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Article

Optimization of the ANN Model for Energy Consumption Prediction of Direct Fired Absorption Chiller for a Short-Term

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Abstract: With an increasing concern for global warming, there have been many attempts to reduce greenhouse gas emissions. About 30 % of total energy has been consumed by buildings and much attention has been paid to reducing building energy consumption. While there are many ways of reducing building energy consumption, accurate energy consumption prediction becomes more significant. As mechanical systems are the most energy-consuming components in the building, the present study developed the energy consumption prediction model for a direct-fired absorption chiller by using the ANN technique for the short term. The ANN model was optimized and validated with the actual data collected through a BAS. For the optimization, the numbers of input variables and neurons, and the data size of training were applied. By changing these parameters, the predictive performance was analyzed. In sum, the outcome of the present study can used to predict the energy consumption of the chiller as well as improve the efficiency of the energy management. The outcome of the present study can be used to develop a more accurate prediction model with a few datasets in that it can improve the efficiency of building energy management.

Keywords: ANN; energy consumption; optimization; direct fired absorption chiller; validation

1. Introduction

According to energy consumption statistics, the building sector accounts for about 30 % of total energy consumption and 80 % of greenhouse gas emissions [1]. To reduce building energy consumption, many attempts have been made to design energy-efficient buildings by improving the thermal performance of building envelopes, using energy-efficient mechanical systems, and installing renewable energy systems. In addition, the optimized control and efficient operation of mechanical systems can make more energy-efficient buildings. Specifically, about half of the building energy was consumed by heating, ventilation, and air conditioning (HVAC) to maintain thermally comfortable indoors [2]. Thus, it is needed to manage the energy consumption of HVAC systems more efficiently in building operations. Recently, the use of building energy management systems (BEMS) can be practically used to manage building energy consumption by providing specific information on building energy usage. It is therefore required to predict accurate building energy consumption for optimizing building energy performance from the building design to operation [3].

In 2014, the Korean government regulated to installation of an energy management system (EMS) to strengthen building energy management. In addition, the Korean government has regulated to installation of BEMS in newly constructed public buildings or extensions, where the gross floor area is bigger than 10,000 m2 from 2017 [4,5]. According to the new laws in 2019 in South Korea, the regulation for the BEMS installation become more significant to strengthen building energy management. Regarding this law, it is required for building energy management to predict building energy consumption by implementing regression analyses or machine learning for hourly and daily energy usage and energy sources [5].

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In South Korea, recent studies have been conducted to predict building energy load [6,7] and consumption[8,9], energy usage patterns[10,11], etc. by using machine learning or artificial intelligence (AI). Moreover, they pointed out that much attention should be paid to the accuracy of predictions by these techniques. Most of those techniques required a number of datasets to predict building energy consumption. If buildings do not equip BEMS or building automation systems (BAS), data generated by simulation tools are generally used. However, the simulated data are different from the measured data. In addition, it is even difficult to achieve the number of measured data for a short period. Thus, an effort needs to be made to improve the accuracy of the prediction with a few datasets for a short period.

The purpose of the present study is to develop the energy consumption prediction model for the short term based on the artificial neural networks (ANN) technique. After optimizing the ANN model, it is validated with the energy consumption data collected from an operation of a direct-fired absorption chiller. The outcome of the present study can be used to develop a more accurate prediction model with a few datasets in that it can improve the efficiency of building energy management.

2. Optimization and Validation of an ANN-based prediction model

The present study used an ANN technique to predict energy consumption for the short term. Since it requires a number of datasets to optimize the ANN model, the energy simulation was performed to generate datasets. Considering the correlation among data, input variables were chosen and preprocessed. The number of inputs and neurons and the data size of training and learning parameters were determined to optimize the ANN model. After optimizing the model, it was validated with measured data. Figure 1 shows the study process for the present study.

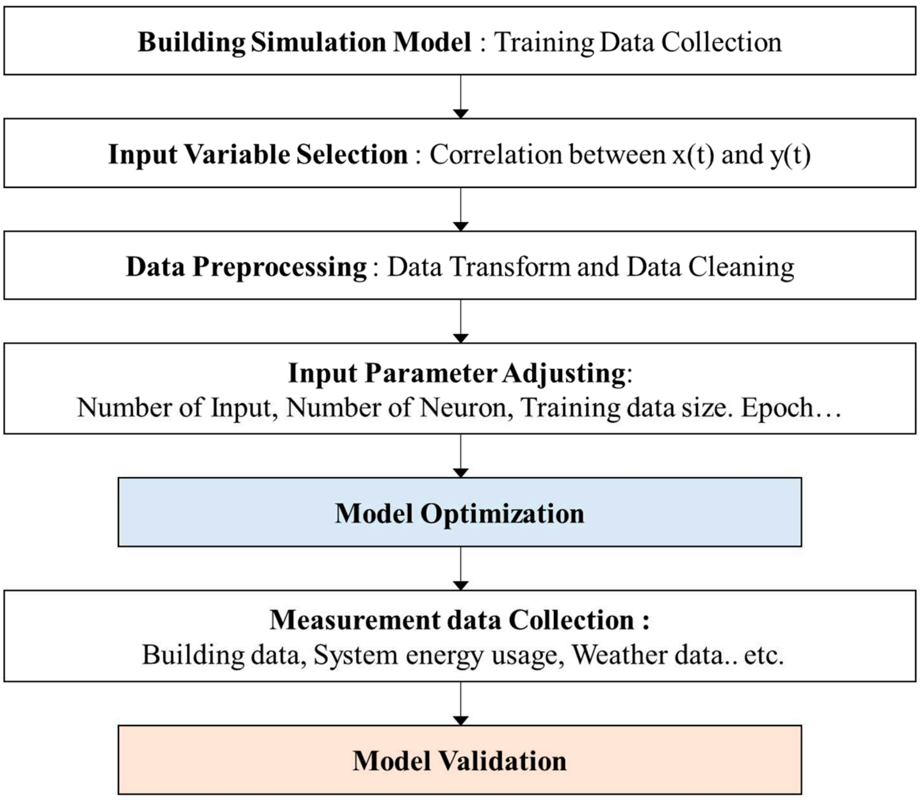

Figure 1. The study process.

2.1. ANN model

Among ANN models, the present study implemented NARX(Nonlinear Autoregressive Network with eXogenous) Feedforward Neural Net-works model which was generally used to

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predict time-series data due to its high accuracy [3]. According to the results of several studies, the NARX model can be used to model non-linear dynamic systems and time-series forecasting models [12,13]. For the ANN model, Neural Networks Toolbox of MATLAB(R2020a) was used to create neural network. NARX Feedforward Neural Networks model was a multi-layer perceptron ANN model, which consists of an input layer, hidden layer, and output layer [14]. In addition, Levenberg-Marquardt algorithm was used to find a minimum of a function over a space of parameters, which is a popular trust algorithm. A similar structure of the ANN model used in the previous studies was used for the present study and the structure is shown in Figure 2 [14,15].

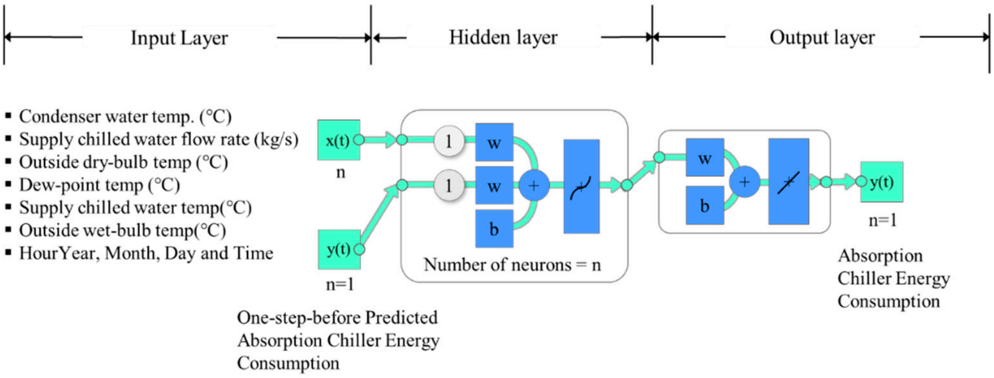

Figure 2. Structure of a multilayer neural network model.

2.2. Assessment of the prediction model

In general, the performance of prediction models can be validated with ASHRAE (American Society of Heating, Refrigerating and Air-Conditioning Engineers) Guideline 14, FEMP (US DOE Federal Energy Management Program), IP-MVP (International Performance Measurement and Verification Protocol)'s M&V (Measurement and Verification) guideline [16–18]. These provide their M&V protocol and have the performance evaluation indicators (Table 1). Among those, the present study evaluated the performance of the prediction model based on ASHRAE Guideline 14. CV(RMSE) refers to the degree of scattering of estimated values in consideration of variance, and MBE is an error analysis index that identifies errors by tracking how close estimates form clusters through data bias, which are presented below as Equations 1 and 2. By using CV(RMSE), the performance evaluation indicators of the predictive model were validated.

$$\text{MBE} = \sum^{n}(y_i - \hat{y}_i)/[(n-p)\times\bar{y}]\cdot 100 \tag{1}$$

$$\text{Cv(RMSE)} = 100\cdot\left[\sum(y_i - \hat{y}_i)^2/(n-p)\right]^{1/2}/\bar{y}, \tag{2}$$

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 $\bar{y}$ is the arithmetic mean of the sample of n observations. In addition, the suitability of the model was evaluated by using R^2. After 10 times of learning, the average, maximum, minimum, and standard deviation were used to evaluate the predictive performance of the ANN-based prediction model.

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Table 1. Acceptable calibration tolerances in building energy consumption prediction.

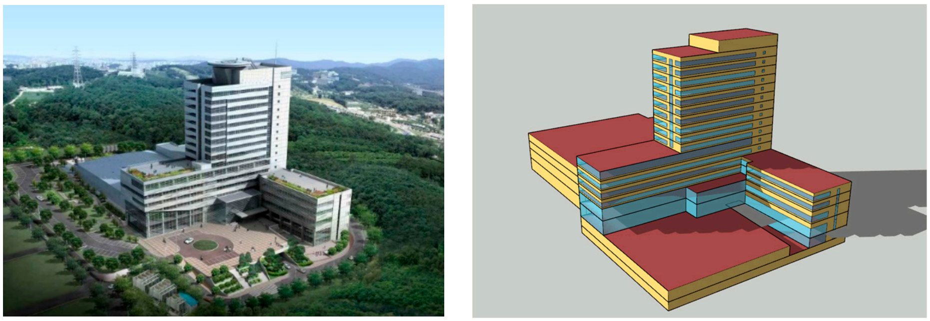
Calibration Type	Index	ASHRAE Guideline 14 [10]	FEMP [11]	IP-MVP [12]
Monthly	MBE_monthly	± 5%	± 5%	± 20%
	CvRMSE_monthly	15%	15%	-
Hourly	MBE_hourly	±10%	±10%	±5%
	CvRMSE_hourly	30%	30%	20%

3. The optimization of the ANN-based model using the simulation data

To improve the predictive performance of ANN models, it generally requires a number of data[19]. For the present study, data generated by simulations were used. The data generated by simulations have the advantage of choosing the data for certain periods when it is not able to gather data from buildings over a long period.

3.1. Energy simulation for generating data

In the present study, an office building was chosen. The reference building has 18 floors with a gross floor area of 41,005 m^2. For heating and cooling, 2 direct-fired absorption chillers were equipped and one chiller was operated. Each chiller's cooling capacity was 600 USRT. For the energy simulation, EnergyPlus 9.3.0 was used. The reference building (a in Figure 3) was modeled by using Openstudio as shown in b in Figure 3. The inputs for the energy simulation such as the operation schedule, occupancy, etc. were the same as the reference building. In addition, the climate data collected from the BAS installed at the reference building were synthesized into TRY format. Table 2 shows the specific inputs for the energy simulation.



(**a**) Overview of target building (**b**) Model using Openstudio

Figure 3. The reference building overview and the model using Openstudio.

Table 2. Simulation conditions.

Component	Features
Site Location	Latitude: 37.27°N, Longitude: 126.99°E
Weather Data	TRY Suwon
Load convergence tolerance value	delta 0.04W (default)
Temperature convergence tolerance value	delta 0.4℃ (default)
Heat Balance algorithm	CTF (Conduction Transfer Function)
Simulated Hours	8760 [hour]
Timestep	hourly
Internal Gain	Lighting 6 [W/㎡] People 20 [㎡/person] Plug and Process 8 [W/㎡]

Envelope Summary	Wall 0.36 [W/㎡·K], Roof 0.20 [W/㎡·K] Window 2.40 [W/㎡·K] SHGC 0.497
Operation Schedule	7:00~18:00

3.2. The optimization process for improving the predictive performance of the ANN model

3.2.1. Input variables

In this stage, input variables were chosen among the data generated by the energy simulation for training. Using the Spearman rank-order correlation coefficient, the correlation between input and output was analyzed. The high prioritized correlated value was chosen as input values. The input layer for a direct-fired absorption chiller consisted of outside dry-bulb temperature, dew-point temperature, outside wet-bulb temperature, supply chilled water temperature, supply chilled water flow rate, condenser water temperature, and seasonal data. In the hidden layer, data were received as an input signal from the input layer through the internal neurons. The output layer predicted the energy consumption from the direct-fired absorption chillers based on the hidden layer calculation result. Table 3 presents the calculation results and ranks from the correlation between input variables (x(t)) and the predicted gas consumption of the direct-fired absorption chiller (y(t)).

Table 3. Correlation between Input variables and energy consumption.

Input Variables [x(t)]	**Condenser water temp. (℃)**	**Supply chilled water flow rate (kg/s)**	**Outside dry-bulb temp. (℃)**	**Dew-point temp (℃)**	**Supply chilled water temp. (℃)**	**Outside wet-bulb temp. (℃)**	**Hour**
Rank	1	2	3	4	5	6	7
Spearman correlation	0.72	0.65	0.54	0.44	-0.38	0.31	0.25

3.2.2. Input parameters

The number of hidden layers was set at 3. As one of the learning parameters, the number of epochs was 100. Since the number of neurons in the hidden layers mainly influences the calculation prediction and time, the number of neurons was changed from 2 to 20 by 2. While the number of input variables was changed from 3 to 7, the size of datasets ranged from 50 %–90 %. Detailed parameter conditions are summarized in Table 4.

Table 4. Parameter conditions for the optimization of the ANN model.

Parameter		**Value**
Fixed	Number of hidden layers	3
	Epochs	500
Variable	Number of Inputs	3~7
	Number of neurons	2~20
	Training Data Size	50%~90%

3.3. The result and discussion

3.3.1. The predictive performance by the number of input variable changes

Figure 4 shows the result of the predictive performance by changing the number of input variables to find the optimized number of input variables. For this work, the number of neurons and the data size of training were set at 10 and 60 %, respectively. As the number of input variables increased, the average values of CVRMSE were in the range of 5.69 %–8.43 % and 12.25 %–24.04 %

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for the training and testing period, respectively. These were within the acceptable values of 30 % by ASHRAE Guideline 14. When the number of input variables was 4, the average value of CVRMSE was the lowest (5.69 %) for the training period. In the case of the testing period, the average value of CVRMSE was the lowest (13.25 %) when the number of input variables was 5. Moreover, the average, minimum, and maximum values of CVRMSE were 12.25 %, 8.56 %, and 16.05 %, when the number of input variables was 5. This showed the most accurate predictive performance. When the minimum number of input variables of 3 was used, the average values of CVRMSE were decreased to 0.58 % and 3.74 % for the training and testing period, respectively. The standard deviation was 2.44 which showed constant predictive performance. When the number of input variables was above 5, the average value of CVRMSE was increased, while the accuracy of the predictive performance was lowered. This can be seen that the predictive performance of the ANN model is lowered when the input variables are not correlated with the input layer. Therefore, the predictive performance was the most acceptable when the number of input variables was 5. According to the result, it is important to consider the correlation between the input layer and input variables rather than increasing the number of input variables. Table 5 shows the values of average, minimum, maximum, and standard deviation with the increase in the number of input variables.

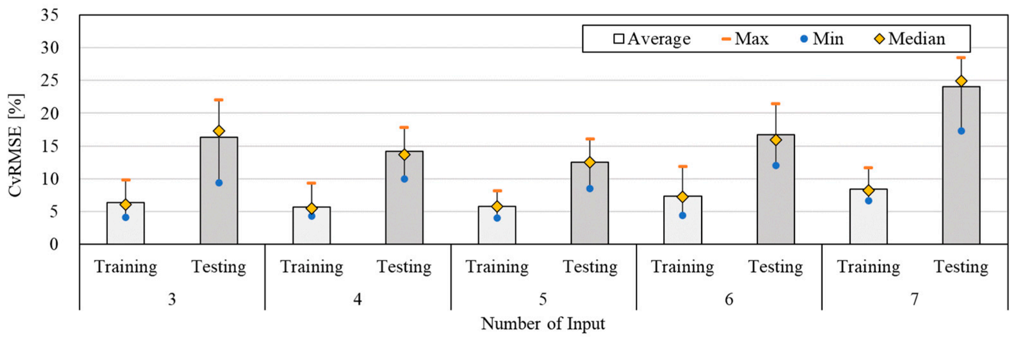


Figure 4. The predictive performance by changing the number of input variables.

Table 5. The predictive performance by changing the number of input variables (Maximum, minimum, average, and standard deviation).

Number of Input	Period	Average	Maximum	Minimum	SD
3	Training	6.35	9.88	4.18	1.67
	Testing	16.30	22.05	9.44	4.30
4	Training	5.69	9.37	4.34	1.49
	Testing	14.23	17.84	9.99	2.60
5	Training	5.77	8.21	4.03	1.40
	Testing	13.25	19.35	8.56	3.49
6	Training	7.38	11.92	4.46	1.94
	Testing	16.74	21.43	12.05	3.21
7	Training	8.43	11.65	6.72	1.45
	Testing	24.04	28.45	17.32	3.92

3.3.2. The predictive performance by the number of neurons changes

In this stage, the predictive performance of the model was analyzed by changing the number of neurons (Figure 5). The number of input variables was 5 and the size of the learning data was set at 60 %. As the number of neurons was increased, the average values of CVRMSE were in the range of 5.61 %–22.44 % and 12.25 %–27.14 % for the training and testing period, respectively. These were within the acceptable values of 30 % by ASHRAE Guideline 14. When the number of neurons was 20, the average value of CVRMSE was the lowest (5.61 %) for the training period. In the case of the testing period, the average value of CVRMSE was the lowest (12.25 %) when the number of neurons was 10.

Moreover, the most accurate predictive performance was obtained when the number of neurons was 10 in which, the values of average, minimum, and maximum CVRMSE were 12.25 %, 8.56 %, and 16.05 % respectively. When comparing the number of neurons between 10 and 2, the average values of CVRMSE for the training and testing period were decreased to 16.66 % and 12.55 %, respectively. When the number of neurons was 10, the predictive performance was improved by decreasing the values of CVRMSE gradually, while it was lowered by increasing the value of CVRMSE when the number of neurons was higher than 12. This indicated that the weight was increased with the increase in the number of neurons in that overfitting was obtained. When the number of neurons was higher than 10, the standard deviation was in the range of 1.42-2.84, which showed more constant predictive performance than that originated from the number of neurons below 10. It showed that the most acceptable predictive performance was obtained when the number of neurons was 10. It can be seen that the increase in the number of neurons was not able to improve the predictive performance of the ANN model. Thus, it is important to find a suitable number of neurons by observing the predictive performance. Table 6 shows the values of average, maximum, minimum, and standard deviation by increasing the number of neurons.

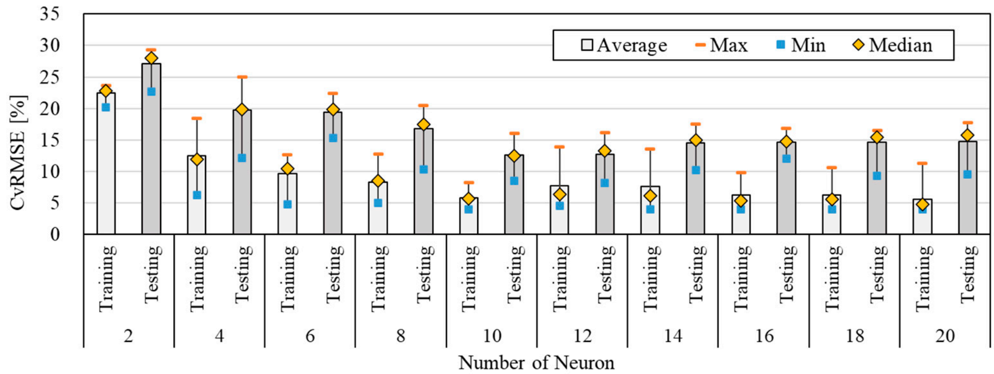


Figure 5. The predictive performance by changing the number of neurons.

Table 6. The predictive performance by changing the number of neurons (Maximum, minimum, average, and standard deviation).

Number of Neuron	Period	Average	Maximum	Minimum	SD
2	Training	22.44	23.65	20.23	1.21
	Testing	27.14	29.33	22.68	2.41
4	Training	12.47	18.43	6.22	3.36
	Testing	19.77	25.01	12.15	3.79
6	Training	9.70	12.66	4.83	2.59
	Testing	19.45	22.40	15.36	2.22
8	Training	8.28	12.76	5.00	2.36
	Testing	16.80	20.50	10.37	3.73
10	Training	5.77	8.21	4.03	1.40
	Testing	12.55	16.05	8.56	2.44
12	Training	7.70	13.95	4.58	3.10
	Testing	12.66	16.14	8.20	2.84
14	Training	7.62	13.59	4.02	3.86
	Testing	14.52	17.55	10.27	2.33
16	Training	6.22	9.81	3.98	1.94
	Testing	14.59	16.82	12.05	1.42
18	Training	6.22	10.64	4.01	2.39
	Testing	14.66	16.50	9.28	2.27

20	Training	5.61	11.33	3.96	2.19
	Testing	14.74	17.72	9.57	2.84

3.3.3. The predictive performance by the data size changes of training

Figure 6 presents the values of CVRMSE by changing the data size of training. Based on the previous results, the number of input variables and neurons was set at 5 and 10, respectively. The data size of training was increased from 50 % to 90 % by 5 %. The average values of CVRMSE were in the range of 5.36 % - 7.74 % and 8.93 % - 17.69 % for the training and testing period, respectively. These were all within the acceptable range of ASHRAE Guideline 14. In addition, it showed a suitable predictive performance of 20 %. When the data size of the training was set at 65 %, the average value of CVRMSE was the lowest (5.36 %) for the training period, while it was 8.93 % for the testing period when the data size of the training was 85 %. Moreover, the average, minimum, and maximum values of CVRMSE were 8.93 %, 6.69 %, and 11.23 %, when the data size of training was 85 %. That showed the most accurate predictive performance. When the data size of training was increased to 85 %, the predictive performance was improved, while the CVRMSE was decreased gradually. However, the predictive performance was degraded with 90 % of the training data size. The standard deviation ranged from 1.88–1.45 when the data size of training was set between 70 % - 85 %. Thus, the ANN model showed the most acceptable predictive performance when the data size of training was set between 80 % - 85 %. Table 7 presents the predictive values of maximum, minimum, and standard deviation by changing the data size of training.

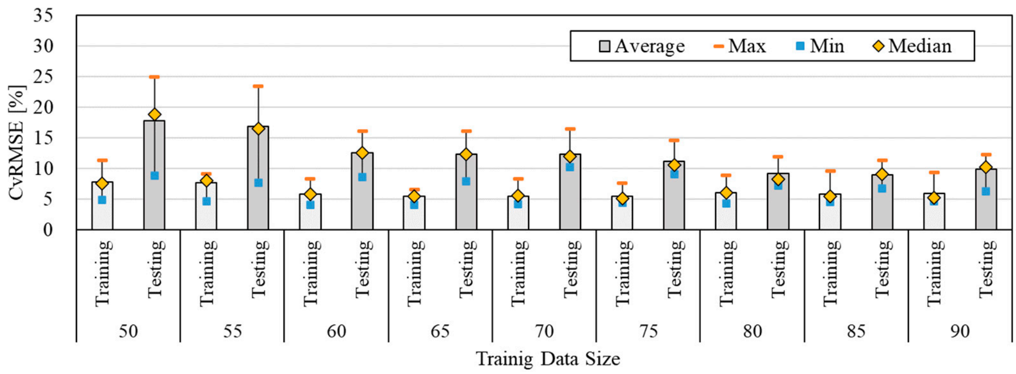


Figure 6. The predictive performance by changing the data size of the training.

Table 7. The predictive performance by changing the data size of training (Maximum, minimum, average, and standard deviation).

Training Data Size [%]	Period	Average	Max	Min	SD
50	Training	7.74	11.25	4.82	1.93
	Testing	17.69	24.88	8.80	5.78
55	Training	7.60	9.08	4.63	1.38
	Testing	16.77	23.43	7.59	4.70
60	Training	5.77	8.21	4.03	1.40
	Testing	12.55	16.05	8.56	2.44
65	Training	5.36	6.53	3.98	0.83
	Testing	12.29	16.04	7.82	2.78
70	Training	5.45	8.24	4.11	1.33
	Testing	12.26	16.42	10.23	1.88
75	Training	5.37	7.59	4.32	1.05
	Testing	11.06	14.54	9.06	1.83
80	Training	6.04	8.84	4.28	1.53
	Testing	9.08	11.85	7.14	1.81

85	Training	5.76	9.58	4.48	1.45
	Testing	8.93	11.23	6.69	1.45
90	Training	5.87	9.30	4.65	1.46
	Testing	9.79	12.20	6.17	2.10

4. The validation of the ANN model for a short term with measured data

Based on the obtained results, the predictive performance of the ANN model for a direct-fired absorption chiller for a short term was validated with actual data. The specific conditions were 5 and 10 for the input layer and neurons, respectively. The size of training was set in the range of 70 % - 85 %. The actual data were collected from the BAS installed in the reference building during the summer (July 1–August 8, 40 days), which was about 952 hours of datasets. The data were preprocessed by using data transformation considering the unit of building energy consumption.

4.1. The validation of the ANN model with measured data

Figure 7 shows the comparison result of the predictive performance by changing the size of the training of measured data. By changing the data size of training, the average values of CVRMSE were in the range of 18.68 % - 21.11 % and 19.99 % - 26.06 % for the training and testing period, respectively. These values were all within the acceptable range of ASHRAE Guideline 14. As shown previously, the predictive performance was improved by increasing the data size of training. The most acceptable predictive performance was obtained with 85 % of the training data size. Specifically, the average, maximum, and minimum values of CVRMSE for the testing period were 19.99 %, 22.02 %, and 17.5 %, respectively. However, the CVRMSE values obtained from the ANN model with the actual data were higher than those obtained from the ANN model with data generated by the simulation. This was caused by the decrease in the number of datasets from 8,760 to 952. In addition, it can be also a result of the quality difference between the simulated and measured data. Table 8 과 같. Even though the average values of CVRMSE obtained by the ANN model with the actual data were higher than that obtained by the model with simulated data, the standard deviation was in the range of 1.36–1.62, constantly. Table 8 shows the average, maximum, minimum, and standard deviation of predictive performance by changing the size of training.

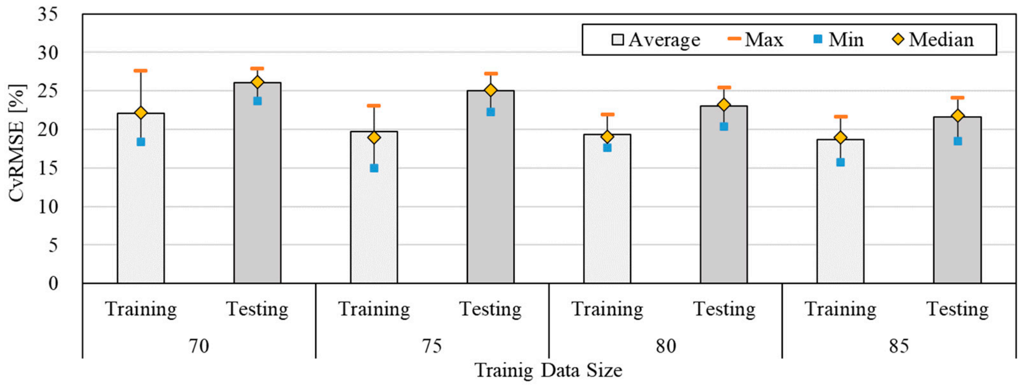


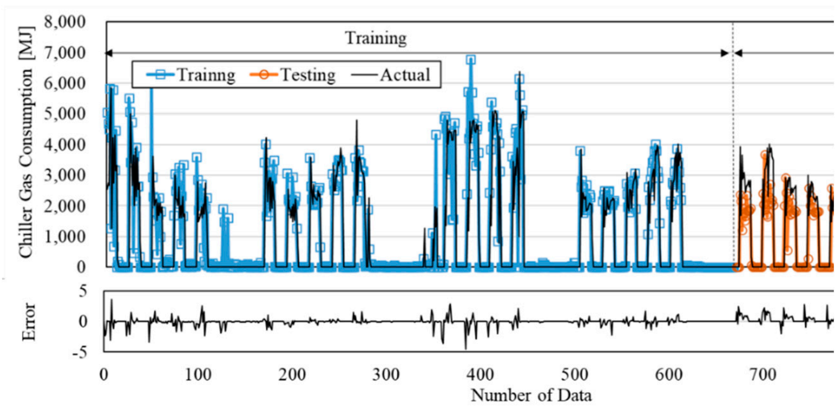
Figure 7. The predictive performance by changing the data size of training by using the actual data.

Table 8. The predictive performance by changing the data size of training by using the actual data (Maximum, minimum, average, and standard deviation).

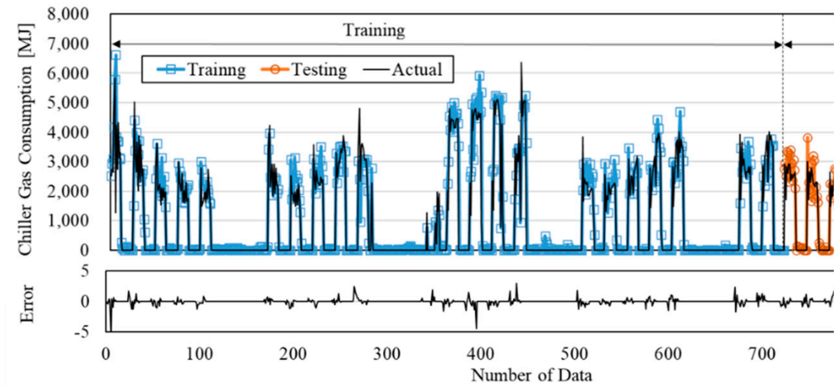
Training Data Size	Period	Average	Max	Min	SD
70	Training	22.11	27.52	18.41	2.48
	Testing	26.06	27.85	23.68	1.53
75	Training	19.73	22.96	14.95	2.64
	Testing	24.87	26.91	22.27	1.62
80	Training	19.34	21.81	17.65	1.46
	Testing	22.77	25.34	20.41	1.57
85	Training	18.68	21.62	15.74	1.72
	Testing	19.99	22.02	17.50	1.36

4.2. The prediction result of the energy consumption for a short term by using measured data

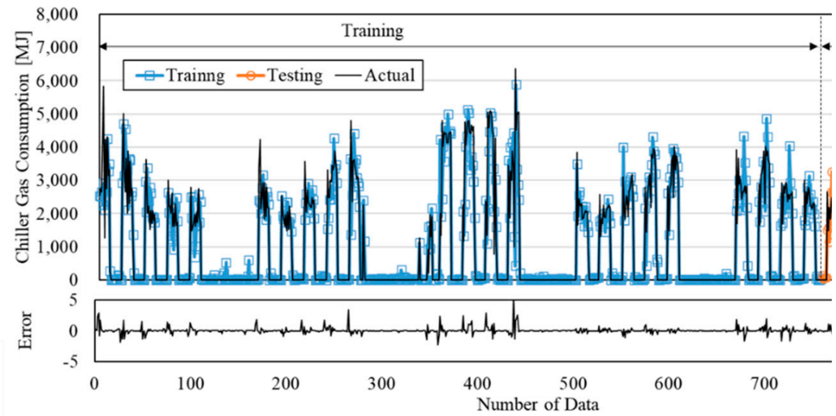
Figure 8 shows the energy consumption comparison between the prediction obtained by the ANN model and the reference building for 952 hours. As shown previously, the standard deviation difference between the prediction and measured data was decreased as the size of training was increased.



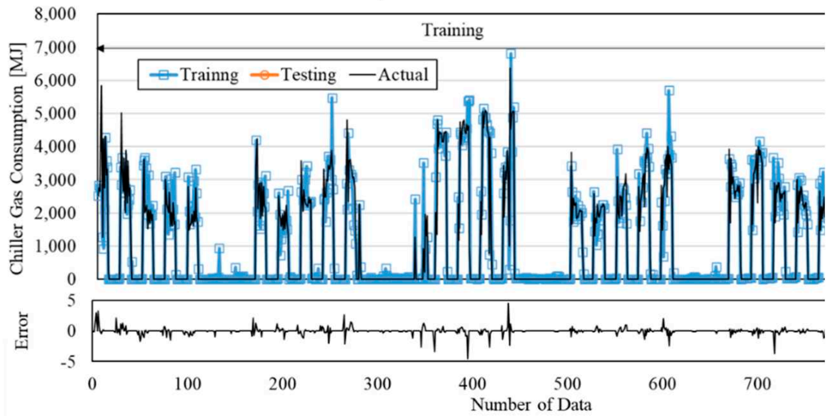
(a) Training Data Size 70%



(b) Training Data Size 75%



(c) Training Data Size 80%



(d) Training Data Size 85%

Figure 8. The energy consumption prediction by using the actual data.

Figure 9 shows the energy consumption comparison between the prediction and the actual data by changing the data size of training including the error rate difference. The total energy consumption of the direct-fired absorption chiller was 998.22 GJ. The error rate difference was 2.16 %, 1.82 %, 1.44 %, and 1.11 % for the training data size of 70 %, 75 %, 80 % and 85 %, respectively. This indicates that the predictive performance of the model was improved by increasing the data size of training data. As shown above, the training data size plays a significant role in the predictive performance of the model with the actual data. Thus, it is important to find a suitable training data size for improving the predictive performance. The summarized predictive performance of the model with the actual data is presented in Table 9.

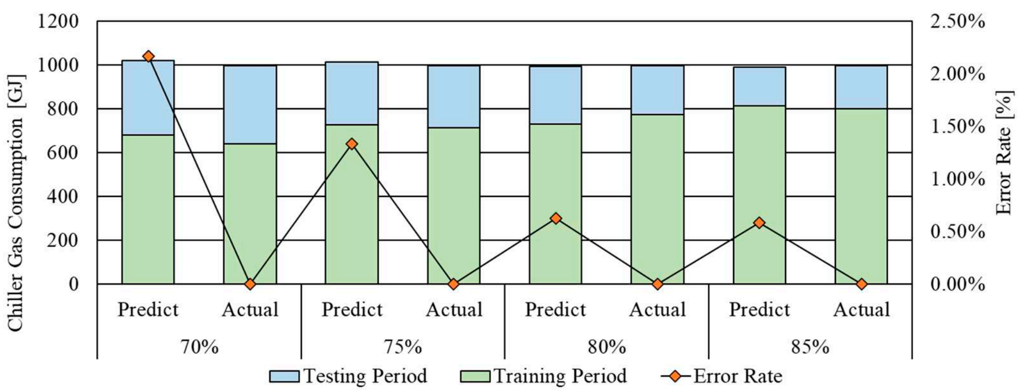


Figure 9. The energy consumption comparison and error rate by changing the data size of the training.

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Table 9. The energy consumption comparison and error rate by changing the data size of the training.

Training Data Size	Period	Predict [GJ]	Actual [GJ]	Error Rate [%]
70%	Training Period	678.83	639.39	5.81%
	Testing Period	341.46	358.83	5.09%
	Total Period	1020.29	998.22	2.16%
75%	Training Period	737.33	713.21	3.27%
	Testing Period	279.42	285.01	2.00%
	Total Period	1016.75	998.22	1.82%
80%	Training Period	754.86	772.42	2.33%
	Testing Period	229.17	225.80	1.47%
	Total Period	984.03	998.22	1.44%
85%	Training Period	812.06	799.14	1.59%
	Testing Period	197.38	199.08	0.86%
	Total Period	1009.44	998.22	1.11%

5. Conclusions

The present study developed the ANN model by using the collected data and the developed model was optimized. By using the energy consumption of the direct-fired absorption chiller, the predictive performance of the ANN model was validated.

When the number of input variables and neurons was set at 5 and 10, and the data size of training was 85 %, the average value of CVRMSE was the lowest in that the predictive performance was the most acceptable. By using the measured data, the ANN model was validated. As a result, the average value of CVRMSE was 19.99 %. Even though the CVRMSE was somewhat increased, the error rate was less than 1 %. This indicated that the predictive performance of the ANN model was acceptable. In sum, the outcome of the present study can used to predict the energy consumption of the chiller as well as improve the efficiency of the energy management.

The present study developed the ANN model to predict the energy consumption of the chiller. However, an HVAC system consists of many components such as air handling units, fans, boilers, pumps, etc. Therefore, it requires to develop ANN models for these components for further study. By applying the methodology used in this study, it can expect to improve the predictive performance of the model for the energy consumption of these components.

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