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Artificial Neural Network–Based Control of a Variable Refrigerant Flow System in the Cooling Season

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Abstract: This study aimed to develop a control algorithm that can operate a variable refrigerant flow (VRF) cooling system with optimal set-points for the system variables. An artificial neural network (ANN) model, which was designed to predict the cooling energy consumption for upcoming next control cycle, was embedded into the control algorithm. By comparing the predicted energy for the different set-point combinations of the control variables, the control algorithm can determine the most energy-effective set-points to optimally operate the cooling system. Two major processes were conducted in the development process. The first process was to develop the predictive control algorithm which embedded the ANN model. The second process involved performance tests of the control algorithm in terms of prediction accuracy and energy efficiency in computer simulation programs. The results revealed that the prediction accuracy between simulated and predicted outcomes proved to have a low coefficient of variation root mean square error (CVRMSE) value (10.30%). In addition, the predictive control algorithm markedly saved the cooling energy consumption by as much as 28.44%, compared to a conventional control strategy. These findings suggest that the ANN model and the control algorithm showed potential for the prediction accuracy and energy-effectiveness of VRF cooling systems.

Keywords: variable refrigerant flow (VRF) cooling systems; artificial neural network (ANN); predictive control algorithm; optimal set-points of system variables

1. Introduction

The amount of energy consumed worldwide has been increasing, causing serious environmental problems, such as global warming, urban heat island phenomenon, resource depletion, and air pollution [1]. The supply-and-demand situation of energy in the Republic of Korea is highly unstable, being the eighth highest country in the world regarding energy use with an annual 6.6% energy consumption growth rate, which is the highest among all Organization for Economic Cooperation and Development (OECD) countries [2,3]. As precautionary measures, the Korean government has suggested many policies and established various institutions for energy reduction, focusing on the building sector, in which the proportion of energy use is about 24% of the total national energy consumption [4,5]. Since the building sector accounts for a large portion of total energy consumption and has a relatively higher potential to reduce energy than other sectors, this could be an effective strategy in reducing energy consumption [6,7].

However, the amount of building energy consumed has been increasing with economic growth, since buildings have recently become larger and higher [8]. The annual electricity consumption in the building sector has continuously increased, from a 558,000 Ton of Oil Equivalent (TOE) in 2000 to 1,655,000 TOE in 2015, which accounts for more than 66% of the total building energy use within 15 years by this sector [9]. In addition, the cooling equipment use has been increasing due to the demands for more comfortable thermal environments [10]. Therefore, sophisticated cooling control systems and strategies are important factors for reducing cooling energy.

In accordance with these efforts, variable refrigerant flow (VRF) cooling systems have been increasingly implemented in large buildings due to their high efficiency, flexible forms, and modest space requirements [11,12]. VRF cooling systems can be grouped into two types: (1) water cooling systems and (2) air cooling systems. Direct expansion (DX) air handling unit (AHU)-water source VRF systems are composed of multiple outdoor units, a cooling tower, a DX AHU, fans, and pumps as shown in Figure 1. The refrigerant is evaporated in the DX coil in AHU which is connected to multiple outdoor units. The compressor unit is water-cooled. It is connected to a cooling tower. The variable refrigerant flow compressor is controlled by a variable speed drive which operates more energy efficiently than conventional compressors of the same size [13]. The conditioned air in the AHU is supplied to each room using fans.

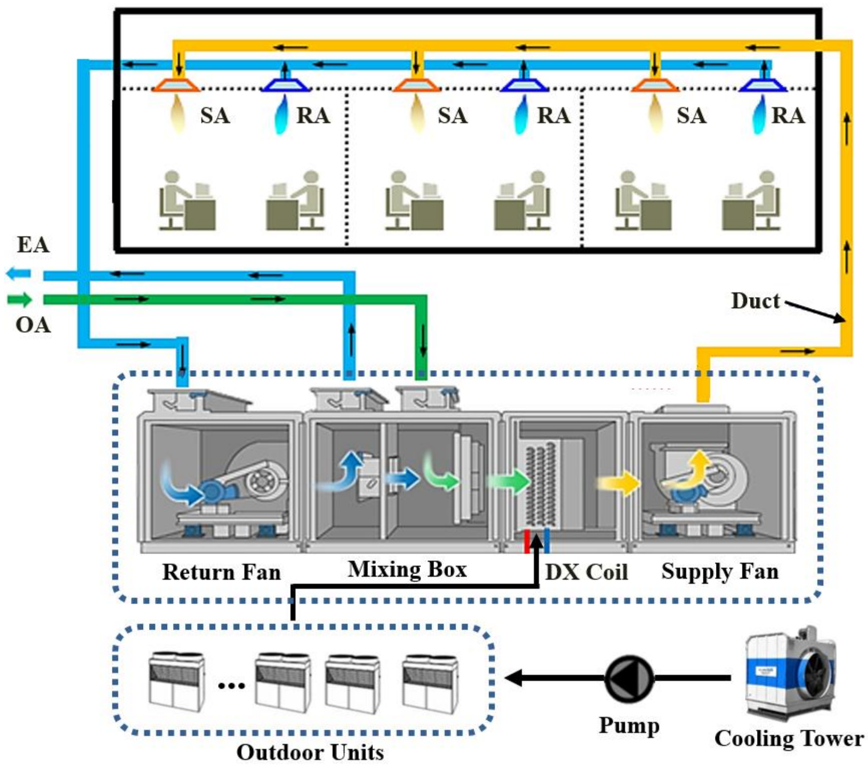

Figure 1. Diagram of the direct expansion DX air handling unit (AHU)-water source variable refrigerant flow (VRF) system. SA: supply air; RA: return air; EA: exhaust air; OA: outdoor air.

One of the noticeable differences of the VRF systems compared to the conventional cooling systems is their high efficiency in partial load operation. In addition, they enable individual control of single rooms by controlling the refrigerant flow rate to various indoor units via electronic expansion valves [14]. The VRF systems circulate refrigerant through a DX coil instead of a water coil, and the refrigerant expands directly in an evaporator through the DX coil via the installed outdoor units of the heat pumps. Therefore, the VRF systems can provide a more comfortable and stable indoor thermal environment by actively responding to the dynamic variation of outdoor weather and can also reduce cooling energy consumption due to their part load variation [15].

Despite the significant advantages of the VRF systems, they have not been fully operated with optimal control strategies. The major control variables of the VRF systems, such as the supply air temperature set-point ($TEMP_{SA}$) of the air handling unit, condenser fluid temperature set-point ($TEMP_{COND}$), and condenser fluid amount set-point ($AMOUNT_{COND}$) are determined by heuristic methods of the operators. Furthermore, the VRF systems have been operated by these control variables that are set constantly without considering energy-efficiency. Therefore, efforts to operate the VRF systems are essential by setting optimal control variables for improving system performance in terms of energy-efficiency and the provision of comfortable indoor thermal environments.

The aim of this study is to develop a control algorithm capable of operating the VRF cooling systems in an energy efficient manner by setting control variables that are optimally determined by an artificial neural network (ANN) model. Two major steps were involved to meet this aim. In the first step, a control algorithm was developed that embedded the ANN model to identify the optimal combination of the VRF system's control variables. The embedded ANN model, which was developed in the preceding study [16], was designed to predict the cooling energy consumption for the operating set-points of the VRF systems. The principal process for developing the ANN model in the preceding study is summarized in Section 2.2.

The second step served to test the performance of the predictive algorithm and the embedded ANN model. Prediction accuracy of the ANN model was validated from the coefficient of determination (R^2) value and the coefficient of variation root mean square error (CVRMSE) value, which are criteria specified in the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) guidelines. In addition, the performance of predictive algorithm was evaluated by analyzing the cooling energy savings compared to the conventional control method.

2. ANN Model for Predicting Cooling Energy of the VRF System

2.1. ANN Literature Review on Building Thermal Controls

Building environment controls have been improved due to remarkable development in computer science and information technology. Artificial intelligence (AI) methods and applications have recently received a lot of attention due to their abilities to solve highly complex problems at high speed [17,18]. Among various AI methods such as ANNs, support vector machine, particle swarm optimization, genetic algorithms, and fuzzy logic, ANN method has shown outstanding abilities in self-learning with adaptability for prediction [19,20].

The ANN, which was first proposed by Warren McCulloch and Walter Pitts in 1943, is based on the human neural system [21]. ANN is a mathematical engineering tool used for a variety of tasks: classification, data mining, prediction, pattern recognition, function approximation, optimization, and association [22,23]. A multi-layer feed-forward network, a representative model of the ANN [24], consists of an input layer, one or more hidden layer(s), and an output layer as shown in Figure 2. Each layer includes various nodes, and each node in one layer is connected to all nodes in the next layer with connection strength, which is referred to as a "weight." The nodes constituting each layer are calculated as the sum of the input values multiplied by the weight when receiving the signal from the previous layer. The output layer produces an output value through the calculation of a transfer function [25].

A back-propagation algorithm, which was first introduced by Werbos [26] and later developed by Rumelhart and McClelland [27], is a learning method to calculate the error contribution of each neuron. At the beginning of the learning stage, all weights in the network are initialized by reducing them to small random values. This propagates the signal backward and adjusts the weight of each layer according to the error between the output value and the target value. A gradient descent method is employed to modify the weight by minimizing the error. An iteration process then produces the desired output value [28]. Figure 3 shows the principle of the back-propagation algorithm.

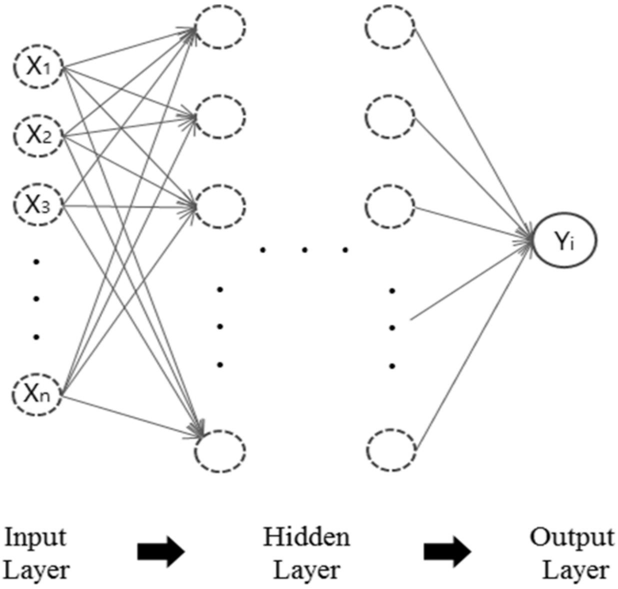

Figure 2. Structure of the multi-layer feed-forward network (X: inputs, Y: output).

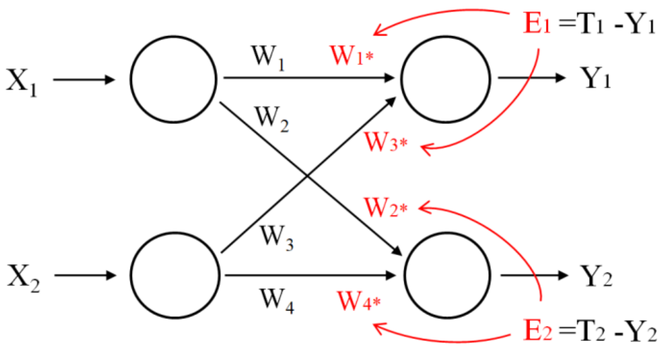

Figure 3. Principle of the back-propagation algorithm.

ANNs have been increasingly applied to building thermal controls. Various ANN models have been developed to predict the energy consumption of heating, ventilation, and air-conditioning (HVAC) systems. Further research has been conducted to advance the control algorithms of HVAC systems which embed the ANN model. A literature review of recent studies relevant to the topic follows.

Azadeh et al. [29] considered environmental and economic factors for the optimum estimation and forecasting of renewable energy. To demonstrate the applicability and superiority of the proposed an ANN model, monthly data were collected for 11 years (1996–2006) in Iran. The results revealed a prediction accuracy of approximately 99.9% in comparison with conventional and fuzzy regression models. Deb et al. [30] used an ANN to predict the diurnal cooling energy load of institutional buildings. Three institutional buildings were examined and the energy consumption data of each were analyzed for two years. The findings revealed that the ANN model trained and accurately predicted next-day energy use (R^2 = 0.94) based on the data of the five previous days. Kalogirou [31] reviewed various ANN applications in a wide range of fields for modeling and predicting energy systems: a solar steam-generator, solar water heating systems, HVAC systems, solar radiation and wind speed predictions, as well as power generation systems.

Moon and Jung [32] developed an ANN model for predicting the optimal start moment of the setback temperature during a normal occupied period. They also developed an algorithm embedded ANN model to enhance indoor thermal comfort and building energy efficiency. The results demonstrated the excellent prediction performance of the ANN model with an R^2 value greater than

0.999 in the simulated results. Additionally, ANN-based algorithms were shown to be superior to conventional algorithms for improving indoor thermal comfort and building energy. Kwon [33] analyzed the cooling energy consumption based on the actual and meteorological data of large complex buildings and proposed an optimal operating strategy for a chiller plant by using an ANN predictive model. Based on information provided by the Korea Meteorological Administration (KMA), the weather data were inputs for the ANN model, such as the outside temperature, relative humidity, solar radiation, cloudiness, wind speeds, and rainfall events.

2.2. Development Process of the Predictive Model

The predictive model development was advanced from preceding research [16] by the addition of three major steps: (1) analysis of the relevant factors for cooling energy consumption, (2) development of initial model, and (3) optimization of the initial model. Table 1 summarizes the outcomes in each step and Figure 4 shows the final ANN model in the preceding study [16].

Table 1. Process and outcomes for developing an artificial neural network (ANN) model.

Steps	Outcomes
(1) Factor analysis	Found 7 relevant factors to the cooling energy cost • average outdoor temperature ($TEMP_{OUT}$, °C) • average outdoor humidity ($HUMID_{OUT}$, %) • average indoor temperature ($TEMP_{IN}$, °C) • internal load that generated from the cooling tower ($LOAD_{COOL}$, kWh) • air handling unit supply air temperature set-point ($TEMP_{SA}$, °C) • condenser fluid temperature set-point ($TEMP_{COND}$, °C) • condenser fluid pressure set-point ($AMOUNT_{COND}$, liter/minute)
(2) Initial model development	• 1 input layer, 1 hidden layer, and 1 output layer • 8 input neurons, 17 hidden neurons, 1 output neuron • Sigmoid function for hidden neurons and pure-linear function for the output neuron • Levenberg-Marquardt learning algorithm • 0.0 goal • 200 training datasets with the sliding-window method
(3) Model optimization	• Removed 1 input neuron (SOLAR) for improving prediction accuracy • Modified structure to 2 hidden layers with 15 hidden neurons in each layer • Modified learning method to 0.3 learning rate and 0.3 moment

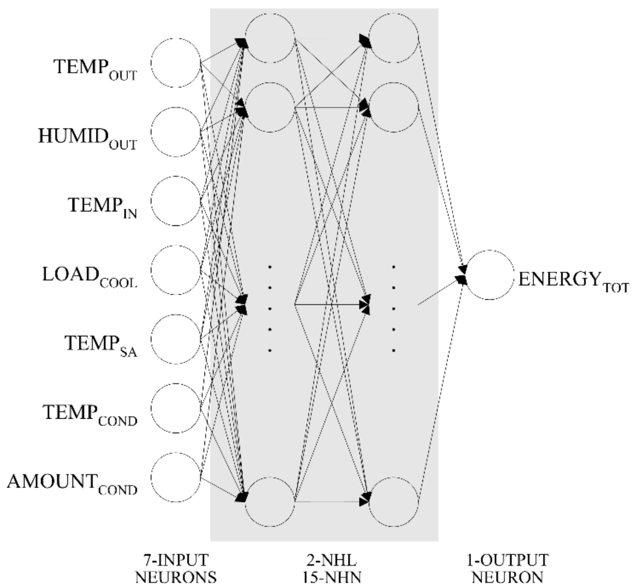

Figure 4. Structure of the optimized ANN model [15].

The ANN model was designed to predict the amount of cooling energy for the next control cycle which was assigned for 1 h. For cooling energy prediction, the ANN model used seven input variables. Among these input variables, $TEMP_{OUT}$, $HUMID_{OUT}$, and $TEMP_{IN}$ are average values for the last one hour using measured values every five minutes. $LOAD_{COOL}$ is the internal load generated from the cooling tower (kWh) for the last one hour. The remaining three variables ($TEMP_{SA}$, $TEMP_{COND}$, and $AMOUNT_{COND}$) were set-points of the cooling system. They will be used for the next control cycle.

To decrease prediction errors, the ANN model was tuned for its structure and learning method. Numbers of hidden layer and neurons as well as learning rate and moment were optimized using parametrical process in a coupled fashion. The final model after tuning process employed two hidden layers and 15 hidden neurons in each layer. A total of 200 training datasets with sliding-window data management method were used for model training [15] with Levenberg-Marquardt learning method that only required just a few seconds. Thus, it would not be a problem for application.

In a preceding study [16], prediction performance of the developed ANN model was verified by comparing predicted and the measured energy consumption. Numerical indicators R^2 and the CVRMSE suggested in the ASHRAE Guideline 14-Measurement of energy and demand savings [34] were evaluation standards for the ANN model. They were used as a measure of difference between actual and predicted values. R^2 of 0.8 or higher and CVRMSE below 30% were judged to be appropriate.

The cooling system in the test building was operated for 188 h from 1 July to 31 August. During operating hours, the amount of predicted cooling energy was similar to the amount of energy actually consumed. The value of R^2 was 0.8136, verifying its prediction accuracy based on ASHRAE guideline. In addition, the CVRMSE value was 11.3% which was within allowable range suggested by ASHRAE. Thus, the applicability of the proposed ANN model was proven to have acceptable accuracy level [16].

3. Development and Evaluation of the Predictive Control Algorithm

The operation algorithm of the VRF system, in which the ANN model was embedded, was developed in this study to determine the optimal combination for the set-points of the system variables. The predictive control algorithm was developed using the MATLAB software and its neural network toolbox. Figure 5 displays the flowchart of the predictive control algorithm. The indoor and outdoor thermal climate conditions ($TEMP_{OUT}$, $HUMID_{OUT}$, and $TEMP_{IN}$) as well as the system operating condition ($LOAD_{COOL}$) are collected, followed by the cooling energy prediction for the three set-points of the system variables ($TEMP_{SA}$, $TEMP_{COND}$, and $AMOUNT_{COND}$), which progress through the ANN model. Each optimal set-point value of the system variables was derived by comparing the energy consumption for the different set-point combinations. The cooling system then operates following the optimal set-points for the next control cycle which was assigned 1 h.

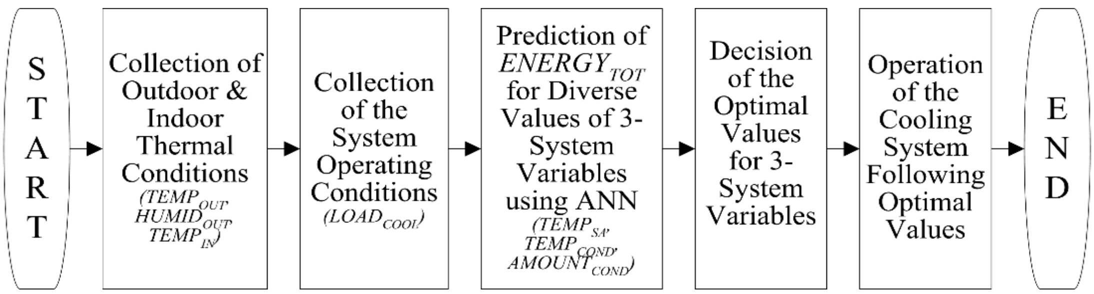

Figure 5. Flowchart of the control algorithm.

The performance of the predictive control algorithm in which the ANN was embedded was evaluated to validate the prediction accuracy and the cooling energy savings. The ANN-based predictive control algorithm was compared with a conventional building control algorithm that used fixed set-points for the VRF system variables, which is the normal strategy applied in the field. Table 2 shows the set-points of the control variables for the conventional and predictive control algorithms and Figure 6 conceptually presents the process conducted for determine the optimal set-point combination in the predictive control algorithm. In the predictive control algorithm, the $ENERGY_{TOT}$ for a series of $TEMP_{SA}$, $TEMP_{COND}$, and $AMOUNT_{COND}$ were compared and the most energy efficient combination was selected. $TEMP_{SA}$ and $TEMP_{COND}$ were compared for every 1 °C and the $AMOUNT_{COND}$ was compared for every 500 L/min, thus the total number of case for comparison was 1287. This process was conducted in one second and repeated for every control cycle. The heating systems would work following the optimal set-point combination, and the amount of energy consumption would be compared with that of the conventional algorithm.

Table 2. Set-points of the control variables in the conventional and predictive control algorithm.

Control Variables	Control Algorithms	
	Conventional	**Predictive**
$TEMP_{SA}$	16 °C	10~18 °C
$TEMP_{COND}$	32 °C	25~35 °C
$AMOUNT_{COND}$	6000 L/min	1000~7000 L/min

for $TEMP_{SA}$ = 10:18

  for $TEMP_{COND}$ = 25:35

    for $AMOUNT_{COND}$ = 1000:500:7000

      Prediction of the $ENERGY_{TOT}$ from ANN model

      Comparison $ENERGY_{TOT}$ for the different set-point combination

      Determination of the optimal combination

    end

  end

end

Figure 6. Structure of the programming code to determine the optimal set-points.

Comparison tests between the conventional and predictive control algorithms were conducted using the following computer simulation programs: EnergyPlus, MATLAB, and Building Controls Virtual Test Bed (BCVTB). Figure 7 shows an overall diagram of the co-simulation process between EnergyPlus and MATLAB via BCVTB. Each program was operated by interacting with each other as follows. First, EnergyPlus created the model of a DX AHU and outdoor units of the VRF cooling system and the test building to read outdoor climate conditions and produce indoor thermal environment.

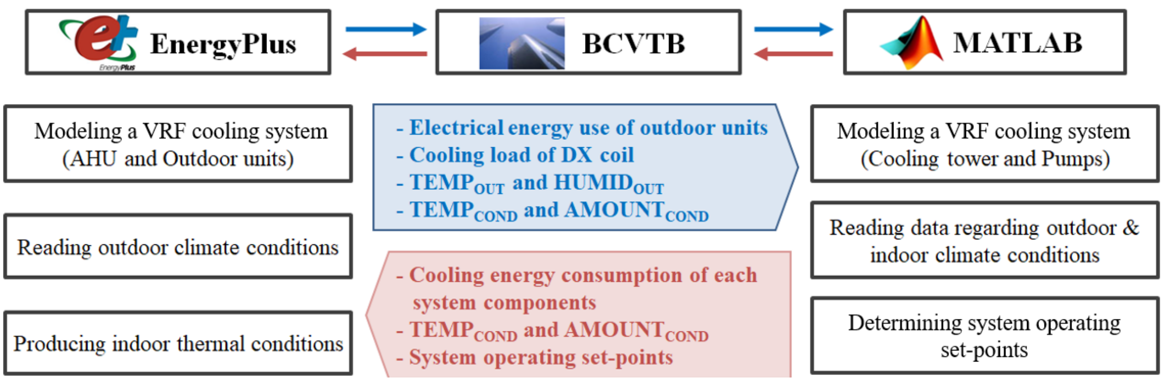

Figure 7. Simulation method using the three software programs.

Second, MATLAB created the model of a cooling tower and a pump of the VRF cooling system. In addition, ANN model was developed using the neural network toolbox in MATLAB and a control algorithm was developed.

Finally, BCVTB functioned as a connection tool for transferring data between EnergyPlus and MATLAB. When EnergyPlus sent data regarding indoor and outdoor thermal conditions, the ANN model and control algorithm in the MATLAB environment determined optimal set-points of system variables. These determined optimal set-points were sent to VRF cooling systems in EnergyPlus for working. New indoor thermal condition was then created and sent to MATLAB. This process was repeated at every control cycle. In addition, EnergyPlus calculated the amount of cooling energy consumption.

The test building was the R&D center located in Seoul, Republic of Korea (37.33° N latitude and 126.58° E longitude), as shown in Figure 8. The building was an 11-story office building composed of a podium, a typical floor, and a roof. The VRF system type implemented in the building was the DX AHU-water source VRF system. One cooling tower, 11 AHUs, and 27 outdoor units composed the VRF system for covering the whole building.

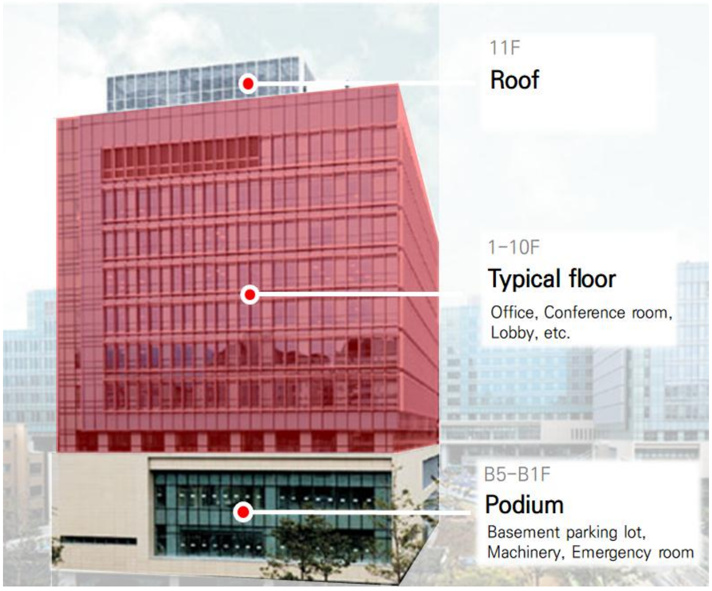

Figure 8. Front view of R&D center.

Figure 9 displays the configuration of actual VRF systems for 11 zones. The capacity of each VRF system after calculating part load ratio and efficiency is summarized in Table 3. Zone-based individual control was applied to the test building. Each room applied its own indoor set-point temperature using thermostat while the indoor set-point temperature was fixed at 26 °C during working hours and 29 °C during the non-working hours for the whole building.

VRF system parameters such as $TEMP_{SA}$, $TEMP_{COND}$, and $AMOUNT_{COND}$ for entire zones were identically changed. Datasets for the ANN model were collected for diverse combinations of these system parameters. Trained ANN model using these datasets could predict the total cooling energy by the entire VRF systems to provide a comfortable thermal environment based on the designated indoor set-point temperature. In addition, the control algorithm could compare total energy for different set-point combinations and determine the optimal combination.

Different amount of interior heat gain was applied based on Tables 4 and 5. Table 4 summarizes the baseline of internal heat gain while Table 5 shows time-based ratio of internal load. Using the baseline and time-based ratio, the internal load in the simulation was considered differently during the whole day.

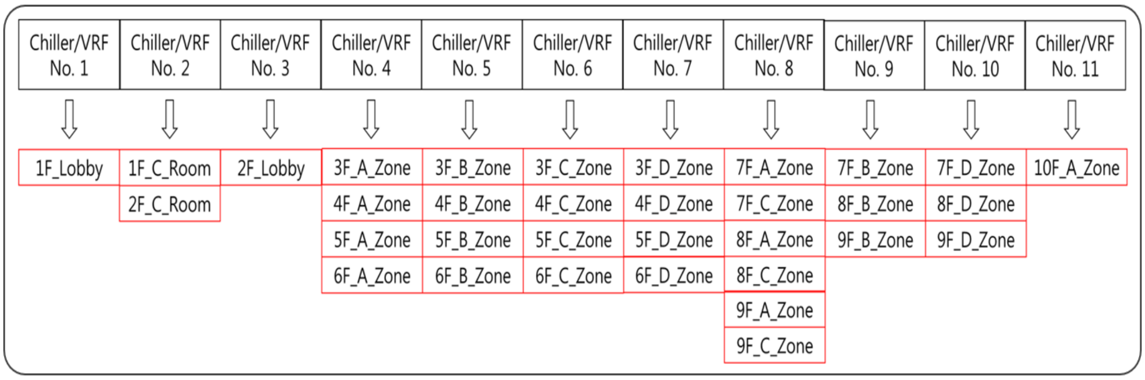

Figure 9. Configuration of VRF systems.

Table 3. Reference capacity of each VRF system.

Capacity (kW)					
VRF No. 1	VRF No. 2	VRF No. 3	VRF No. 4	VRF No. 5	VRF No. 6
83.1	52.8	83.3	112.3	111.7	112.8
VRF No. 7	VRF No. 8	VRF No. 9	VRF No. 10	VRF No. 11	
111.6	178.4	82.2	82.0	67.4	

Table 4. Baseline of internal heat gain.

Components	Unit	Input Value
Occupants	Person/Area	0.078 person/m^2
Lighting	Watts/Area	21.52 W/m^2
Electric Equipment	Watts/Area	16.14 W/m^2

Table 5. Cooling schedules for internal heat load.

Cooling Schedule	Occupants (Ratio)	Lighting (Ratio)	Electric Equipment (Ratio)
Weekdays	00:00~06:00 (0.000) 06:00~22:00 (0.500) 22:00~23:59 (0.025)	00:00~23:59 (0.250)	00:00~23:59 (1.000)
Saturday	00:00~06:00 (0.000) 06:00~08:00 (0.500) 08:00~12:00 (0.150) 12:00~17:00 (0.050) 17:00~23:59 (0.000)	00:00~06:00 (0.012) 06:00~08:00 (0.025) 08:00~12:00 (0.075) 12:00~17:00 (0.037) 17:00~23:59 (0.012)	00:00~06:00 (0.300) 06:00~08:00 (0.400) 08:00~12:00 (0.500) 12:00~17:00 (0.350) 17:00~23:59 (0.300)
Sunday	00:00~23:59 (0.000)	00:00~23:59 (0.012)	00:00~23:59 (0.300)

The modeling process was conducted through applications of the reference schedule and internal loads from the office building based on ASHRAE Standard 90.1 [35]. Table 6 shows input conditions which were applied to the building simulation. The cooling systems were operated for 24 h to analyze the energy performance according to the part load operation of the cooling systems.

The AHU and outdoor units were modeled by the energy management system (EMS) of EnergyPlus. However, to model the VRF system, EnergyPlus cannot provide a tool for the water source VRF system. Therefore, an air source VRF system (Coil:Cooling:DX) was substituted as a workaround.

The EnergyPlus models (AHU and outdoor units) and MATLAB models (the boiler and the pumps) were calibrated to verify the accuracy of the models. Test data were compared to three-month measurements from the building energy management system (BEMS) in the actual R&D center.

Among the four models of the AHU, the outdoor units, the boiler, and the pumps, the performance of modeling the outdoor units was analyzed using three performance curves: the low temperature curve, the high temperature curve, and the boundary curve. After the calibration of the models, the CVRMSE between the simulated- and measured amount of energy consumption was found to be 15.2%. Thus, the accuracy of the simulation models could be verified within the tolerance range (under 30%) suggested in ASHRAE Guideline 14-Measurement of energy and demand savings [34].

Table 6. Simulation conditions.

Category	Input Value
Simulation program	EnergyPlus v8.5
Site/weather location	Seoul/Republic of Korea
Window-to-wall ratio	40%
Chiller based conventional AHU/water-cooled VRF schedule	24 h
Cooling setpoint	26 °C
COP	4.787
Pump motor efficiency	90%
Infiltration	0.0003167 $m^3/s\text{-}m^2$

4. Performance of the Predictive Control Algorithm

The performance of the predictive control algorithm was tested at three stages: (1) the prediction accuracy of simulation results in comparison with the predicted outcomes, (2) the optimal set-points of the VRF system variables, (3) the results of the cooling energy amount from the conventional and predictive control algorithms.

First, the comparison between the simulated energy consumption ($ENERGY_{SIM}$) and the predicted energy consumption ($ENERGY_{PRED}$) for the entire building is shown in Figure 10. $ENERGY_{SIM}$ was an EnergyPlus output, while $ENERGY_{PRED}$ was derived from the ANN model. The number of cycles (iterations) during the cooling system operation was 1488 h, that is, 62 days from the 1 July to the 31 August. Figure 11 shows the coefficient of determination (R^2) between the $ENERGY_{SIM}$ and $ENERGY_{PRED}$. R^2 was calculated as 0.9462, which meets the ASHRAE guideline criteria of 0.8 or higher.

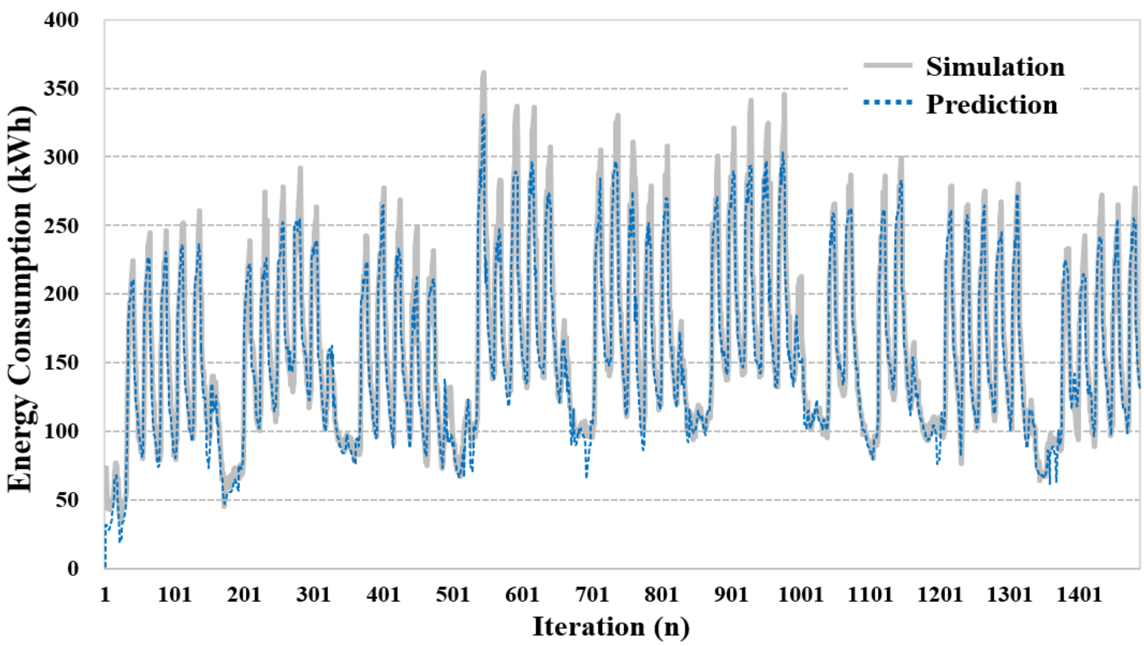

Figure 10. Comparison of the cooling energy consumption between the simulation and prediction.

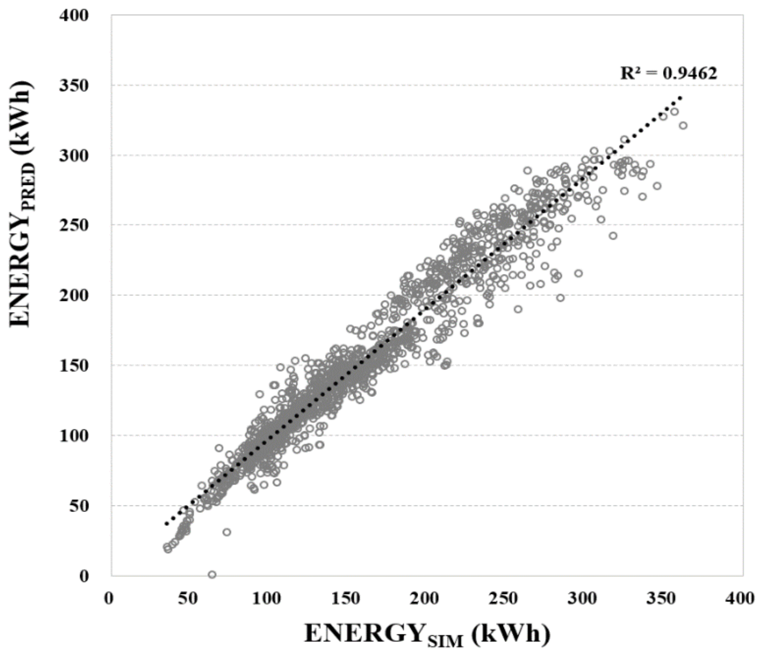

Figure 11. The regression line and coefficient of determination (R^2) between simulated energy consumption ($ENERGY_{SIM}$) and predicted energy consumption ($ENERGY_{PRED}$).

CVRMSE between $ENERGY_{SIM}$ and $ENERGY_{PRED}$ was 10.3%, which demonstrated the reliability of ANN prediction. In addition, the number of cases and the results of CVRMSE (%) were analyzed according to the difference between $ENERGY_{SIM}$ and $ENERGY_{PRED}$ in Figure 12. For more than 80% of cases, the difference between $ENERGY_{SIM}$ and $ENERGY_{PRED}$ was between −20 and 20 kWh and CVRMSEs for these cases were significantly smaller, which indicated the stability of the ANN prediction.

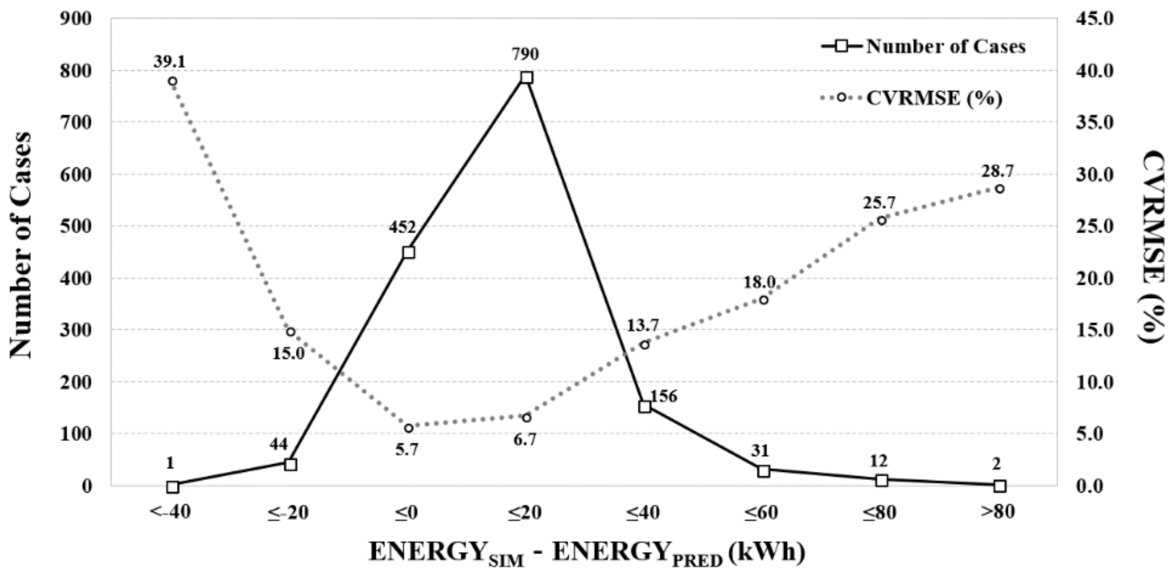

Figure 12. Number of cases and CVRMSE (%) for difference between simulated energy consumption and predicted energy consumption.

Second, the optimal set-points of the system variables were determined by the predictive control algorithm, in which the ANN model was embedded and the prediction results were used. Figure 13 displays the set-points that had resulted for the three system variables: $TEMP_{SA}$, $TEMP_{COND}$, and $AMOUNT_{COND}$. The optimal set-point of $TEMP_{SA}$ was in the stable range of 10–18 °C in the iteration progress, while the set-points of $TEMP_{COND}$ and $AMOUNT_{COND}$ were within the ranges of 25–35 °C and 1000–7000 L/min, respectively.

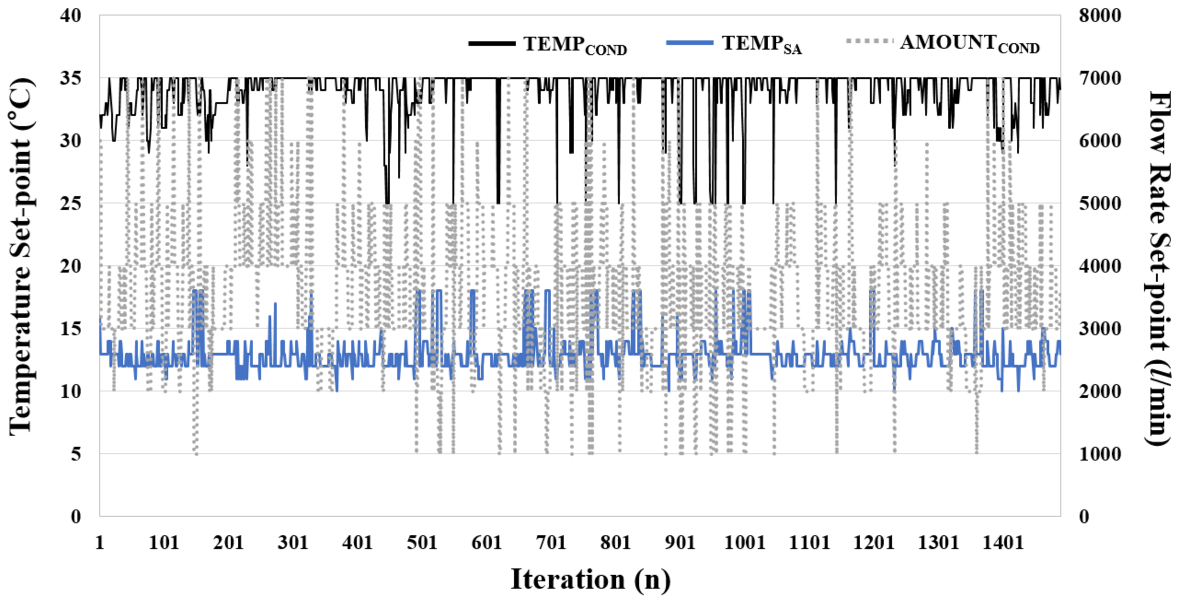

Figure 13. Optimal set-points of the system variables.

While the set-points of all system variables changed for each moment, each system variable was primarily set as a specific point or range: the set-points of $TEMP_{SA}$ were 12–14 °C, $TEMP_{COND}$ 35 °C, and $AMOUNT_{COND}$ 3000–5000 L/min.

Finally, the cooling energy consumption of VRF system components was compared between the conventional and predictive control algorithm. Figure 14 exhibits the results of the cooling energy consumption from two VRF system types, which were operated by conventional and ANN-based predictive control algorithms.

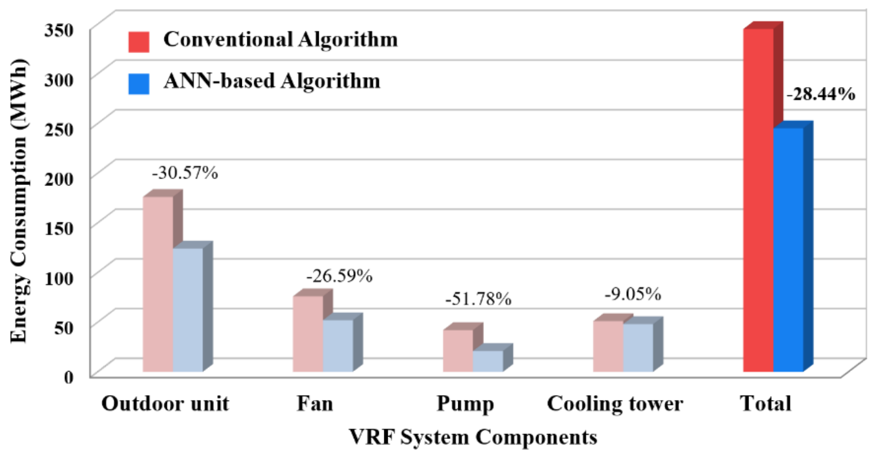

Figure 14. Cooling energy consumption comparisons between conventional and ANN-based control algorithms.

The results show the total cooling energy savings and the energy consumption of the outdoor units, the fans, the pumps, and the cooling tower in detail. The VRF system with ANN saved 28.44% of the total cooling energy, while the energy consumption of the outdoor units, the fans, the pumps, and the cooling tower was reduced by 30.57%, 26.59%, 51.78%, and 9.05%, respectively. Accordingly, the energy efficiency improved by 28.44% and the amount of energy savings was 95,509 kWh, which can be converted to 13,562,278 Korean won (12,054 U.S. dollars), since the unit cost of 1 kWh was 142 Korean won in 2017.

5. Conclusions

In this study, a control algorithm was developed to operate an intermittently working VRF cooling system in an energy-effective way. This algorithm determined the optimal set-points of the system variables by using an ANN model to predict the cooling energy consumption for the upcoming control cycle. The performance of the predictive control algorithm was compared in computer simulations regarding the prediction accuracy, the set-points' determination, and the cooling energy savings. The study results are summarized below.

(1) The prediction model embedded in the control algorithm showed an acceptable prediction accuracy. For the number of cycles (1488 h), the results revealed the CVRMSE of 10.3% between the simulated and predicted cooling energy.
(2) The ANN-based predictive control algorithm determined the optimal set-points of the VRF system. For most of the cases, $TEMP_{SA}$, $TEMP_{COND}$, and $AMOUNT_{COND}$ were in the stable range of 12–14 °C, 35 °C, and 3000–5000 L/min, respectively
(3) The algorithm also markedly saved the cooling energy consumption of the VRF cooling system during the 62 days from the 1 July to the 31 August. The total cooling energy saved was 28.44%, which corresponds to an electrical energy reduction of approximately 95,509 kWh or 13,562,278 Korean won (12,054 U.S. dollars).

From the study findings, it is concluded that the ANN-based predictive control algorithm possesses a verified prediction accuracy and that it is appropriate for operating a VRF cooling system in terms of energy-effectiveness. For further research, field tests will be needed to validate actual performance by implementing the ANN-based predictive control algorithm in existing buildings. In addition, diverse control algorithms such as PID-based methods need to be developed and comparatively tested their performance with the proposed predictive algorithm in the further study.

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Nomenclature

ANN	artificial neural network
OECD	organization for economic cooperation and development
TOE	ton of oil equivalent
DX AHU	direct expansion air handling unit
R^2	coefficient of determination
CVRMSE	coefficient of variation root mean square error
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
SA	supply air
RA	return air
EA	exhaust air
OA	outdoor air
$TEMP_{SA}$	air handling unit supply air temperature set-point (°C)
$TEMP_{COND}$	condenser fluid temperature set-point (°C)

$AMOUNT_{COND}$	condensing warm fluid amount set-point (liter/minute)
$TEMP_{OUT}$	average outdoor temperature (°C)
$HUMID_{OUT}$	average outdoor humidity (%)
SOLAR	average solar radiation (W/m^2)
$TEMP_{IN}$	average indoor temperature (°C)
$LOAD_{COOL}$	internal load that generated from the cooling tower (kWh)
$ENERGY_{TOT}$	predicted total cooling energy for the next 1 h (kWh)
NHL	number of hidden layer
NHN	number of hidden neuron in each hidden layer
LR	learning rate
MO	moment

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