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Article

Modeling and Optimizing a Chiller System Using a Machine Learning Algorithm

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Abstract: This study was conducted to develop an energy consumption model of a chiller in a heating, ventilation, and air conditioning system using a machine learning algorithm based on artificial neural networks. The proposed chiller energy consumption model was evaluated for accuracy in terms of input layers that include the number of input variables, amount (proportion) of training data, and number of neurons. A standardized reference building was also modeled to generate operational data for the chiller system during extended cooling periods (warm weather months). The prediction accuracy of the chiller's energy consumption was improved by increasing the number of input variables and adjusting the proportion of training data. By contrast, the effect of the number of neurons on the prediction accuracy was insignificant. The developed chiller model was able to predict energy consumption with 99.07% accuracy based on eight input variables, 60% training data, and 12 neurons.

Keywords: chiller energy consumption; artificial neural network (ANN); HVAC

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1. Introduction

The energy consumption of a building system can be controlled by employing an energy-saving design as well as by proper operation of the building. Therefore, such design, referred to as a building energy management system (BEMS), has been adopted for building operations to ensure effective energy consumption and management. The integrated measurement, control, management, and operation in a BEMS provide efficient energy management and allow the desired indoor environment to be maintained. However, currently a BEMS is limited to a simple on/off switch that allows comparisons of the actual value with a set value determined by the operator. Rational energy management tools should be able to perform sophisticated functions that help managers make good BEMS decisions. Collection and analysis of available data are necessary in order to develop and provide such advanced management tools.

Recently, machine learning algorithms have been actively applied to optimize new type of heating, ventilation, and air conditioning (HVAC) systems [1–6]. For example, Jang et al. [7] proposed a solution for predicting the optimal heating time in winter by using artificial neuron network (ANN) technology. For this type of application, ANN models utilize input data such as the indoor/outdoor temperature, indoor/outdoor temperature difference, indoor temperature change, and outdoor temperature change. Jeong et al. [8] compared the accuracy of different building energy consumption predictions obtained by using three machine learning algorithms: ANN, a support vector machine, and random forest (RF). The performance was ranked in the order of RF, ANN, and support vector machine. For their study, Jeong et al. [9] investigated the sensitivity and importance of these variables for predicting the energy consumption in elementary schools and commercial buildings and then evaluated the performance of the machine learning models according to building function. For the elementary school buildings, the average coefficient of variance of the root mean squared error (CvRMSE) determined by ANNs was 5.4% and the average CvRMSE for commercial buildings based on the RF model was 10.9%.

Jeon et al. [10] conducted a study of energy load predictions for a building unit. Their study used an ANN and a test reference year. For each training period, the average CvRMSE for the prediction of the energy load was 25%. Park et al. [11] proposed an ANN model that can predict the cooling load according to the setback temperature in order to minimize the cooling energy consumption. Their results confirm a CvRMSE of 21.3%, which reflects a better performance than the conventional criterion of 30.0%. Ahmed et al. [12] investigated the performance of power load predictions associated with ANN and RF algorithms for a single building unit using meteorological data. Their ANN model obtained an average CvRMSE of 4.9% through normalization, extraction, and elimination of input variables to improve prediction performance. The RF model led to an average CvRMSE of 6.1%.

Seong et al. [13] developed and verified a building energy prediction model based on time series auto-regressions artificial neural networks based on the input variables of dry bulb and outdoor air temperature, hour of day, and type of day. As a result, CvRMSE was 40.9% for the numerical analysis model and 28.3% for the ANN model, which improved the accuracy. Seong et al. [14] developed an artificial neural network-based air flow prediction model to observe changes in accuracy with the number of input values. As a result, it was found that the predicted performance improved significantly as the number of inputs increased. Kim et al. [15] developed an artificial neural network-based energy consumption prediction model for fans to evaluate the accuracy according to input conditions. Mean bias error (MBE) showed a distribution of 1.7% to 2.95% of the learning period and 2.3% to 4.5% of the utilization period, while CvRMSE showed high predictive accuracy as it was distributed of 2.9% to 4.4% of the learning period and 3.6% to 7.9% of the utilization period.

There are many attempts to reduce energy consumption for the chiller systems including by using multiple linear regression analysis, interaction analysis of each components, and data-driven analysis [16–18].

In sum, various studies of machine learning methods, including ANN models, have been conducted in the field of building energy. The estimation of the energy consumption of a building, cooling load, etc. has been studied with results of high accuracy. However, most of the previous research has focused on the entire building system, and thus, management tools such as a BEMS need to be able to predict also the energy usage of subsystems such as air conditioners, heat source equipment, and transportation equip. To that end, the authors have developed management software for a centralized HVAC system. As shown in Figure 1, the centralized HVAC management software is composed of a real-time operation and performance monitoring function, energy performance prediction and optimization application, a performance evaluation report, and all the functions that utilize real-time data collected from a BEMS. Figure 1 shows the schematic diagram of a centralized HVAC management software, energy performance prediction and optimization function (EPPOF).

The developed software, referred to as energy performance prediction and optimization function (EPPOF), uses machine learning techniques to calculate control variables for predicting and optimizing energy consumption in a centralized HVAC system. To predict the energy consumption of the system, a prediction model based on ANNs was developed for the air conditioner, air handling unit, and heat source equipment that constitute the main energy consumers in an air conditioning system.

In this study, the authors investigated the accuracy of this developed model that is based on ANNs with respect to the input parameters, i.e., the number of input variables, proportion of training data, and number of neurons. The generated chiller operational data were generated and used to evaluate correlation between possible parameters in the chiller model. Section 2 presents the predictive energy consumption model for HVAC system with ANN. In Section 3, the accuracy for the predicted models with respect to input variations was evaluated and then Section 4 predicts the prediction of energy consumption based on the optimized input variations. Section 5 shows the conclusion based on the comparison between the simulated results and predicted results.

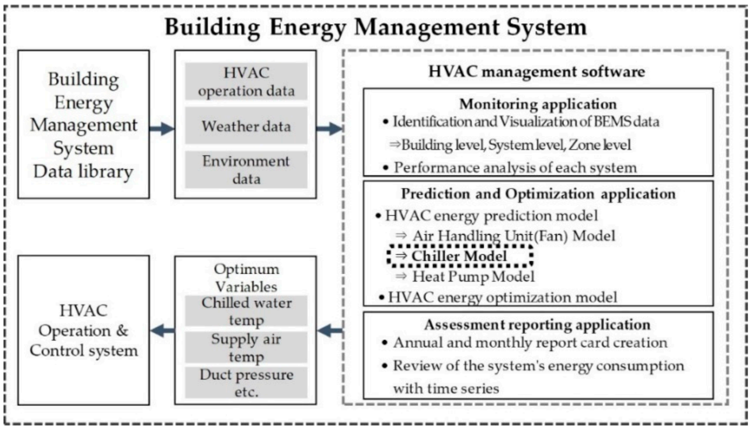


Figure 1. Schematic diagram of centralized heating, ventilation, and air conditioning (HVAC) management software, energy performance prediction and optimization function (EPPOF).

2. Predictive Model for Energy Consumption of a Chiller in an HVAC System

2.1. Modeling of the Reference Building Unit

A large amount of data is required for both training and testing with ANNs. For this study, the authors modeled a large-scale office building, designated in the commercial prototype building models in the U.S. Department of Energy (DOE) Building Energy Codes Program [19], and modified the related input variables for comparable buildings in Korea. Specifically, the climate data for Seoul, Korea were collected using the TRY (test, reference, year) format. This study generated the necessary data in accordance with the requirements for the DOE reference building model that has a standard pattern for energy consumption (annual energy consumption per area). Several parameters were considered to generate the reference building model: The heat source equipment, HVAC equipment, and energy performance variables, including core size, roof type, structure, construction year, heat flow rate, window area ratio, etc. Energy simulation software (Energyplus) was used to generate the related chiller operational data. The generated building was 12 storeys and a basement with floor area of 46320 m^2, and rectangular shape with aspect ratio of 1.5. Table 1 presents detailed boundary condition associated with reference building.

Table 1. Simulation condition of reference building large scale office.

Component	Features
Weather Data and Site Location	TRY Seoul (latitude: 37.57°N, longitude: 126.97°E)
Building Type	Large Scale Office
Total Building Area (m^2)	46320
Hours Simulated (hour)	3761
Envelope Insulation (m^{2}K/W)	External Wall 0.35, Roof 0.213, External Window 1.5
Window-Wall Ratio (%)	40
Set Point (°C)	Cooling 26, Heating 20
Internal Gain	Lighting 10.76 (W/m^2), People 18.58 (m^2/person), Plug and Process 10.76 (W/m^2)
HVAC Sizing	Auto Calculated
HVAC Operation Schedule	7:00–18:00

Table 2 presents the specification chiller system used in this study.

Table 2. Chiller specification.

Type	Nominal Capacity	Nominal Efficiency	Initial Design Size Reference Chilled Water Flow Rate	Design Size Reference Chilled Water Flow Rate	Design Size Reference Condenser Water Flow Rate	Design Chilled Water Temperature
Electric:EIR	5114517 W	5.5 W/W	0.12 m^3/s	0.18 m^3/s	0.26 m^3/s	6.7 °C

2.2. Determination of Input Values

Among the many variables in the dataset that were generated for the reference building model, some were selected to be used as input values for the ANN model. The accuracy of the final results could be affected if little or no correlation exists between the variables used as input values in the ANN model and the energy consumption of the chiller. Therefore, the correlation between the energy consumption of the chiller and the Spearman rank-order correlation coefficient for each variable was analyzed. The Spearman rank-order correlation coefficient had a value between −1.0 and +1.0, similar to other correlation coefficients.

Table 3 presents the Spearman rank-order correlation coefficient for each variable used for the ANN analysis of the proposed chiller's energy consumption. Nine variables were originally considered: Chilled water flow rate, cooling water temperature, outside dry-bulb temperature, outside wet-bulb temperature, dew-point temperature, outside relative humidity, hours, type of day, and supply chilled water temperature. The correlation coefficients indicate that the outside dry-bulb temperature, outside wet-bulb temperature, and outside relative humidity are the main parameters. The negative correlation coefficient of supply chilled water temperature results in the increase of chiller energy consumption as the water temperature decreased. Table 3 shows the correlation between variables and chiller energy consumption.

Table 3. Correlation between variables and chiller energy consumption.

Variables	Chilled Water Flow Rate (kg/s)	Cooling Water Temp. (°C)	Outside Dry-Bulb Temp. (°C)	Outside Wet-Bulb Temp. (°C)	Dew-Point Temp. (°C)	Outside Relative Humidity (%)	Hour	Type of Day	Supply Chilled Water Temp. (°C)
Spearman correlation coefficient	0.99	0.90	0.89	0.88	0.83	0.16	0.06	0.04	−0.67

2.3. Development of a Predictive Model of Energy Consumption of the Chiller Using the ANN Model

An ANN model is a network created by connecting nodes. It processes learning based on the weight of the nodes between the input and target values and outputs the result. An ANN model consists of an input layer, hidden layer, and output layer. An input value for training is derived and the input signal is transmitted to the next node in the input layer. The hidden layer is connected to all the nodes in the input layer, receives the input signal, and performs the neural network operation through the connection of the hidden layer nodes. Then, the output layer calculates the final result through the operation value of the hidden layer. For this study, the input values for the input layer were selected after making a list in the ANN to find the most accurate model to predict the energy consumption of the chiller. Figure 2 presents a schematic diagram of the ANN model used in this study as derived using MATLAB (version R2018a). A feed-forward automatic nonlinear NARX (nonlinear autoregressive network with exogenous) method, which uses measured values as inputs to dynamic neural networks, was employed to improve the predictive performance of the model. The NARX method is preferred to predict a time series dataset [20,21]. Figure 2 shows the schematic diagram of the predictive model of chiller energy consumption using the ANN model.

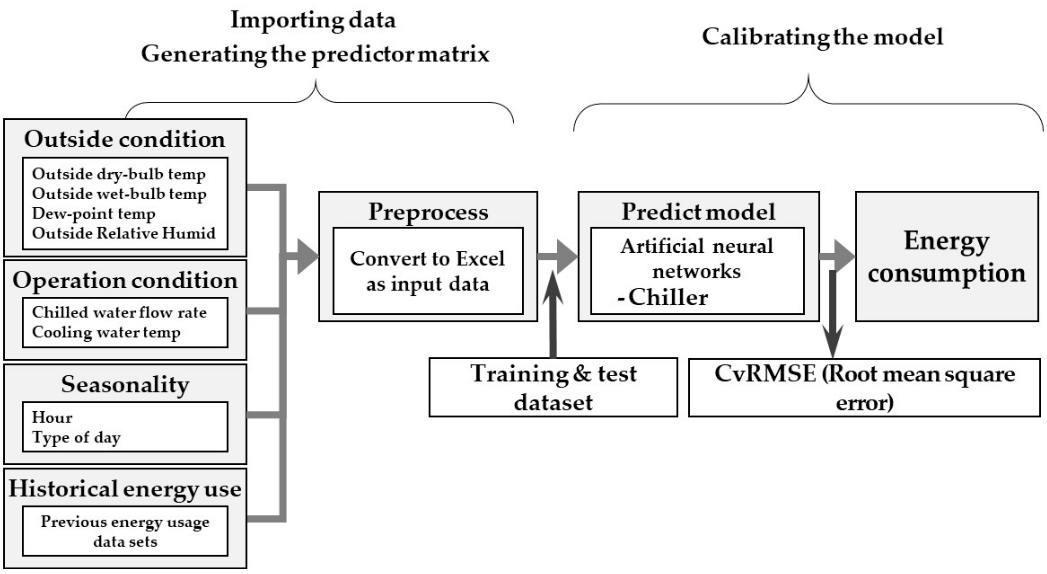


Figure 2. Schematic diagram of the predictive model of chiller energy consumption using the artificial neuron network (ANN) model.

Table 4 summarizes the input and output settings for the predictive model. The accuracy of the predicted results for chiller energy consumption according to the input setting was analyzed and tested to find the optimal conditions for the proposed ANN model. To do that, three input variables were considered: The number of input data points, the number of neurons and their size, and the amount (proportion) of the training data. By applying these input variables, the accuracy of the predicted results could be compared. Eight input values were used instead of the original nine, because the supply chilled water temperature had a negative correlation coefficient among the data generated. The eight remaining input values were added in order of their correlation coefficient from highest to lowest, and the accuracy of the results was compared according to the number of input values, which correlated to eight 'cases' for this study.

Table 4. Input/output conditions for chiller energy prediction model.

Input Data	Chilled water flow rate (kg/s) Cooling water temperature (°C) Outside dry-bulb temperature (°C) Outside wet-bulb temperature (°C) Dew-point temperature (°C) Outside relative humidity (%) Hour (h) Type of day (weekdays, weekend)
Number of Neurons	2–20
Proportion of Training Data	50%–90% (of 3761 data sets)
Predicted Target Y(t)	Chiller energy consumption (kWh)

For the training data, the amount of the data shows that the accuracy of the predicted results varied between 50% and 90% of the 3761 datasets that corresponded to the cooling period (warmest seasons) from May to September. Those data were generated based on the reference building model discussed in Section 2.1. The number of neurons is also one of the most important variables in a neural network. In this study, the accuracy of the results and computation speed were compared based on a range from two to twenty neurons. Table 4 shows the input/output conditions for the chiller energy prediction model.

ASHRAE (American Society of Heating, Refrigeration, and Air Conditioning Engineers) Guideline 14, Measurement of Energy and Demand Savings [22], was used to confirm that the test results were reliable when the tolerance limits were within the range of specified tolerances, as shown in Table 5. The accuracy and reproducibility of the predictive model were verified through the CvRMSE of the results obtained from 10 runs per condition. The chiller energy usage was predicted using the conditions with the highest accuracy. Table 5 shows the acceptable calibration tolerances.

Table 5. Acceptable calibration tolerances.

Calibration Type	Index	Acceptable Value *
Monthly	MBE CvRMSE	±5% 15%
Hourly	MBE CvRMSE	±10% 30%

Note: MBE is mean bias error; CvRMSE is the coefficient of variance of the root mean squared error. * Lower values indicate better calibration.

MBE and CvRMSE are defined by Equations (1) and (2):

$$\text{MBE} = \left\{ \left[\sum_{i=1}^{n} (y_i - \hat{y}_i) \right] / \left[(n-p) \times \overline{y} \right] \right\} \times 100, \tag{1}$$

$$\text{CvRMSE} = 100 \times \left[\sum (y_i - \hat{y}_i)^2 / (n-p) \right]^{1/2} / \overline{y}, \tag{2}$$

where n is the number of data points, p is the number of parameters, y_i is the utility data used for calibration, $\hat{y}_i$ is the simulation predicted data, and $\overline{y}$ is the arithmetic mean of the sample of n observations.

3. Results and Discussion

The accuracy of the predictions of the chiller's energy consumption was based on the results for the number of input variables, amount (proportion) of the data, and number of neurons during both the training and testing periods. The following sections present and discuss these results.

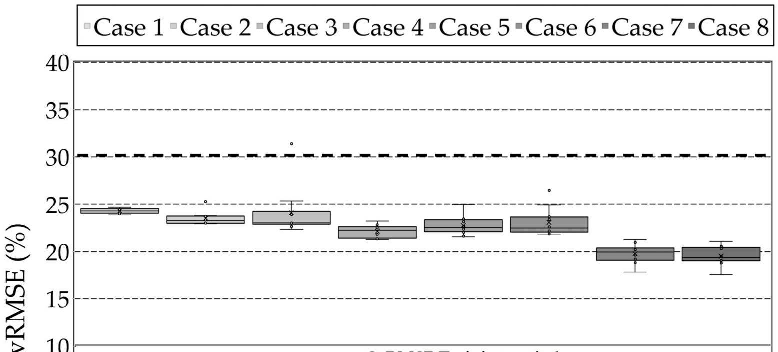
3.1. Effect of the Number of Input Variables for the Training Period and Testing Period

The accuracy of the predicted results was investigated according to the number of input variables. The input variables were added sequentially one by one starting from the chilled water flow rate with the highest correlation coefficient, as summarized in Table 6. The amount of training data was fixed at 50% of the total dataset, and the number of neurons was fixed at 20. Table 6 shows the conditions for the input variables.

Figure 3 shows the CvRMSE of the predicted energy consumption of the chiller for each case (number of inputs) during the training period. For most of the cases, the predicted values did not exceed the ASHRAE Guideline standard of 30% at a fixed training period of 50%. In Case 1 with one input parameter (chilled water flow rate), the repeatability was good with a standard deviation of 0.3. The results were comparable with Case 4 and Case 5, even when the number of input variables was only one. Case 2 and Case 3 were 57.7% and 31.3%, respectively, which exceed the limit of 30%. If the number of input variables is few, this factor will affect the reproducibility of the predicted results. When the number of input variables was 7 (min. 17.7%, max. 21.2%, and mean 19.8%) or 8 (min. 17.5%, max. 21.1%, and mean 19.5%), the predicted results were more accurate than for the other conditions. Figure 3 shows the accuracy according to the number of input variables for the training period.

Table 6. Conditions for the input variables.

Number of Inputs	Possible Input Variables							
	Chilled Water Flow Rate (kg/s)	Cooling Water Temp. (°C)	Outside Dry-Bulb Temp. (°C)	Outside Wet-Bulb Temp. (°C)	Dew-Point Temp. (°C)	Outside Relative Humidity (%)	Hour	Type of Day
Spearman correlation coefficient	0.99	0.90	0.89	0.88	0.83	0.16	0.06	0.04
Case 1	○							
Case 2	○	○						
Case 3	○	○	○					
Case 4	○	○	○	○				
Case 5	○	○	○	○	○			
Case 6	○	○	○	○	○	○		
Case 7	○	○	○	○	○	○	○	
Case 8	○	○	○	○	○	○	○	○



CvRMSE-Training period	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Min.	23.8	22.9	22.3	21.3	21.5	21.8	17.8	17.5
Max.	24.8	57.7	31.3	23.2	24.9	26.4	21.2	21.1
Mean	24.3	26.3	23.8	22.1	22.7	23.0	19.8	19.5
Standard deviation	0.3	9.5	2.4	0.6	0.9	1.4	0.9	0.9

Figure 3. Accuracy according to the number of input variables for the training period.

Figure 4 shows the CvRMSE of the predicted energy consumption of the chiller during the testing period for each case (number of inputs). For most cases, the CvRMSE is in the range of 30% to 60%. The accuracy and reproducibility were shown to have decreased compared to the CvRMSE results during the training period. However, the accuracy and reproducibility of the predicted results gradually improved as the number of input variables increased. When the number of inputs was more than 7, the CvRMSE was an average of less than 30%, which is the ASHRAE standard. Case 8 shows the best results with a min. of 19.4%, max. of 30.2%, mean of 22.8%, and standard deviation of 3.0. The predicted values for energy usage during the training interval and testing interval according to the variation in input variables confirmed that the prediction accuracy improved as the number of variables increased. Even though variables such as outside relative humidity, hour, and type of day were not closely correlated with chiller energy usage, but those variables also helped to improve accuracy. Figure 4 shows the accuracy according to the number of input variables for the testing period.

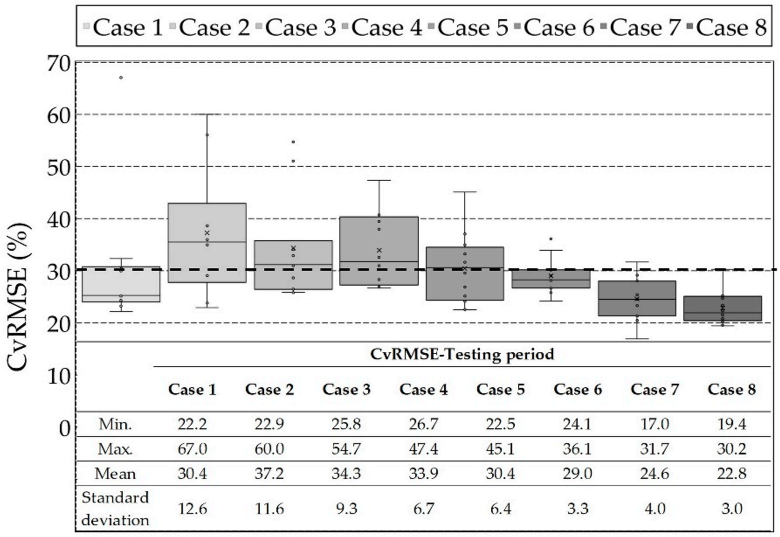


Figure 4. Accuracy according to the number of input variables for the testing period.

3.2. Effect of Amount of Data For Training Period and Testing Period

The accuracy of the predicted energy consumption was evaluated also by varying the amount of training data from 50% to 90%, while the number of input variables and the number of neurons were fixed at 8 and 20, respectively. Table 7 shows the conditions for training and testing data size.

Table 7. Conditions for training and testing data size.

	Case 9		Case 10		Case 11		Case 12		Case 13	
	Training period	**Testing period**	**Training period**	**Testing period**	**Training period**	**Testing period**	**Training period**	**Testing period**	**Training period**	**Testing period**
Data size (%)	50	50	60	40	70	30	80	20	90	10

Figure 5 shows the accuracy for energy consumption with respect to the amount of the training dataset. For the training period, the results confirmed that the accuracy improved as the proportion of data used for prediction was increased. The reproducibility and accuracy of the predictions were excellent, with a standard deviation less than 1 for all cases. Figure 5 shows the accuracy according to changes in the proportion of training data for the training period.

Figure 6 presents the prediction accuracy for energy consumption with respect to the proportion of the testing dataset in terms of the percentage used during the testing period. The best results were obtained with the CvRMSE average of 18.2% and standard deviation of 1.1 when 60% and 40% of the training data were used, respectively. The accuracy and reproducibility of the prediction decreased as the amount of data used during the testing period was decreased. Since ANNs provide a technique for performing predictions through data learning, the amount of datasets used for learning has a great influence on the accuracy of the predictions. Therefore, the accuracy varied according to the proportion of overall data used respectively in the training period and testing period. In this study, the predicted results indicated that an optimal method to obtain accurate prediction results was to proportion the data to be 60% for the training period and 40% for the testing period. Figure 6 shows the accuracy according to changes in proportion of the testing data for the testing period.

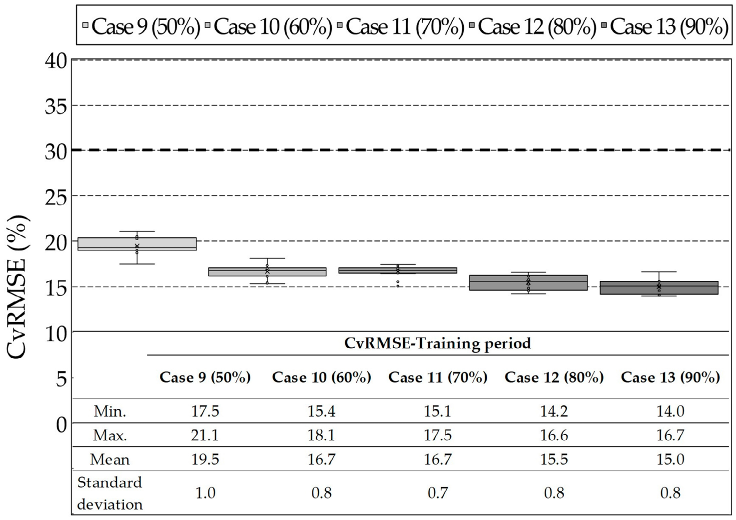


Figure 5. Accuracy according to changes in the proportion of training data for the training period.

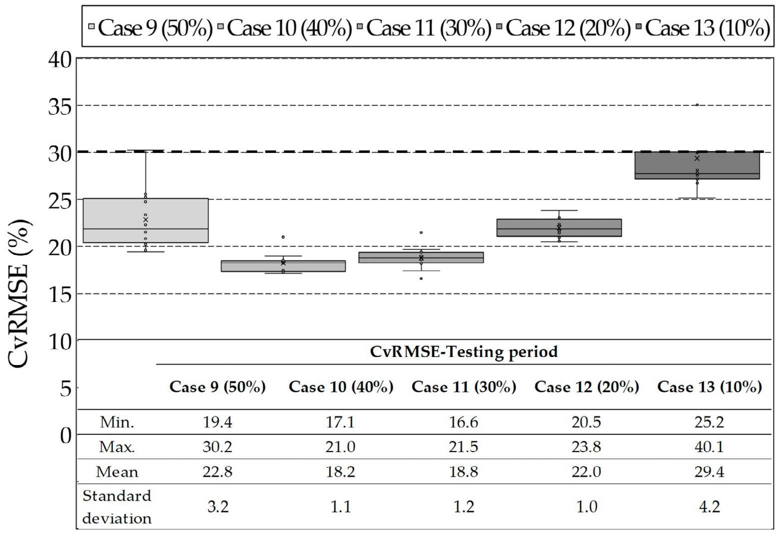
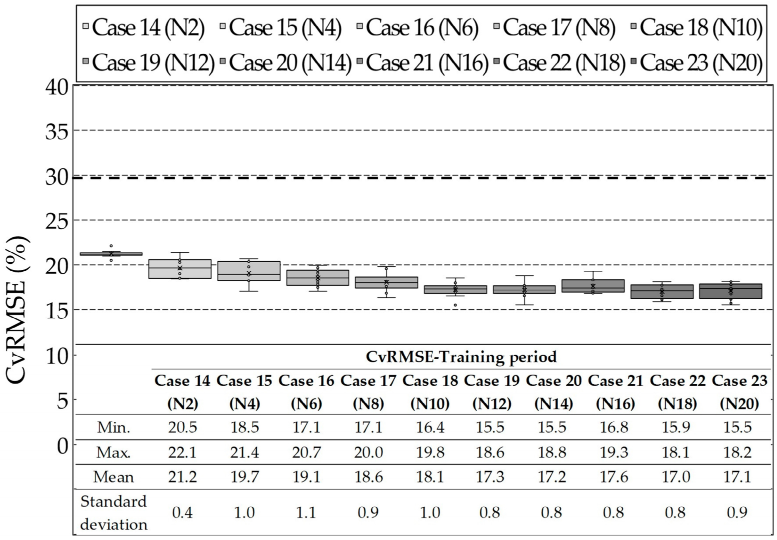


Figure 6. Accuracy according to the changes in proportion of the testing data for the testing period.

3.3. Effect of Number of Neurons for Training Period and Testing Period

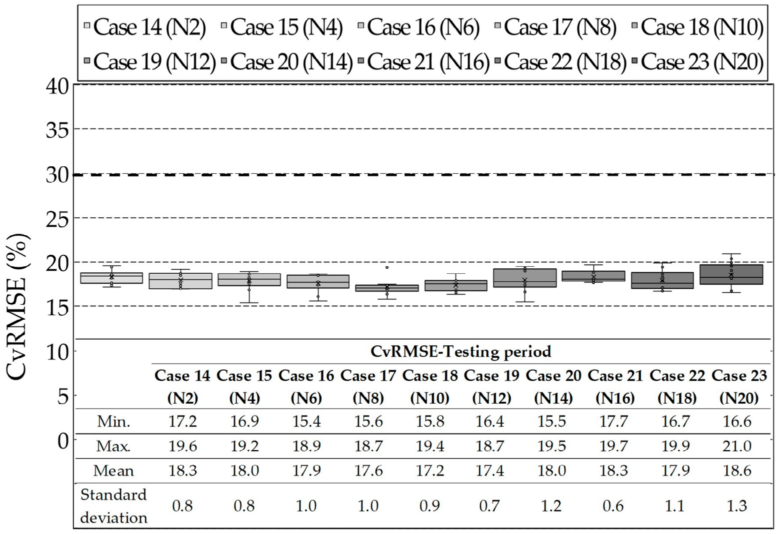
In this study, the number of neurons was varied from 2 to 20, and the number of input variables was fixed at 8 with 60% training data. Figure 7 shows that the average CvRMSE was less than 20% accurate in every case except Case 14 (with two neurons, referred to as N2). These results indicate that increasing the number of neurons to a certain level improves the accuracy of the predicted results; however, no significant change was evident after more than 12 neurons were employed. Figure 7 shows the accuracy according to number of neurons used in the training period.

For the testing period, as shown in Figure 8, the mean value of the CvRMSE was also less than 20% accurate except for Case 14 (N2). No significant difference was evident in all cases, but when the number of neurons was 12 (N12), the best predicted result was obtained with the mean of 17.4% and standard deviation of 0.7. Based on these results, the use of 12 neurons showed the best accuracy for both the training period and testing period in this study. No significant effect on accuracy with respect to the number of neurons was evident because the optimized number of input variables and amount of training data were used. Since an increase in the number of neurons could delay the execution time for ANN algorithms, the number of neurons should be considered carefully after selecting the number of input variables and proportioning the amount of training data. Figure 8 shows the accuracy according to number of neurons for the testing period.



	Case 14 (N2)	Case 15 (N4)	Case 16 (N6)	Case 17 (N8)	Case 18 (N10)	Case 19 (N12)	Case 20 (N14)	Case 21 (N16)	Case 22 (N18)	Case 23 (N20)
Min.	20.5	18.5	17.1	17.1	16.4	15.5	15.5	16.8	15.9	15.5
Max.	22.1	21.4	20.7	20.0	19.8	18.6	18.8	19.3	18.1	18.2
Mean	21.2	19.7	19.1	18.6	18.1	17.3	17.2	17.6	17.0	17.1
Standard deviation	0.4	1.0	1.1	0.9	1.0	0.8	0.8	0.8	0.8	0.9

Figure 7. Accuracy according to the number of neurons used in the training period.



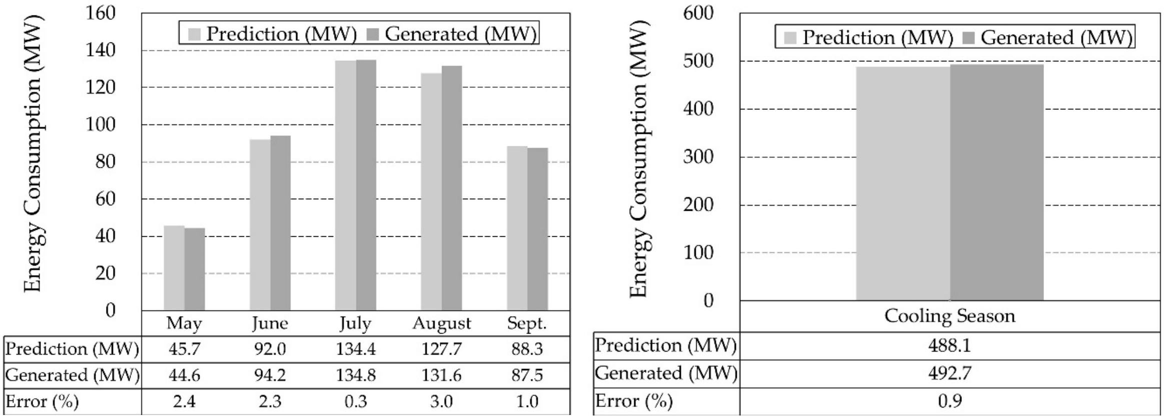
	Case 14 (N2)	Case 15 (N4)	Case 16 (N6)	Case 17 (N8)	Case 18 (N10)	Case 19 (N12)	Case 20 (N14)	Case 21 (N16)	Case 22 (N18)	Case 23 (N20)
Min.	17.2	16.9	15.4	15.6	15.8	16.4	15.5	17.7	16.7	16.6
Max.	19.6	19.2	18.9	18.7	19.4	18.7	19.5	19.7	19.9	21.0
Mean	18.3	18.0	17.9	17.6	17.2	17.4	18.0	18.3	17.9	18.6
Standard deviation	0.8	0.8	1.0	1.0	0.9	0.7	1.2	0.6	1.1	1.3

Figure 8. Accuracy according to the number of neurons for the testing period.

4. Prediction of Chiller Energy Consumption

The accuracy of the prediction of the energy consumption of the chiller was evaluated with respect to the various input conditions for the proposed ANN model. The condition that led to the highest level of accuracy was composed of eight input variables, 60% training data, and 12 neurons. The energy consumption of the chiller based on these derived optimal conditions was computed and compared with the data generated through the reference building in accordance with the large-scale office building used in DOE guidelines.

Figure 9 shows the energy consumption of the chiller system during warm/hot weather. The prediction period was from May to September, which comprises the seasons when cooling is most needed. The training period (60%) was selected as May to July and the testing period (40% of the dataset) was from August to September. Figure 9a presents a comparison of the monthly energy usage computed during the training period (from May to July) and the usage generated for the reference building. The error was 0.3%–2.4%. The error for August was 3.0% (predicted value of 127.7 MW versus the generated value of 131.6 MW). The error for September was 1.0% (predicted value of 88.3 MW versus the generated value of 87.5 MW). Figure 9b shows the total energy consumption prediction for the chiller with the error of 0.9% (predicted value of 488.1 MW versus the generated value of 492.7 MW) for the entire range of the cooling period (May to September). The predicted MW values closely matched the actual MW values. Figure 9a shows the monthly energy consumption and Figure 9b shows the total energy consumption.



(**a**) Monthly energy consumption (**b**) Total energy consumption

Figure 9. Prediction of chiller energy consumption (monthly for five months).

5. Conclusions

This study was conducted to find optimal conditions for a chiller in a centralized HVAC system by using an ANN algorithm. The developed chiller energy consumption model was evaluated for accuracy in terms of the following input parameters: Input conditions, number of input variables, amount of training data, and number of neurons. The limited findings were as follows.

With regard to optimizing the input variables, the prediction accuracy was secured in this study by increasing the number of input variables even if the correlation with the output value is low. With eight input variables, the CvRMSE reflected the highest accuracy of 19.5% and standard deviation of 0.9 in the training period, and the CvRMSE of 22.8% and standard deviation of 3.0 in the testing period.

With regard to optimizing the amount of training data, the prediction accuracy was similarly secured by increasing the percentage of the training data. However, increasing the training data means decreasing the testing data. The study results confirmed that prediction accuracy decreased gradually when the amount of data was decreased.

With regard to optimizing the number of neurons, when the number of input variables and amount of training data were fixed as per the previously verified conditions, no significant change in accuracy was found in terms of the number of neurons.

In order to obtain highly accurate predictions, various parameters such as conditions and number of input variables, sufficient available data, and the appropriate proportion of training versus testing data must be considered. In this study, by estimating the chiller energy usage based on eight input variables, 60% training data and 40% testing data, and 12 neurons, the predicted monthly energy consumption could be compared to the actual energy consumption generated by the DOE reference building. The comparison results indicated high prediction accuracy for the proposed chiller model with an error of only 0.9% of the total energy usage, which means that the proposed chiller was 99.1% accuracy.

For broadening the research, a deep learning model with more hidden layers and various cross validation method will be needed for the future works.

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