the ANN input layer: i) indoor temperature; ii) outdoor temperature; iii) indoor temperature variation; iv) outdoor temperature variation, and; v) variables for indoor-outdoor temperature difference. Schedules for office buildings are consistent for the day. [27] Office buildings generally have clear patterns for weekdays and weekends, and the patterns of the heat load during the day are unchanging because of the time of a regular commute. [28,29] This is because the HVAC control of the building is regularly applied at a certain time, and the indoor environment shows regular temperature changes with hours. So the time variable in the office building can be a good predictor of room temperature changes of the building. However, existing researches mainly use typical parameters, and studies using time variable to predict the heating timing are rare. Therefore, the effect of traditional variables and time variables on the preheating time of buildings was analyzed through a correlation coefficient.

In this study, in addition to the above-mentioned five variables, information on the time at which the BEMS sensor measured the data was included, and therefore, a total of six variables were used as the input variables. As the time when the heating facility is activated is closely related to the outdoor and indoor temperatures, they also should be considered.

As shown in Fig. 7, the time of day is cyclic data that repeated regularly. (For example, if the current time is 23:00, the number becomes smaller at 01:00 after 2 h.) Time is not ordinal data because it repeats continuously, so it is necessary to modify the following equation.

$$\text{Hour} = \left(\cos\left(\frac{2\pi \times h}{24}\right),\ \ \sin\left(\frac{2\pi \times h}{24}\right)\right)$$

(h = the time at which the BEMS sensor measured the data)

In particular, the correlation coefficients between the six input variables of the ANN and the heating timing (output variable) are as shown in Fig. 8. From the analysis of correlation coefficients, it can be seen that the correlation coefficients of the indoor temperature and time are significantly high compared to the other variables.

Therefore, as shown in Fig. 9, the ANN model was developed based on six input variables in this research.

Since ANN has two or more hidden layers, the number of hidden layers is modeled for two to five. In addition, as the number of hidden

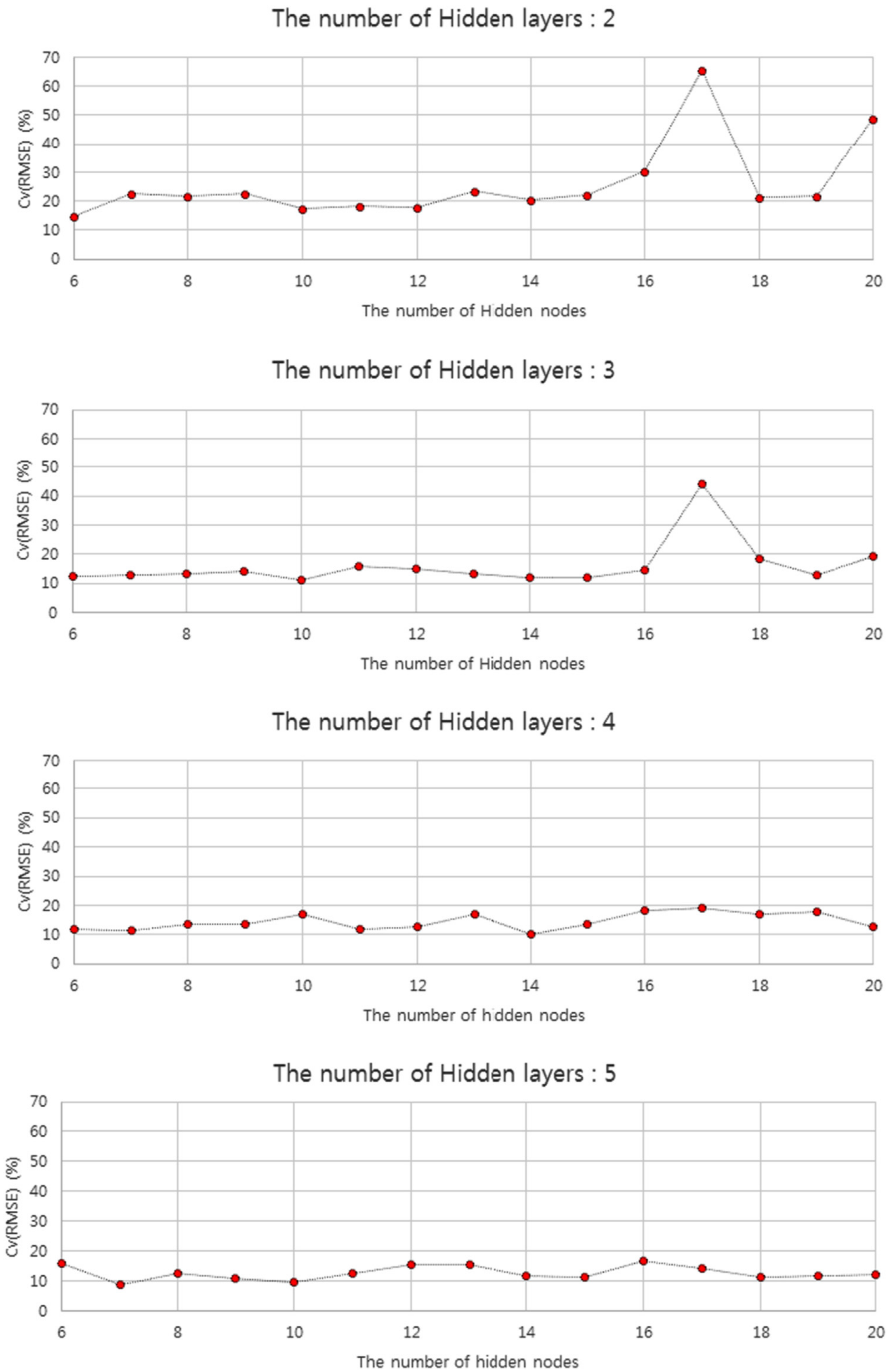

Fig. 10. CvRMSE of ANN Model with Time Variable (Layer : 2–5, Node : 6–20).

nodes is generally larger than the number of layers, optimal parameter values are obtained by setting its initial value as 6–20 as shown in Table 5.

3.2. Producing optimal parameter of ANN

In this section, the prediction accuracy is evaluated to check whether the performance of the ANN model is improved when the time variable is added to the five variables frequently used in the previous studies. For this, the optimal numbers of hidden layers and nodes were calculated for six variables, and the prediction accuracy was compared with that of the ANN model in which time variable was not included as the input variable, under the same condition.

3.2.1. Optimal heating timing of the ANN model with time variable

The ANN model with the time variable, consists of six input variables: i) indoor temperature, ii) outdoor temperature, iii) indoor temperature variation, iv) outdoor temperature variation, and v) indoor-outdoor temperature difference. Fig. 10 illustrates CvRMSE, the prediction accuracy, in order to find out the optimal number of the hidden

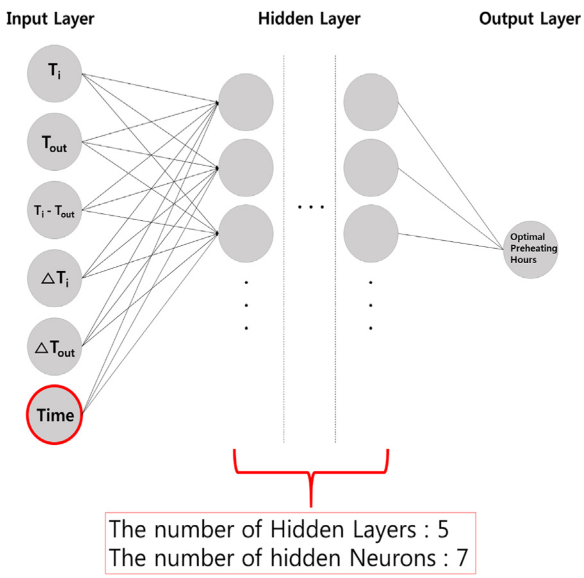

Fig. 11. Optimal Number of Hidden layers & nodes of ANN Model with Time Variable.

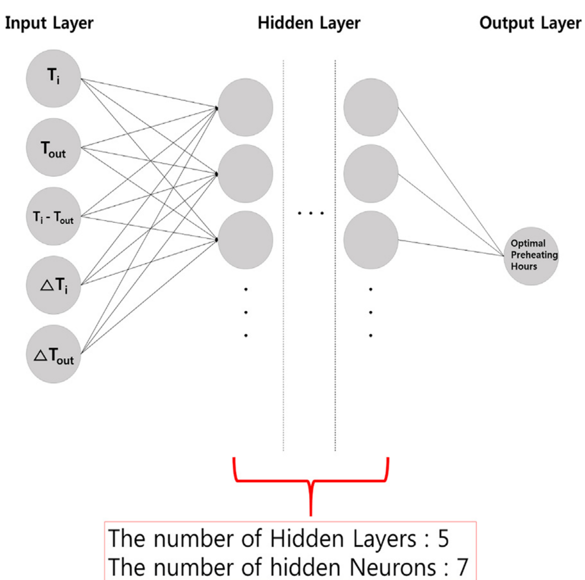

Fig. 12. Optimal Number of Hidden layers and nodes of ANN Model without Time Variable.

Table 6
Comparison between ANN Model with & without Time Variable.

Accuracy	ANN Model with Time	ANN Model without Time	ASHRAE Guideline 14
CvRMSE	13.13%	25.63%	30%
MBE	0.197%	6.93%	± 10%
Condition	No. of Hidden layers: 5 No. of Hidden Nodes: 7		

layers and nodes of the ANN model with the time variable.

Fig. 11 shows the results of the modeling; the optimal numbers of hidden layers and nodes of the ANN model for the heating operation are five and seven. Here, the prediction accuracy of CvRMSE is about 13.13% and that of MBE is about 0.197%, both of which fall into the range of the confidence limit, defined by ASHRAE Guideline 14. In particular, considering that the MBE value is significantly low, it is confirmed that the prediction results are evenly distributed.

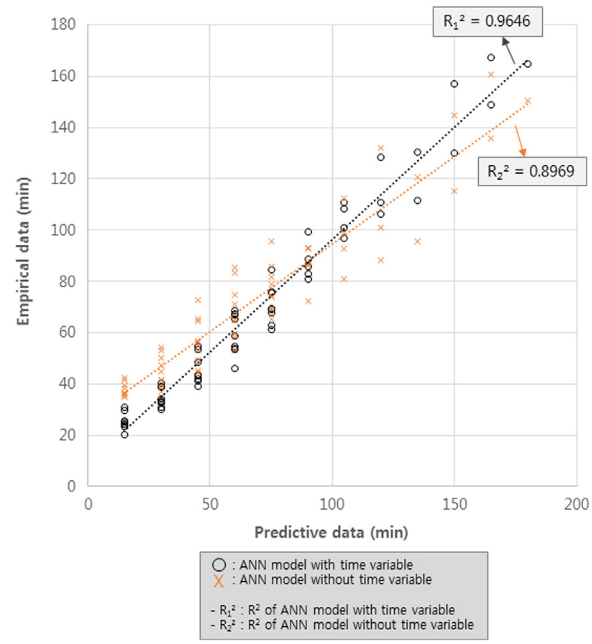

Fig. 13. Comparison with ANN model with time and ANN model without time.

3.2.2. Optimal heating timing of the ANN model without time variable

The prediction performance of the ANN model without the time variable was derived in order to check how its prediction accuracy of the optimal heating timing changes depending on the time variable. The structure of the ANN model is based on five hidden layers and seven hidden nodes, which turned out to be the most accurate case when the ANN model included the time variable. As shown in Fig. 12, the input variables of the ANN model are as follows: i) indoor temperature, ii) outdoor temperature, iii) indoor temperature variation, iv) outdoor temperature variation, and v) indoor-outdoor temperature difference.

Here, the value of CvRMSE was about 25.63% and that of MBE was about 6.93% when the ANN model did not include the time variable. This indicates that the ANN model with the time variable has a significantly higher accuracy than the model without the time variable. In particular, the results of the ANN model without the time variable are significantly biased as its MBE value is high.

4. Evaluation of prediction accuracy of ANN model

Table 6 compares the results of the two cases. It shows that the prediction of the ANN model with time as its input variable is more accurate than the model without time as its input variable, although both models satisfied the ASHRAE Guideline 14. Therefore, compared with the model using only physical variables, such as indoor and outdoor temperatures, the ANN model with the time variable has greater prediction accuracy, which means that time is a significant variable and has a huge impact on the prediction accuracy of the model.

Fig. 13 shows the prediction accuracy of the ANN model with time and without it. In the case of adding a time variable to the ANN model, the accuracy of the prediction improves about 10% compared with not using a time variable. Particularly, when the preheating time is less than 100 min during the morning, the distribution of graph's data is concentrated near the trend line, indicating that the prediction accuracy of a day with less preheating time is more accurate. It is considered that the longer the preheating time is, the more affected by other external environmental factors. And if the preheating time is long, the prediction accuracy of the ANN model is lowered. Especially, if the

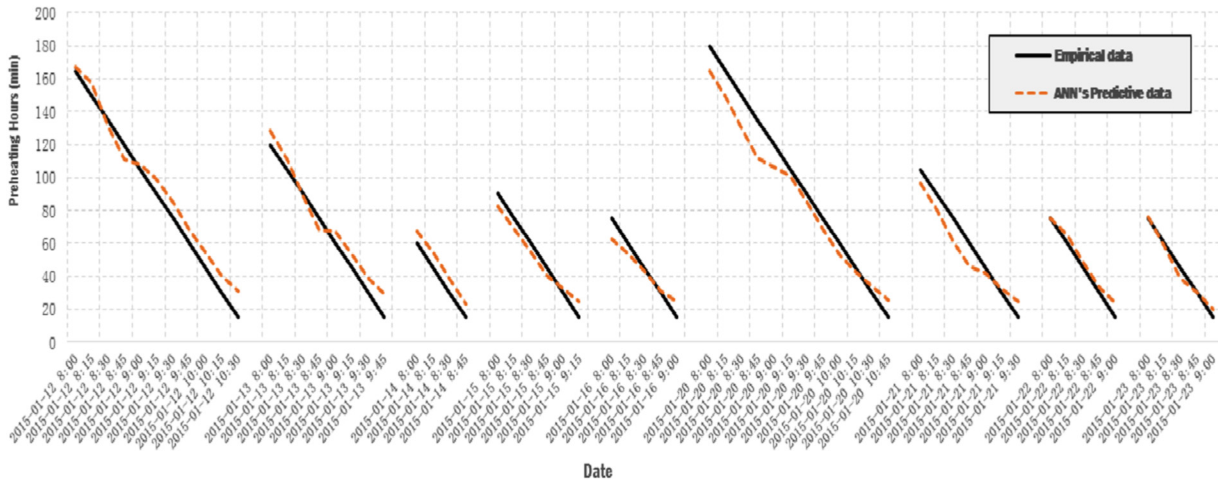

Fig. 14. Comparison between Predictive and Empirical Data by Date.

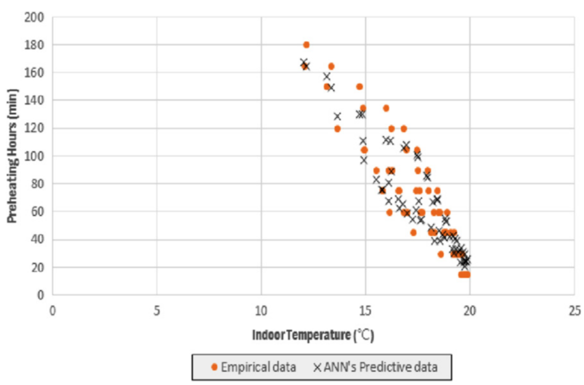

Fig. 15. Comparison between Predictive and Empirical Data by Indoor Temperature.

preheating time is less than 100 min, the model using time variable shows more accurate appearance rather than the ANN model without a time variable.

Fig. 14 compares the predictive data with the empirical data of the ANN model for each day, and it shows that the accuracy results are significantly similar to the empirical data collected from the BEMS. Here, the coefficient value of determination, R^2, is 0.9646, which means that the prediction of the ANN model is accurate.

In particular, by analyzing the correlation coefficient of the operation timing and variables, it was found out that the correlation coefficient of the variable of indoor temperature has a high absolute value of 0.85, which means that the heating timing is closely related to the indoor temperature. Fig. 15 shows the relationship between the indoor temperature and heating timing. When the indoor temperature decreases, the time needed to warm up the building increases gradually as the correlation coefficient between the two variables is high. In addition, the distributions of the empirical and predictive values shown in this graph are very similar.

5. Conclusion

This study predicts the optimal heating timing as a measure to reduce energy consumption during the operation of a building. For this, a model was developed using ANN and the empirical data actually collected from the BEMS of the subject building was used for training ANN. The conclusions of the heating timing prediction by using ANN in this study are as follows:

(1) Analysis of the energy consumption characteristics of the subject building showed that buildings consume more energy for their operation on winter mornings. This is because in winter, the building requires a large amount of preheating energy as its building structure cooled down during dawn. Therefore, it is concluded that in winter, it is important to manage energy during morning hours as enormous energy loads are expected to be consumed in buildings.

(2) Research was conducted to predict the heating timing for reducing energy consumption in the morning by using the ANN model. The empirical data that was collected from the building with BEMS from 1 December 2014–23 January 2015 was used as the learning data for the model. In particular, correlation coefficient analysis was conducted using the following variables and the output variable (heating timing): i) indoor temperature; ii) outdoor temperature; iii) indoor temperature variation; iv) outdoor temperature variation; v) indoor-outdoor temperature gap, and vi) time. As a result, the correlation coefficient between the heating timing and the variables (indoor temperature and time) was found to be significantly high, indicating that these two variables are important.

(3) The prediction accuracy of the ANN model was evaluated according to its inclusion of the time variable. When it is included, the optimal parameter value of the model was five hidden layers and seven hidden nodes. In order to compare the gap in prediction accuracy between the models with and without the time variable, the results of both cases were predicted under the same condition. As a result, it was found that when time is included as a variable, the value of CvRMSE was 13.13% and that of MBE was 0.197%, whereas for the model without the time variable the value of CvRMSE was 25.63% and that of MBE was 6.93%. It was found that when time is added as an input variable, the prediction accuracy of the model was significantly improved, and its prediction results satisfied the standard, recommended in the ASHRAE Guideline 14.

The ANN model's accuracy depends on how the data is preprocessed and what kind of input data is used. Existing research that predict the indoor thermal related to heating timing in office buildings often uses only typical variables. (i.e. outdoor temperature, indoor temperature … etc.) and has rarely used time as a variable to predict indoor thermal information. However, since time is an important variable showing the variation of temperature during the day, it seems to have an important effect on the accuracy of prediction model as the result of this study.

In this study, there is a difference in prediction performance between model with time variables and not. In office buildings, people always go to work every day at a regular time, but conditions for the outside environment (i.e., outdoor temperature, rate of outdoor temperature) and indoor environment (i.e., indoor temperature, rate of indoor temperature) are always changing. The outside environment is affected by solar radiation, so when the sun rises, the temperature rises. When the sun goes down, the temperature goes down. The temperature change at specific times varies depending on the climate. In addition, the indoor environment is affected by occupants. When people go to work in the morning, the temperature is maintained at the set-point temperature during work hours (i.e., 08:00–18:00). The pattern in which these environmental conditions change varies over time. Therefore, using this pattern as input variables of the ANN model can improve its prediction performance. Using the time series data as input variable, as in this study, the accuracy of the ANN model for predicting the non-linear structure can be considerably improved.

However, this research is limited to ways to predict heating timing in winter season. So the ANN model in this study is required to predict cooling timing to reduce building's annual energy. There are still limitations about the number of data sets. In this study, about 300 data sets were used. It is a small number of data in ANN model. Therefore, it is necessary to make a model by training ANN with a larger amount of annual data in future research. In addition, this study has not reached the stage of demonstration because of early stage research. If the ANN model is applied to real buildings in future research, this study will demonstrate the accuracy of the ANN model and potential for energy savings.

Therefore, it is expected that the ANN model proposed in this study would play a significant role in providing a pleasant thermal comfort to buildings' occupants and reducing the energy consumption, when the heating timing is predicted using the empirical data of BEMS. In addition, as the utilization of big data increases with the development of IoT based sensors, the variable selection method of this study and the ANN model will contribute to better predict the optimal heating timing in real time.

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