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Predictive Model for the Optimized Mixed-Air Temperature of a Single-Duct VAV System

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Abstract: As global warming accelerates due to greenhouse gas emissions, more efforts are required to reduce greenhouse gas emissions. One of the methods used to save building energy is the efficient management of building mechanical systems. The economizer control of HVAC systems is an energy-efficient measure that improves operating methods by introducing outdoor air to save cooling energy when the outdoor-air temperature is sufficiently low. When the HVAC system is operated using economizer control, cooling energy can be saved, and the set-point of the mixed-air temperature is kept constant. Several studies are being conducted on the saving of energy using economizers. Although various studies have been conducted on the control of economizers, there is insufficient research dealing with the optimal control of mixed-air temperature in economizers that consider real-time changes. Therefore, in this study, predictive model-based mixed-air temperature optimization for a single-duct VAV system was constructed. For this, an ANN (Artificial Neural Network) that could be analyzed regardless of the variables was applied to predict the load and energy consumption and a simulator was constructed for the optimized mixed air temperature of the system. The predictive model-based control was evaluated in terms of its thermal comfort and energy, along with the existing economizer control. According to the application of the optimal economizer control, the energy consumption of the building was reduced by 28.9% compared to the existing dry-bulb temperature control, and was within ±1 °C of the indoor-air temperature set point.

Keywords: economizer; mixed-air temperature; predictive model; ANN (Artificial Neural Network)

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1. Introduction

As global warming accelerates due to greenhouse gas emissions, efforts to reduce these emissions are required. Building energy use accounts for approximately 25% of the total energy used, and this is increasing in South Korea. Most energy consumption is consumed by HVAC systems [1]. One method for saving energy in HVAC (heating, ventilating, and air conditioning) system is to improve the operating method. The economizer control of a HVAC system is an energy-efficient measure by improving the operating method that introduces outdoor air to save cooling energy when the outdoor-air temperature is sufficiently low. There are two types of economizer control: dry-bulb temperature control and enthalpy control. Each control adjusts the outdoor-air intake ratio by comparing indoor and outdoor temperatures or enthalpy, and at this time, the mixed air set-value is constant [2]. Cooling energy can be saved when the HVAC system is operated by an economizer control. When the system is operated by enthalpy control, more energy can be saved compared to dry-bulb temperature control [3–5].

Various studies are being conducted on saving energy through the use of economizers. Son et al. evaluated the control methods of various economizers while considering the mixed-air temperature, outdoor-air intake ratio, and cooling-energy consumption. In addition, economizer controls in various climate environments have been evaluated in terms of their cooling-energy consumption [6]. Yao et al. evaluated energy consumption by economizer controls in six climate zones in China using a simulation [7]. Wang et al. simulated the optimal economizer operating range for cost reduction caused by mechanical cooling and humidification and confirmed that energy was saved through an experiments [8]. In addition, studies on mixed-air temperature control in economizers has been conducted and is as follows: Gang et al. set up a steady-state energy model of the AHU system; they derived the optimal supply air temperature set point value for minimizing energy costs when controlling the economizer [9]. Lee et al. analyzed the relationship between the mixed-air temperature and energy consumption using the BIN method and a simulation; it was confirmed that the set point value of the mixed-air temperature at which energy consumption was minimized was not constant depending on the operating conditions. Accordingly, an optimal economizer control that adjusts the mixed-air temperature variable according to the load using an ANN (Artificial Neural Network) was presented [10] As such, the economizer is an energy-saving operation method, and the mixed air temperature set-point is controlled constantly in the existing control. Although various studies have been conducted on the control of economizers, there is insufficient research dealing with economizer optimal control that control the mixed air temperature set-point in consideration of real-time dynamic conditions (outdoor air condition, indoor occupancy etc.) in building. For economizer optimal control, it is necessary to predict the future state by considering all applicable conditions based on the current state.

ANNs are neural network-based learning algorithms used in biology that were developed by Warren McCulloch and Walter Pitts. An ANN can be used for analyses regardless of the variables involved because empirical inferences based on the learned data are possible without theoretical explanations. An ANN consists of an input layer that receives input data and delivers data, a hidden layer that processes input values and produces results, and an output layer that calculates the system output values according to the input values and system states. Each layer is composed of nodes, and the result is calculated by the links between the nodes and the transfer function [11,12].

ANN can process the relationships between non-linear variables accurately and quickly and is most widely used in the field of building performance and energy, and various related studies have been conducted. [13,14] Turhan et al., predicted the heating load of a building using an ANN model and evaluated it compared to a building-energy simulation tool. As a result of the evaluation, the percentage error between the ANN model and the energy simulation result was small and the prediction rate was high [15]. Kang et al. developed an ANN-based real-time predictive control and optimization algorithm for a refrigerator-based cooling system and its cooling-energy saving effects were analyzed by applying it to an actual building. The ANN was used to derive the optimal set point values for the refrigerator and condenser. The developed ANN model showed high accuracy, and energy consumption was saved during ANN-based control [16]. Bae et al. constructed a performance prediction model of a hydrothermal heat pump system using a dynamic simulation utilizing the hydrothermal heat pump system in combination with artificial intelligence technology [17]. Kang et al., developed a prediction model for the cooling-energy consumption of a VRF system using an ANN as a preliminary step to develop an optimal control algorithm for improving the energy performance of the VRF system. The performance of the developed prediction model met the standards of ASHRAE Guideline 14 [18]. As such, the ANN model can be used as a tool for predicting building performance, energy consumption, and system optimal control.

Therefore, in this study, a predictive model-based economizer control for optimized mixed-air temperature was developed. A load and energy prediction model was developed using an ANN (artificial neural network) that could be analyzed regardless of the variables involved. Additionally, a simulator for the predictive model-based control of optimized mixed-air temperature was constructed and the developed method was analyzed in terms of its mixed-air temperature set point changes and energy use, along with the existing economizer control.

2. Predictive Model for Optimized Mixed-Air Temperature

The economizer controls the outside, return, and exhaust dampers of the HVAC system in order to satisfy the mixed-air temperature set point, and generally keeps the mixed temperature set point constant. However, when the mixed-air temperature set value is changed in relation to indoor and outdoor conditions, energy savings are possible compared to the existing control method; so, this study proposed an economizer control method using predictive model-based mixed temperature optimization. To do this, a load prediction model was developed, and an energy prediction model was developed to derive a set value in a scenario where energy use was minimal. In addition, a co-simulation between EnergyPlus and Matlab was established through BCVTB. The detailed control method is as follows, and Figure 1 depicts the optimization concept.

Step 1. Prediction of the load based on the operating data: Predicted building load based on the operating data of the system.

Step 2. Prediction of energy use using the operating data, mixed temperature set point, and predicted load: Energy consumption was estimated through iterative prediction using the operating data, predicted load, and mixed-air temperature set point.

Step 3. Derivation of the economizer optimal mixed-air temperature set value: Based on the result predicted in Step 2, the mixed-air temperature set value for a scenario with minimal energy consumption was derived.

Step 4. The derived mixed-air temperature set point value was applied as the economizer control set point value of the next time step.

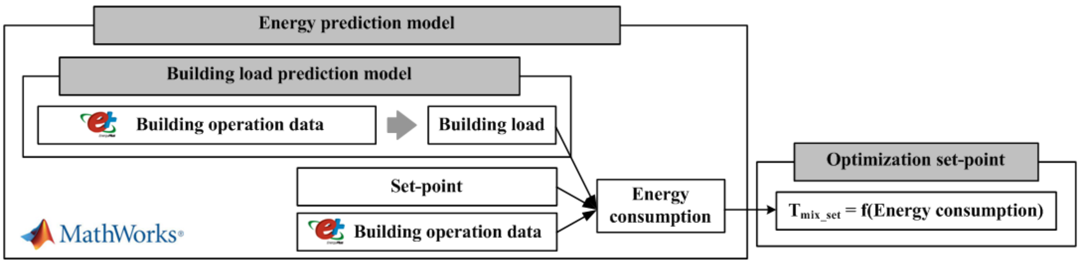


Figure 1. Schematic of the mixed temperature optimization process.

3. Development of the ANN Model

This study developed a load and cooling energy prediction model using an ANN for a predictive model-based economizer control. The ANN model development proceeded in the order of training data collection, input variable selection, and model development and validation.

3.1. Collecting Training Data

In this study, by using EnergyPlus, the data were collected through repeated simulations while changing the set value of the mixed-air temperature and were utilized as learning data to develop a load and energy prediction model. Learning data were collected at 1-hour intervals through a simulation. The data collected through the simulation were the building load, outdoor-air temperature, outdoor-air intake ratio, and supply airflow rate.

3.2. Selection of Input Variables

This study selected the initial input variables for the load prediction model based on the load calculation formula, and the initial input variables of the cooling energy prediction model were selected based on the cooling energy calculation formula. Equation (1) is the same as the equations for calculating the indoor load of the building and the load of the machine, respectively. Hence, the wall thermal transmittance rate, room area, outdoor-air temperature, indoor-air temperature, supply airflow rate, and specific heat of the air affected the load. At this time, the wall thermal transmittance rate, room area, and indoor temperature set values were constant, so the outdoor-air temperature and supply airflow rate were selected as the load prediction model input variables.

$$Q = mc\Delta t \tag{1}$$

Equation (2) was used to calculate the cooling-energy consumption. Energy consumption can be calculated from the enthalpy of the mixed and supply air, the design airflow rate, and the air density. At this time, the air density and the design airflow rate were constant, and since the mixed-air enthalpy is affected by the outdoor-air temperature and outdoor-air intake ratio when controlling the economizer, the outdoor-air temperature and the outdoor-air intake ratio were selected as input values. In addition, the mixed-air temperature was also used as an input variable for optimal energy calculation by changing the mixed-air temperature set point value, and the previously predicted building load was also used as an input factor.

$$E_c = \rho\dot{Q}(h_{mix} - h_s) \tag{2}$$

Table 1 lists the input and output variables of the developed prediction model. The input variables had different ranges and units, so a normalization process was performed to improve the learning and prediction performance of the ANN model.

Table 1. Input and output variables of the ANN model.

Category	Load Prediction Model	Energy Prediction Model
Input	Outdoor-air temperature (°C) Supply air flow rate (kg/h)	Outdoor-air temperature (°C) Indoor Load (kJ/h) Outdoor-air intake ratio (-) Mixed-air temperature (°C)
C	Indoor load (kJ/h)	Cooling energy (kWh)

3.3. Development and Prediction Models

A building load and cooling energy prediction model was developed using an ANN to develop the predictive model-based economizer control. At this time, the built-in Matlab function was used. For the optimization of the ANN prediction model, it was important to determine the number of neurons in the hidden layer and the number of hidden layers. In order to derive the optimal number of hidden layer neurons and hidden layers, each CV(RMSE) evaluation was performed after developing a predictive model while changing the number of hidden layer neurons and the number of hidden layers. Table 2 shows the final prediction model developed through the optimization process. The load prediction model consisted of 1 input layer, 4 hidden layers, and 1 output layer, and each node had 2, 5, and 1 nodes; the energy prediction model consisted of 1 input layer, 4 nodes, 1 hidden layer, and 4 nodes, as well as 1 output layer and 1 node. Moreover, 70% of the total data were used for training, 15% of the data not used as training data was used for validation, and the remaining 15% was used for testing.

Table 2. Parameter composition of the ANN model.

Category			Load Prediction Model	Energy Prediction Model
Function	Activation		Sigmoid	Sigmoid
	Performance		Mean squared error	Mean squared error
	Epoch		1000	1000
Structure	Input layer	Number of layers	1	1
		Number of neurons	2	4
	Hidden layer	Number of layers	4	1
		Number of neurons	5	4
	Output layer	Number of layers	1	1
		Number of neurons	1	1

To verify the ANN model developed in this study, the CV (RMSE; Coefficient of Variant Root Mean Square Error)—which are the error rata analysis methods suggested by the ASHRAE Guidelines—and R^2 were used.

4. Composition of the Simulator

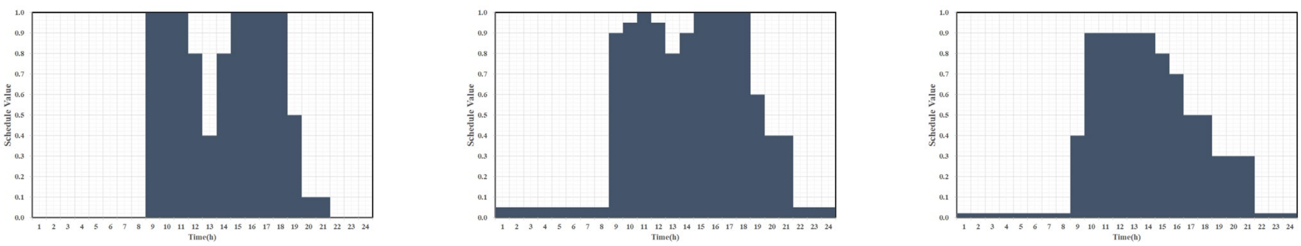
In this study, to compose an optimal predictive model-based economizer control using a simulation, a co-simulator using the EnergyPlus (V8-5-0), Matlab (R2020b) [19], and BCVTB (v1.6.0) programs was established. EnergyPlus is a program that integrates the advantages of DOE-2 and BLAST and enables dynamic analysis under abnormal conditions as well as the precise analysis of the heat transfer phenomena of radiation, convection, and conduction through the building envelope and was developed by U.S. department of Energy [20,21]. Matlab is a programming language and numeric computing environment developed by MathWorks. The BCVTB (Building Controls Virtual Test Bed) is software that combines disparate programs for co-simulations. For combination with BCVTB, EnergyPlus can be mapped through three interfaces: ExternalInterface:Schedule, ExternalInterface:Actuator, and ExternalInterface:Variable. The result can be transferred to BCVTB using the Output:Variable and EnergyManagementSystem:Output Variable [22]. When Matlab which neural network toolbox is available and EnergyPlus are linked using BCVTB, simulation by applying ANN model is possible.

4.1. Overview of the Simulation Model

The target building used in this study had an area of 927.20 m^2 and consists of 5 zones. HVAC with VAV system is installed, and differential dry-bulb temperature control is applied to HVAC system. The low limit for the economizer was 4 °C, and the high limit was 19 °C, andthe mixed-air temperature set value was 13 °C. In addition, the simulation was conducted at 15 min intervals for about 1 month, and during the simulation, weather information from Daegu, Korea was used. Table 3 lists the detailed simulation conditions, Figure 2 shows a schedule of the internal heat gain, and Figure 3 shows the system diagram.

Table 3. Overview of the simulation.

Category			Contents
Building	Area		927.20 m^2
HVAC system	System		HVAC with VAV system,
	Operating schedule		08:00–21:00
	Economizer	Control type	Differential Dry-bulb Control
		Low limit	4 °C
		High limit	19 °C
		Mixed air set value	13 °C
Simulation	Time-step		15 min
	Period		1 month
	Weather		Daegu, Korea



(**a**) (**b**) (**c**)

Figure 2. Internal heat gain schedules: (**a**) Occupancy; (**b**) Lighting; (**c**) Equipment.

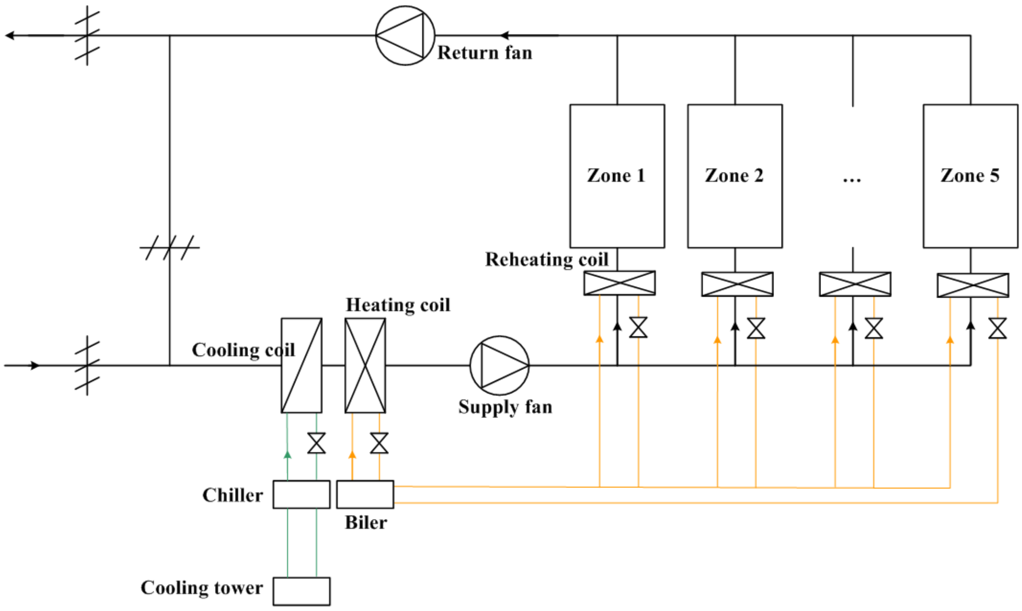


Figure 3. System diagram.

4.2. Co-Simulation

This study constructed a co-simulator using EnergyPlus, Matlab, and BCVTB. Table 4 shows the data exchanged between EnergyPlus and Matlab. The outside air temperature, outdoor-air intake ratio, and supply air fraction were transmitted from EnergyPlus to Matlab, and the set value of the mixed-air temperature was transmitted from Matlab to EnergyPlus. Figure 4 shows the integrated control system using BCVTB.

Table 4. Data exchange list.

Category	Contents
EnergyPlus to Matlab	Outdoor-air temperature (°C) Outdoor-air intake ratio (-) Supply air fraction (-)
Matlab to EnergyPlus	Mixed-air temperature (°C)

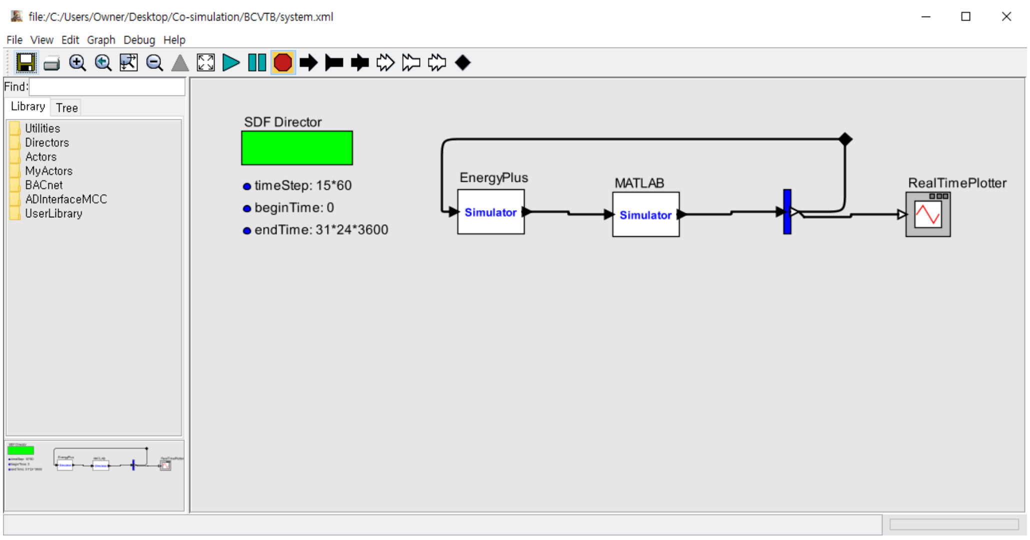


Figure 4. System model that links EnergyPlus with Matlab.

5. Results and Discussion

5.1. Validatating the Prediction Models

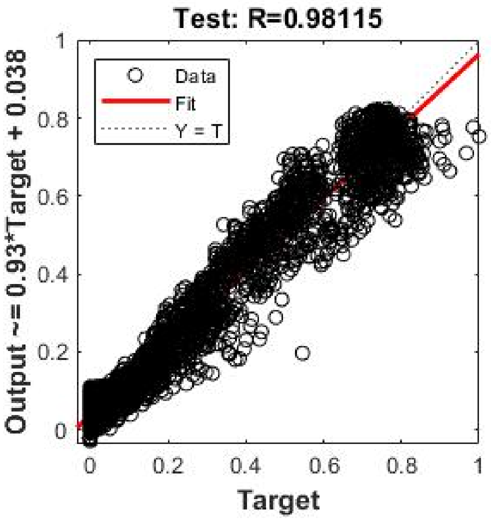
The developed building load and energy prediction model were verified using data for verification from the constructed learning data, and evaluated using the CV(RMSE) and R^2. According to ASHRAE Guideline 14-2014, this is appropriate when the CV(RMSE) is 30% or less for hourly data [23]. Table 5 and Figure 5 show the results of the developed prediction model. In the case of the load prediction model, the CV(RMSE) and R^2 were 21.8% and 0.96, respectively, and 20.6% and 0.86, respectively, in the case of the energy prediction model. All models showed smaller values than the verification criteria presented in ASHRAE Guideline 14.

$$\text{RMSE} = \sqrt{\frac{\sum(y_p - y_s)^2}{n}} \tag{3}$$

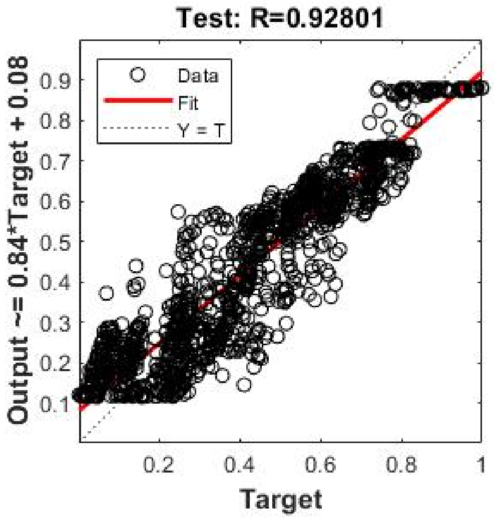
$$\text{CV}(\text{RMSE}) = \frac{\text{RMSE}}{\overline{y_s}} \times 100 \tag{4}$$

Table 5. Verification of the ANN model.

Category	Load Prediction Model	Energy Prediction Model
CV(RMSE)	21.8%	20.6%
R^2	0.96	0.86



(**a**)



(**b**)

Figure 5. ANN model regression using test data: (**a**) Load prediction model; (**b**) Energy prediction model.

5.2. Predictive Model-Based Economizer Control

1. Hourly AHU mixed-air temperature control status

A predictive model-based economizer control was developed and evaluated by a simulation. Figure 6 shows the change in the mixed-air temperature set point and the cooling energy consumption according to the application of the predictive model-based control for one day during the simulation. At this time, it was confirmed that the mixed-air temperature set point value was not constant but continuously changing.

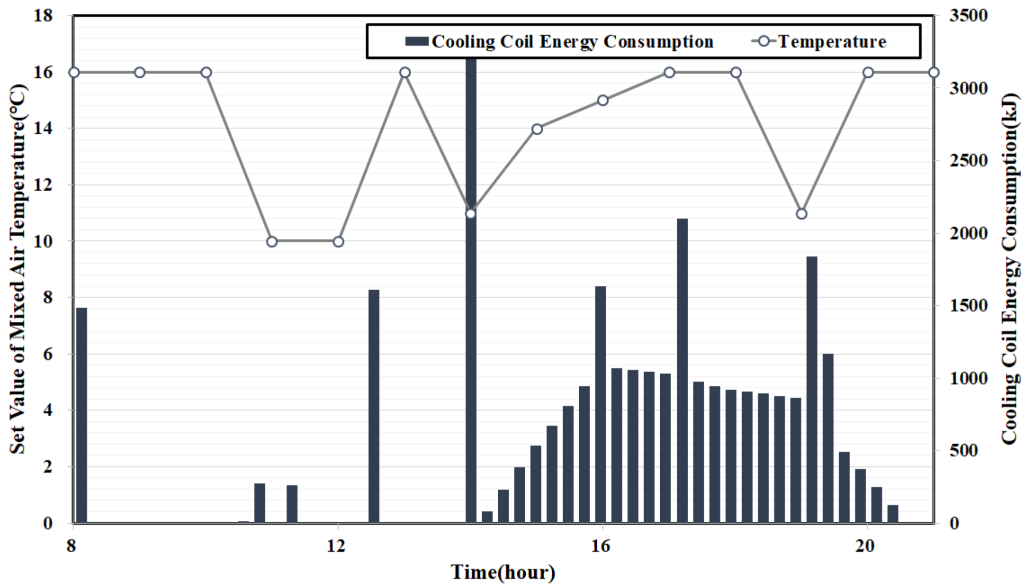


Figure 6. Hourly mixed-air temperature set point and cooling energy consumption.

2. Energy consumption

The predictive model-based economizer control for the optimized mixed-air temperature set point was evaluated in terms of its energy use along with the existing control, which kept the mixed-air temperature set point value constant. Figure 7 shows the evaluation results; the results are shown for 23 days in a month (31 days), excluding weekends, when the system was not operating. When controlling with the predictive model-based control, the cooling energy was reduced in all sections compared to the base operation control. The monthly cooling energy consumption with the base operation was approximately 1,620,865 kJ. On the other hand, the monthly cooling-energy consumption when operated by the predictive model-based control was about 859,997 kJ, saving about 760,868 kJ of energy. In addition, the day with the greatest energy savings was 3 March (the 3rd data point in Figure 7), in which approximately 110,639 kJ of energy were saved.

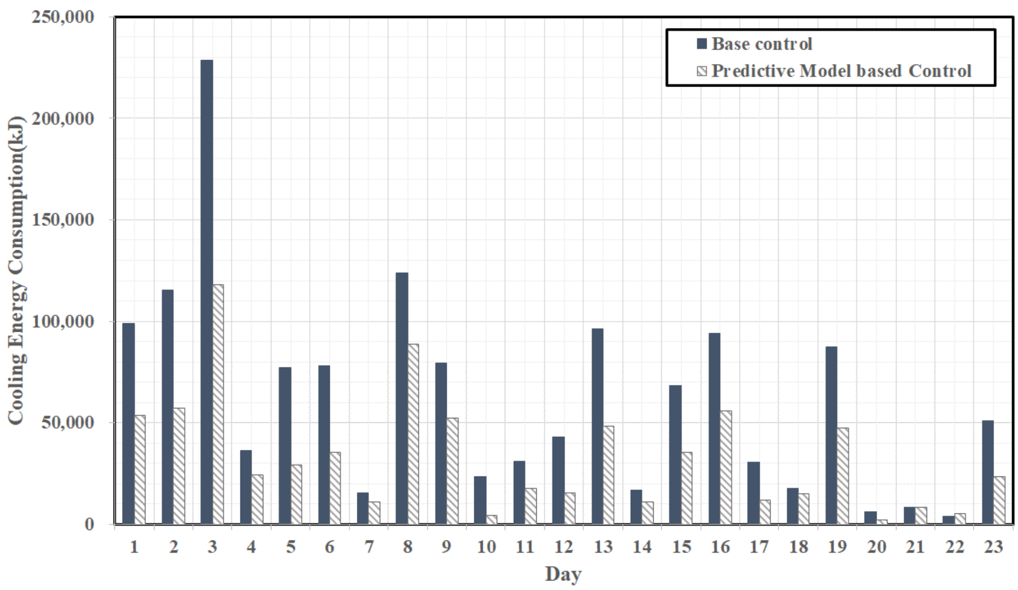


Figure 7. Comparison of cooling coil energy consumption.

The energy consumption in the buildings was evaluated for the cooling coil, fan, the chiller, and the pump. Compared to the base control, when controlled by the predictive model-based control, the energy consumption of the chiller and pump were reduced, whereas the fan energy consumption increased. The fan energy consumption was 823,486 kJ with the base control and 823,926 kJ with the predictive model-based control. The energy increase amount was 440 kJ, indicating a 0.05% increase rate. Furthermore, the chiller energy consumption was 2,374,292 kJ and 1,600,102 kJ in the base and predictive model-based control, respectively. The energy consumption of the pump in the base and predictive model-based control was 1,083,547 kJ and 915,127 kJ, and 168,420 kJ of energy was saved. According to the predictive model-based economizer control of the building, the total energy saving in the building was approximately 3,194,029 kJ—showing an energy saving of approximately 28.9% (Figure 8).

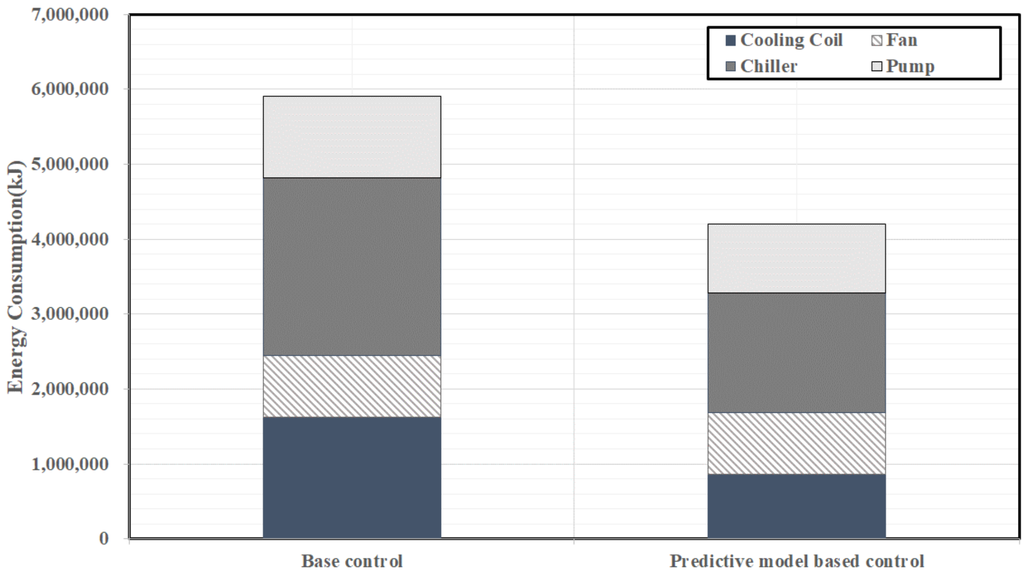


Figure 8. Total energy consumption.

6. Conclusions

In this study, a predictive model-based economizer control for optimized mixed-air temperature was established to reduce the cooling energy, and the detailed results are as follows:

1. When controlling the economizer of the HVAC system, a control using the optimal mixed-air temperature set point considering both indoor and outdoor conditions was proposed.
2. A co-simulation was established using EnergyPlus, Matlab, and BCVTB to configure a simulation-based real-time economizer optimal control system. The building and systems were modeled using EnergyPlus; the control logic was simulated using Matlab. Different programs were combined through BCVTB.
3. A building load and cooling energy prediction model was developed using an ANN. The load prediction model consisted of one input layer, four hidden layers, and one output layer. In addition, the input layer consisted of two nodes, the hidden layer consisted of five nodes, and the output layer consisted of one node. Moreover, the energy prediction model consisted of one input layer, four nodes; one hidden layer, four nodes; and one output layer, one node. The developed prediction models were verified using CV(RMSE) and R2. The CV(RMSE) of the building load and cooling energy prediction model was 21.8% and 20.6% and the R^2 was 0.96 and 0.86, indicating a high prediction rate.
4. A predictive model-based economizer control was evaluated using a simulation. The results confirmed that the set point value of the mixed-air temperature continuously changed. Moreover, the total energy consumption of the building was reduced compared to the existing economizer control by 28.9%.

An economizer control using predictive model-based mixed-air temperature optimization was proposed and its evaluation was conducted through a simulation. In the future, it will be necessary to evaluate the model's performance through field application of the technology, and to verify the technology through real-time interlocking of the automatic control system and the data analysis program.

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