Performance Prediction and Calibration of a Clean-Room Air Conditioner Using an Embedded Artificial Neural Network

Myung-Sup Yoon

Dong-Hyuk Yi

Myung-Kyo Seo

Seung-Yup Ryu

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Myung-Sup YOON[1]*, Dong-Hyuk YI[2], Myung-Kyo SEO[3], Seung-Yup RYU[4]

[1]Energy Technology Center, Korea Testing Laboratory,
Seoul, Korea (msyun95@ktl.re.kr)

[2]Energy Technology Center, Korea Testing Laboratory,
Seoul, Korea (dhyi@ktl.re.kr)

[3]Engineering Team, Fläkt Korea,
Seoul, Korea (mkseo@flaktkorea.co.kr)

[4]System Department, Seungil Electronics,
Bucheon, Korea (globalsales@si-tec.co.kr)

* Corresponding Author

ABSTRACT

This study is about the application of an artificial neural network (ANN) to implement supervised learning for the performance prediction of a clean-room air conditioner (CRAC) installed on-site. To measure accurately the cooling capacity and efficiency of an HVAC product such as an air conditioner, the temperature and humidity should be fixed in a well-defined standard chamber. However, at an actual site where air conditioners are installed, it is unreasonable to expect a well-defined testing chamber environment. To resolve this difficulty, various temperature and humidity environments were simulated under the laboratory conditions in advance. Moreover, the sensing and performance data measured by the sensors inside of the CRAC product were recorded along with the data measured in an air enthalpy-type standard chamber. After simultaneous acquisition of the CRAC and standard-chamber data in a simulated chamber environment, supervised learning by an artificial neural network was carried out and the trained ANN was transferred into an embedded chipset. Finally, accuracy analyses of the control-group ANN (using chamber sensors) and experimental-group ANN (using product sensors) are compared for selected test conditions. Although the experimental-group ANN shows worse prediction performance than the control-group ANN does, it shows better results than the product calculation results. The experimental-group ANN of the CRAC might exhibit prediction as good as the control-group ANN, if the precision of the product sensors is improved.

1. INTRODUCTION

Usually, air source heat pumps or cooling air conditioners are tested in a well-defined chamber environment where the temperature and humidity conditions are precisely controlled in order to measure capacity and efficiency of products (ISO 5151, 2017). On the other hand, in the case of a water-to-water heat pump, it is possible to measure the capacity and efficiency on-site by installing a flow meter and thermometers in the inlet and outlet pipes. The reason these two product groups were studied using a chamber environment test and a field test is that a nozzle chamber (according to AMCA: ANSI/AMCA, 2016 and ISO standard: ISO 5151, 2017) is usually required to measure the air volume and heat capacity for the air side.

For example, when using a room air conditioner at home or using air conditioner equipment such as a clean-room air conditioner (CRAC) in the field, sometimes we need to know the cooling or heating performance of a product instantly and precisely, However, the current technology generally provides information only on the environmental temperature, humidity and power consumption, and not on the product's air volume, cooling capacity, and efficiency of the product. This technical limitation is due to the afore-mentioned reason.

Recent advances in AI fields such as machine learning and deep learning have opened up the possibility of overcoming these difficulties. Srivastav *et al*. (2007) and De Menezes *et al*. (2018) applied artificial neural networks (ANNs) in the field of water treatment and chemical processes to predict performance. Yamamoto *et al*. (2017) and Si *et al*. (2020) used ANNs to calibrate low-cost temperature sensors and particle sensors used in meteorological measurements, compared to a reference system. Kamar *et al*. (2013), Datta *et al*. (2019), Park *et al*. (2019), and Puttige *et al*. (2021) used ANN modeling to predict the thermal performance of automobile air conditioners and on-site heat pump systems. Somehsaraei *et al*. (2020) applied in flow measurement using multi-hole pressure probes.
In this study, ANN supervised learning was used to determine the potential of predicting the performance (e.g., cooling capacity, efficiency, airflow) of a CRAC product, even at an installation site. An electrically commutated (EC) plug fan, along with temperature and humidity sensors that could roughly measure the air volume and enthalpy values, were installed inside of the CRAC product to allow it to estimate the performance data independently. At the same time, supervised learning was conducted by matching accurate performance data in a standard air-enthalpy type chamber in which various environmental conditions of the indoor and outdoor sides were simulated.

2. EXPERIMENTAL APPROACH

A CRAC is mainly used for cooling server rooms or data center equipment. It is a kind of air conditioner that can precisely control temperature and keep humidity constant annually within a set range. Performance prediction in various environmental conditions is possible after acquiring 2,816 steady state data sets (includes chamber data, product data) and doing supervised machine learning. These 2,816 AI training data sets were obtained using the air enthalpy-type ISO standard chamber shown in Figure 1.

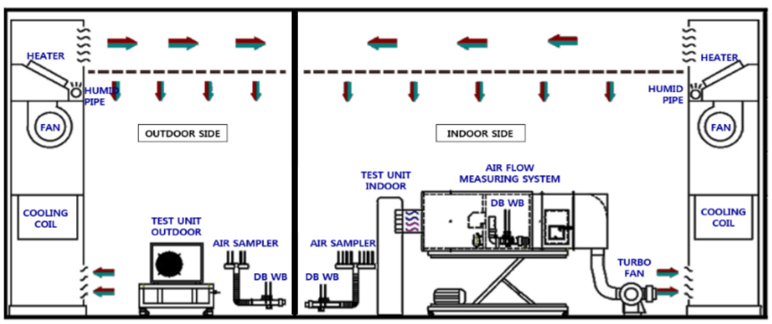

Figure 1: Used air enthalpy-type ISO chamber

2.1 Test Product Specification

The test product can mainly control the compressor speed (COM), electronic expansion valve openness (EEV), indoor fan rpm, and outdoor fan rpm. Table 1 shows the product's rated specifications. However, in this study, COM and EEV values under a part-load operating condition (looser than the rated cooling capacity in Table 1) were used to obtain the test data also in unfavorable conditions, including overload (e.g., extremely high and low temperature or humidity). That is, COM was set lower (= 10) and EEV set higher (= 40) than the rated operating conditions. Due to the problem of the large number of test cases needed and the test time constraints, the COM and EEV values were fixed as one combination (10, 40) and only the speed of the indoor fans was adjusted to 11 stages (see, Section 2.4). The values of (COM, EEV) = (x, y) match ($53x$ + 1000) rpm and y% openness.

Table 1: Tested CRAC product specification

Compressor type	Installation type	Rated cooling capacity	Rated power input	Refrigerant
Inverter compressor	Split floor stand	9,500 W @ (COM, EEV) = (55, 28)	3,600 W @ (COM, EEV) = (55, 28)	R410a, 7 kg

2.2 Indoor Fan Specifications

In the case of room wall-mounted and stand-type air conditioners, a cross flow fan and an axial (or swirl fan), respectively, were installed in the indoor unit. However, in the case of large capacity commercial air conditioners, like a CRAC, an EC plug fan suitable for high static pressure (as shown in Figure 2) is preferable. Furthermore, in this study, to have the product independently calculate the rough air volume and cooling capacity, an indoor fan with a pressure tap was required (Δp in Figure 2).

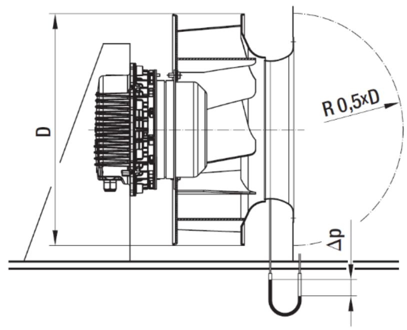

Figure 2: CRAC indoor fan (EC plug fan)

The amount of air volume q passing through the fan can be roughly obtained using Equation (1). Factor k is given for individual products by the fan manufacturer.

$$q = k\sqrt{\Delta p} \tag{1}$$

2.3 Embedded Chipset

Because a bulky PC cannot be mounted on a CRAC product at the installation site, a small-capacity Raspberry Pi chipset was used (Table 2). In Sections 3.1 and 3.2 of this paper, the ANN is trained using a laptop computer. Then, this trained neural network was transferred to the Raspberry Pi chipset and used to perform what is explained in Section 3.3. This chipset was developed as part of an education project and is based on an embedded Linux operating system (Nayyar and Puri, 2015).

Table 2: Specifications of the chipset

Model name	CPU	RAM	Ports	GPIO
Raspberry Pi 3 model B	Quad core 1.2 GHz Broadcom 64 bit	1GB	4 USB 2.0	40-pin extended

2.4 Number of Cases for Training Data Acquisition

Although formal ISO standard (ISO 5151, 2017) test conditions involve several specific conditions (e.g., T1, T2, T3), we used the extensive temperature and humidity (or DB and WB temperature) ranges in environmental conditions that may exist under actual CRAC operating situations and got realistic training data for the supervised machine learning. In this study, the four environmental cooling conditions of each outdoor DB, outdoor humidity, indoor DB, and indoor humidity had respectively four test points inside the range (20 – 40 °C), (30 – 90%), (10 – 40 °C), and (30 – 90%). Therefore, a total of (4^4 =) 256 cases of environmental test conditions were set. The percent relative humidity was implemented experimentally by converting it to a wet bulb (WB) temperature.

In fact, not only environmental conditions, but also training data under the various conditions according to the set values of the CRAC product (e.g., inverter compressor rpm: COM, EEV openness: EEV, indoor fan rpm: IF_{rpm}, outdoor fan rpm: OF_{rpm}) are required. However, in this study, to reduce the extensive training data acquisition time, the set values of all parts of the CRAC components were fixed and only IF_{rpm} was varied using 11 cases of rpm output between 55 and 70%. Because each of 256 environmental conditions has 11 cases of IF_{rpm} variation, a total 2,816 sets of training data were ultimately obtained.

Although AI training data were obtained simultaneously with product data and chamber data (as shown in Figure 3), two separate neural networks were constructed and used throughout this study by making them (product data and chamber data) independent on the input layer, as shown in Figure 4. This is because, on site, where the actual CRAC product was used, expensive and bulky ISO chamber equipment could not be installed at the same time in reality. In other words, when predicting the performance of the product, it is difficult to obtain accurate chamber data immediately in the field, so it is necessary to obtain data under various environmental conditions in advance using simulated laboratory conditions.

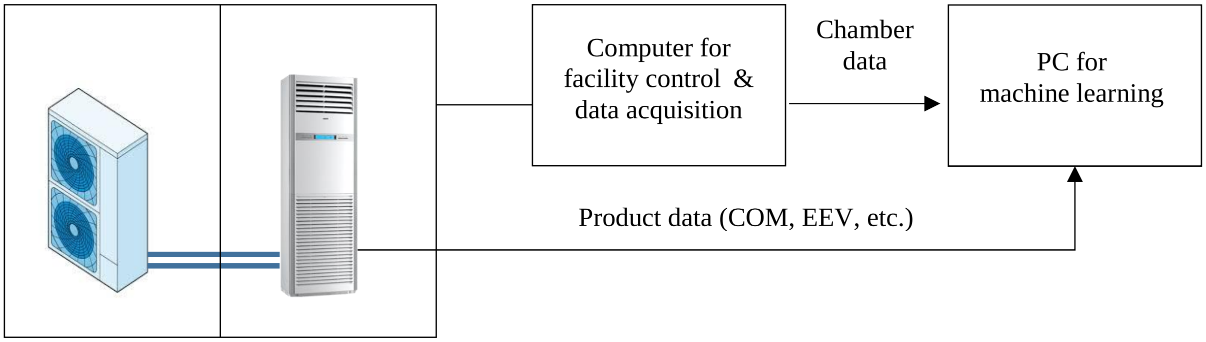

Figure 3: Training data acquisition in a standard ISO chamber (air-enthalpy type)

There are several preliminary studies about training ANNs of an HVAC product in a standard ISO chamber (Yoon and Yoon, 2021; Yoon *et al*., 2020). In a standard ISO chamber, we were able to simulate the various desired training environments (i.e., temperature and humidity) accurately. This simulated environment can be implemented statically fixed or dynamically varied depending on the purpose of the study. In this study, we simulated various fixed temperature and humidity cases of 256 (= 4^4).

2.5 Artificial Neural Network (ANN) Model

Figure 4 shows the ANN of the control group (left) and the experimental group (right). The ANN on the left side can guess the accuracy of the ANN model and chamber data independently using the accredited chamber data. On the other hand, the ANN on the right is a neural network for using the data of products equipped with low-cost measuring sensors. The chamber data set of the left-side ANN input layer includes outdoor DB/WB temperatures (°C), indoor DB/WB temperatures (°C), test product discharge DB/WB temperatures (°C), code tester nozzle differential pressure (Pa), code tester nozzle inlet temperature (°C), measured current (A), and measured power input (W) using the chamber shown in Figure 1 (total of 10 input data). The product data set on the right-side ANN input layer includes outdoor unit intake air temperature (°C), indoor unit return air temperature (°C) and humidity (%), indoor unit supply air temperature (°C) and humidity (%), differential pressure (Pa) (Δp in Figure 2), simple power meter current (A), and power input (W). All these data were collected using the sensors inside the product (total 8 input data). In the future, it will be possible to install additional sensors in CRAC products.

The output layer nodes of the control-group and experimental-group ANNs include the same accurate chamber data (chamber measured air volume, cooling capacity, and COP).

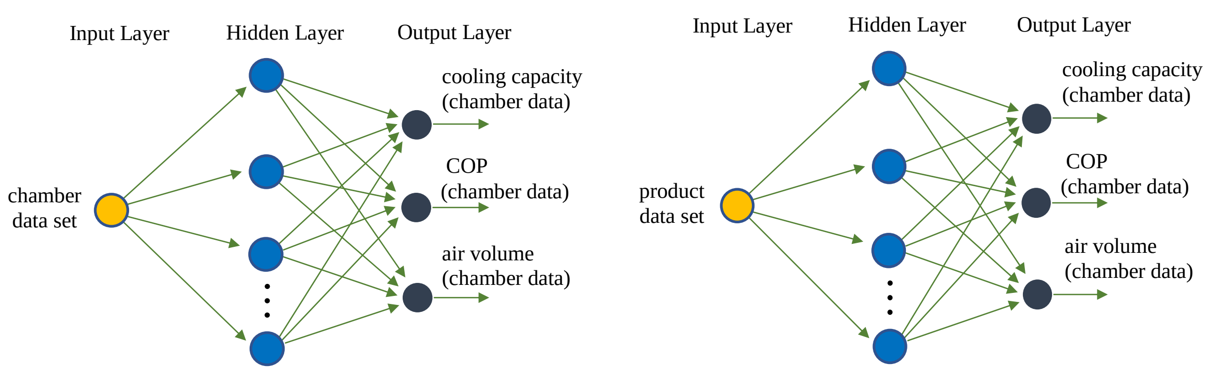

Figure 4: Control-group ANN(left) and experimental-group ANN(right)

The ANN model was calculated using Keras' sequential structure, and 64 nodes were set up in the middle-hidden layer. The Adam optimizer, MSE (mean square error) loss function, and leaky ReLU (rectified linear unit) activation functions were used. Among the 2,816 datasets, 80% of the data were used to train each ANN (training data set), and 20% of the data were used to verify (validation data set).

3. RESULTS AND ANALYSIS

As stated in Section 2.4, a total of 2,816 data (simultaneous chamber data and product data) were obtained for more than a month from the equipment shown in Figure 1. According to the air conditioner standard (ISO 5151, 2017), the averaged data must be obtained for about 30 minutes after environmental stabilization. However, in this study, the amount of data was so large that it is necessary to proceed with data collection immediately after each environmental condition and product performance was stabilized. After acquiring data, supervised learning was performed through a laptop computer and the results were analyzed. First, ANN model training and prediction were conducted only with clean and accurate chamber data obtained with accredited test equipment (control group: left side of Figure 4), and then, training and prediction were made with product data obtained through a relatively low-cost product sensor (experimental group: right side of Figure 4). After analyzing and confirming the validity of the experimental results, the trained ANN model was transferred into a small Raspberry Pi chipset connected to the CRAC product. Last, the data measured through the chamber equipment and the data predicted by the newly transferred product ANN were compared for several test conditions.

3.1 ANN Model Prediction Using Chamber Data Set Input (Control Group)

Figure 5 shows the trend of change of the mean square error (MSE) loss value as the epoch (combination of feed forward and back propagation) progresses for prediction.

$$MSE\ loss = \frac{1}{N}\sum_{i=1}^{N}(y_i - t_i)^2 \tag{2}$$

Here, y_i is the output of the neural network (NN) estimated value, t_i is the given data of the output node (target value), and N is the number of data.

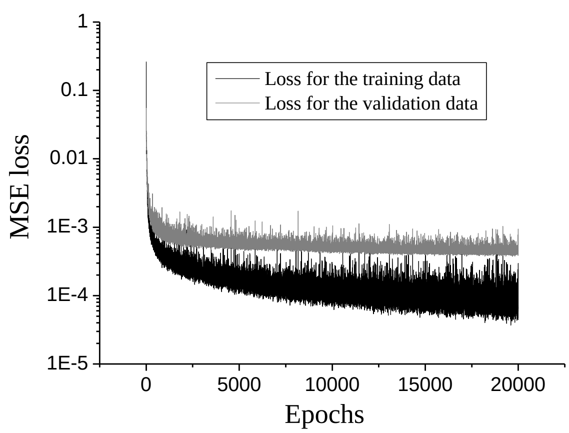

Figure 5: Loss for the training data set (2,252) and validation data set (564)

MSE loss converged up to 20,000 epochs. In the case of training data, the MSE loss value fell to a value of 1.E-4 and to a value of 1.E-3 in the case of validation data. Both training and validation data show very low MSE loss because the accurate chamber experimental equipment (including accurately calibrated sensors and physically standard formula) data were used (left ANN in Figure 4). All of this satisfied ISO standard for the measurement of air conditioner performance measurement. The reason why the loss value of training data oscillates greater than the value of validation data is that the loss value of training data is so small (log scale of 1.E-4).

Graphs comparing the ANN prediction value and the actual value measured using the training data set and the validation data set, are shown in Figure 6 and 7, respectively. The physical quantity of cooling capacity, air volume, and efficiency (COP), which are the most important factors in air conditioning, is shown in the left, middle and right parts, respectively.

All of the graphs in Figures 6 and 7 show high linearity between the prediction and real measured data. This means that the ANN model using the chamber data was well trained to predict CRAC performance. In other words, performance prediction was adequate with only input data and trained neural networks, even without physical calculation formulas for the CRAC cooling capacity and efficiency.

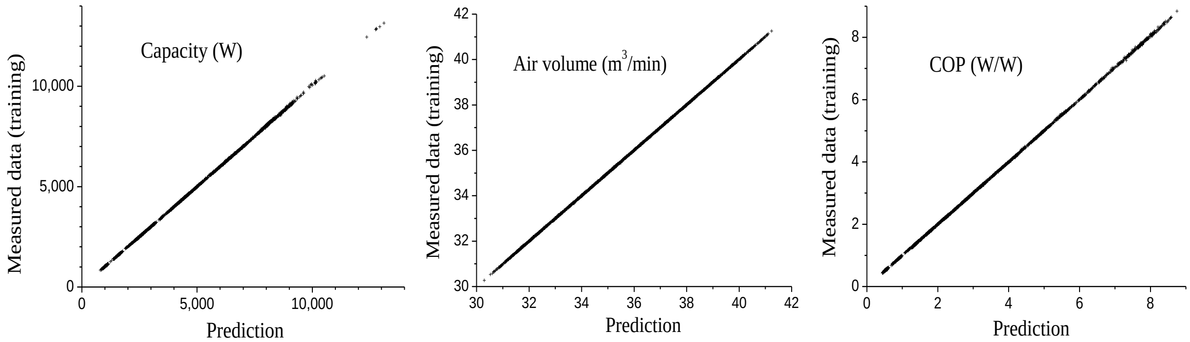

Figure 6: Prediction and real measured value for the training data (2,252 points) of the control group

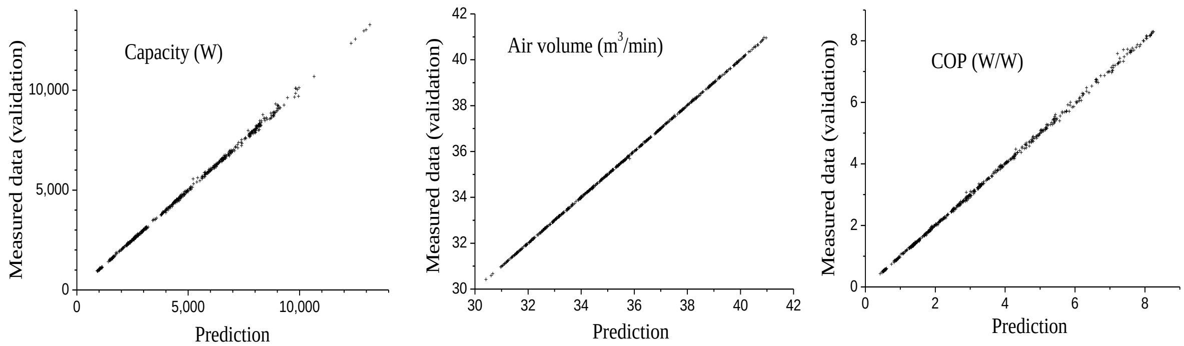

Figure 7: Prediction and real measured value for the validation data (564 points) of the control group

CVRMSE defined in equation (3) was used to determine the prediction accuracy of each physical quantity. CVRMSE is an indicator of performance prediction in the building air conditioning sector (Granderson *et al*., 2015). The smaller the CVRMSE, the more accurate the prediction. In equation (3), y_μ is the mean value of the population y_i.

$$CVRMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - t_i)^2}}{y_\mu} \times 100 \tag{3}$$

Table 3 shows the CVRMSE of the control-group ANN prediction. In the case of the training data, it was less than 0.6%, and in the case of the validation data, it showed an accuracy of < 1.5%. The CVRMSE for the validation data are usually greater than for the training data due to the number of data points (training data: 2,252, validation data: 564) or due to the problem of overfitting in the trained ANN model.

Table 3: CVRMSE summary table of the control group

Physical quantity / **Data type**	**CVRMSE % (Capacity)**	**CVRMSE % (Air volume)**	**CVRMSE % (COP)**
Training data	0.50	0.04	0.58
Validation data	1.39	0.05	1.46

3.2 ANN Model Prediction Using Product Data Set Input (Experimental Group)

After acquiring the control-group ANN model, we implemented training of the experimental-group ANN using product input data. The MSE loss decreases as the epoch progresses, as in Figure 8. However, comparing this with Figure 5, it is clear that the MSE loss does not undergo 1.E-4 and 1.E-3 for the training and validation data, respectively. These results are believed to be due to the quality of the product sensing data, and this becomes clear when comparing the graphs in Figure 9 and 10 with Figures 6 and 7.

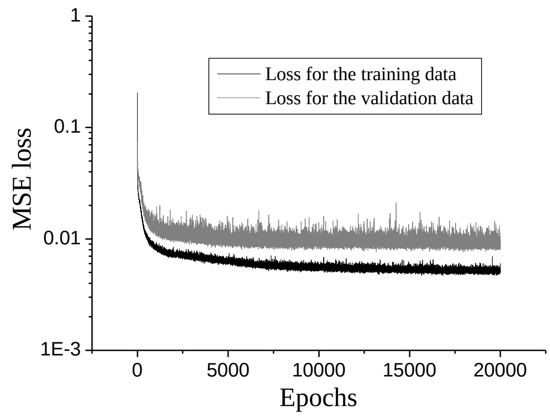

Figure 8: Loss for the training data set (2,252) and validation data set (564)

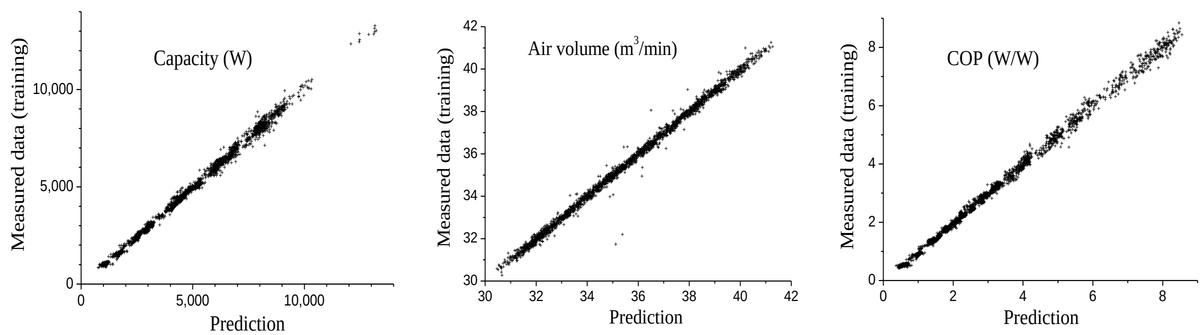

Figure 9: Prediction and real measured value for the training data (2,252 points) of the experimental group

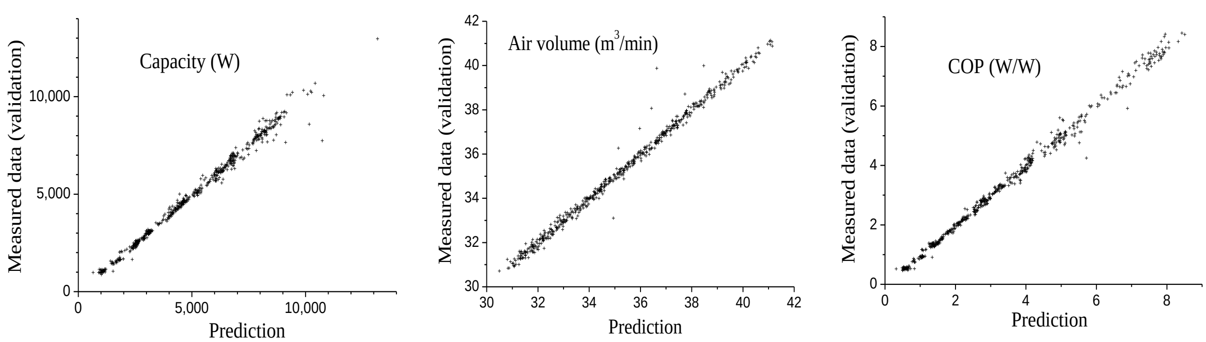

Figure 10: Prediction and real measured value for the validation data (564 points) of the experimental group

The CVRMSE for the experimental group appears in Table 4. Comparing this with the results in Table 3, larger error values appear both in the training and in the validation data cases.

Table 4: CVRMSE summary table of the experimental group

Physical quantity / **Data type**	**CVRMSE % (Capacity)**	**CVRMSE % (Air volume)**	**CVRMSE % (COP)**
Training data	3.43	0.52	3.78
Validation data	5.07	0.71	4.72

3.3 Final Test Using an ANN Transferred to a Chipset

The ANN weight information ('h5' file for neural network weight) trained using each neural network in Figure 4, were transferred to a Raspberry Pi chipset (see Figure 11) and then the final predictions were checked. Figure 11 shows the chipset and CRAC products used in this paper. As shown in Table 5, the results were compared under a total of 10 stabilized laboratory conditions. The contents in parentheses in the first column mean outdoor room temperature/humidity, indoor room temperature/humidity, and product indoor fan percent output, respectively. Test conditions #1 to #6 are the results of the prediction when the values of the input data are within the range of prior training data, as explained in Section 2.4. Test conditions #7 to #10 were arbitrarily set as the outrange of the training data for some test conditions (bold characters).

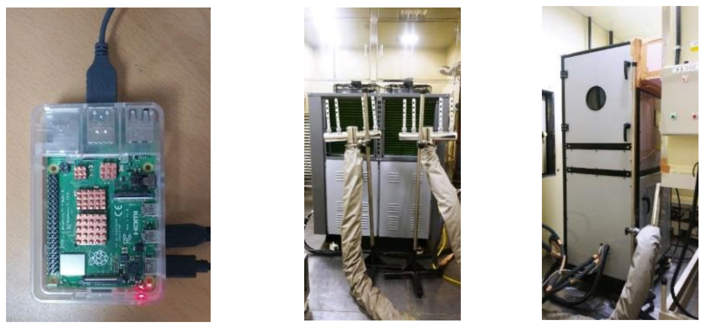

Figure 11: Photographs of the Raspberry Pi chipset, CRAC outdoor unit, and indoor unit

The reference value column (2nd column) of Table 5 is a value precisely measured in the ISO chamber and may be viewed as the real target value closest to the true value. The control-group ANN predicted value column (3rd column) and experimental-group ANN predicted value column (5th column) are on-chip predicted values using the same ANN used in prior training, as shown in Figure 4. The input node is given chamber-sensor and product-sensor values for each prediction neural network. The fourth column of the product self-data is a calculation result of the non-neural network method provided by the product manufacturer on the product. Control-group ANN predicted values show very accurate prediction results except in the test conditions of cases #8 and #10. Test condition #8 has indoor fan output of 40%, lower than the training range (55 – 70%). Test condition #10 also has an outdoor temperature of 15 °C, out of training range (20 – 40 °C). Therefore, control groups in cases #8 and #10 can have errors > 3.5% relative error in prediction results on capacity, air volume, and COP.

In fact, what we expected in this study was to predict accurately the performance of the CRAC product using the experimental-group ANN on the chip. However, as can be seen from the last column of Table 5, capacity and COP show somewhat lower levels of predictive performance except for the good air volume (AV) predictions. These results are in line with the results of Section 3.2. From the CVRMSE (%) values in Table 4, a high CVRMSE is shown in capacity and COP (> 3%), except air volume (< 0.71%) for the prior neural network training. For predicting air volume, it seems that one independent variable of the differential pressure (Δp) in Figure 2 plays the most import role, whereas six temperature and humidity sensors were most important for the capacity and COP prediction. Therefore, it seems that the measurement uncertainty in capacity and efficiency may have increased due to the use of many temperature and humidity measurement sensors. The same trend is shown in Table 3 (CVRMSE of 0.05% or less for air volume, 1.5% or less for capacity and humidity).

Finally, Figure 12 compares the chamber measurement for electric current (A) and power input (W) with the product measurement values. The power meter installed in the CRAC shows good measurement quality of high linearity.

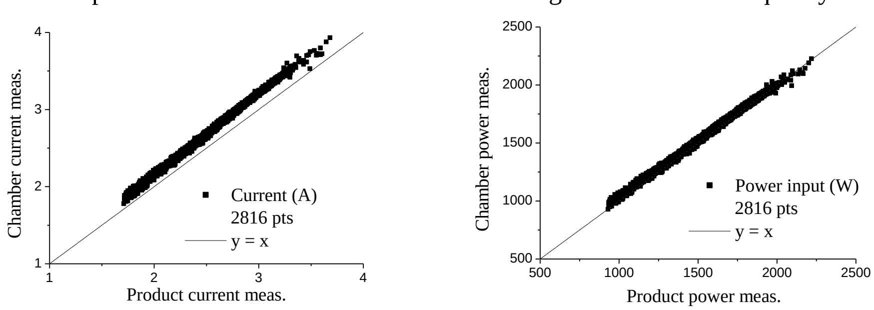

Figure 12: Electric measurement comparisons between chamber and CRAC

Table 5: Final test result accuracy (relative error) comparison for arbitrary test conditions

Physical quantity / Test condition	Reference value (Chamber meas.)			Predicted value (Control group ANN)			Product self-data (Product calculated)			Predicted value (Exp. group ANN)		
	Capa.	AV	COP	Capa.	AV	COP	Capa.	AV	COP	Capa.	AV	COP
#1- (35/24°C, 27/19°C, 55%)	4139	32.09	2.544	4109	32.06	2.544	3848	32.89	2.329	4399	31.76	2.631
				-0.72%	-0.09%	0%	***-7.03%***	2.49%	***-8.45%***	***6.28%***	-1.03%	3.42%
#2- (35/24°C, 27/19°C, 60%)	4320	34.75	2.598	4340	34.73	2.616	4199	35.58	2.484	4381	34.66	2.557
				0.46%	-0.06%	0.69%	-2.80%	2.39%	***-4.39%***	1.41%	-0.26%	-1.58%
#3- (20/15°C, 27/19°C, 55%)	5477	32.07	4.439	5471	32.09	4.425	5974	32.99	4.783	4924	32.77	3.838
				-0.11%	0.06%	-0.32%	***9.07%***	2.87%	***7.75%***	***-10.1%***	2.18%	***-13.5%***
#4- (20/15°C, 27/19°C, 70%)	5874	40.39	4.342	5877	40.42	4.332	5830	41.44	4.267	4470	40.88	3.314
				0.05%	0.07%	-0.23%	-0.75%	2.60%	-1.73%	***-23.9%***	1.21%	***-23.7%***
#5- (35/24°C, 20/15°C, 55%)	3013	31.79	1.830	2909	31.79	1.821	3889	33.01	2.325	3306	30.61	2.051
				-3.45%	0%	-0.49%	***29.1%***	***3.84%***	***27.0%***	***9.72%***	***-3.71%***	***12.1%***
#6- (35/24°C, 20/15°C, 70%)	3257	39.98	1.821	3178	39.99	1.820	4161	41.62	2.303	3259	39.21	1.881
				-2.42%	0.03%	-0.05%	***27.8%***	***4.10%***	***26.5%***	0.06%	-1.93%	3.29%
#7- (35/24°C, 27/19°C, **75%**)	4468	43.44	2.437	4475	43.51	2.435	3959	44.62	2.123	3838	44.31	2.048
				0.15%	0.16%	-0.08%	***-11.4%***	2.72%	***-12.9%***	***-14.1%***	2.00%	***-15.9%***
#8- (35/24°C, 27/19°C, **40%**)	3535	22.41	2.304	3675	23.52	2.407	3788	22.50	2.433	448	25.73	0.384
				3.96%	***4.95%***	***4.47%***	***7.16%***	0.40%	***5.59%***	***-87.3%***	***14.8%***	***-83.3%***
#9- (**15**/10°C, 20/15°C, 55%)	4622	31.40	3.914	4601	31.44	3.928	5948	32.66	4.988	4716	31.92	3.799
				-0.45%	0.13%	0.36%	***28.7%***	***4.01%***	***27.4%***	2.03%	1.66%	-2.9%
#10-(**15**/10°C, 20/15°C, **40%**)	4268	22.53	3.880	4719	23.42	4.321	4963	23.24	4.471	2472	27.60	2.466
				10.5%	***3.95%***	***11.4%***	***16.3%***	3.15%	***15.2%***	***-42.1%***	***22.5%***	***-36.4%***

4. CONCLUSIONS

In this study, a variety of environmental (temperature, humidity) conditions simulated in an ISO standard chamber, and their performance prediction was attempted using ANN supervised learning. The control-group ANN receiving the sensor data from the ISO chamber, and the experimental-group ANN receiving the sensor data of the product, were set to compare the prediction performances of the capacity, air volume, and the efficiency of the clean-room air conditioner. A total of 2,816 data sets were obtained according to 256 diverse indoor and outdoor environments and 11 product airflow stages. Of these 2,816 data, 80% were used for ANN model training, and 20% were used for model validation.

The control-group ANN using chamber-sensor input data showed better prediction performance than the experimental -group ANN using product-sensor input data. However, the experimental-group ANN showed results that are slightly better than the product self-calculation results. In future study, if the “precision” of the product’s temperature and humidity sensor is further improved, then it should be possible to predict accurately the performance of the product in the field even though the “accuracy” of the product sensors is low. This means that biased sensor measurement can be calibrated effectively by the ANN models if the sensor precision is assured.

NOMENCLATURE

ANN	artificial neural network	(-)	COP	coefficient of performance	(W/W)
CRAC	clean room air conditioner	(-)	COM	compressor speed indicator	(-)
IF_{rpm}	indoor fan rotation speed	(rpm)	EEV	elec. expansion valve openness	(%)
OF_{rpm}	outdoor fan rotation speed	(rpm)	DB	dry bulb temperature	(°C)
WB	wet bulb temperature	(°C)	N	number of data	(-)
MSE	mean square error	(-)	k	factor of the fan air volume	(-)

ReLU	rectified linear unit	(-)	y_i	ANN predicted output value	(-)
Δp	differential pressure of EC fan	(Pa)	t_i	given target value of output	(-)
q *or* AV	air volume of the fan	(m^3/min)	CVRMSE	coefficient of the variation of the root mean square error	(%)
y_μ	mean value of the y_i	(-)			

Subscript

i	index of the individual data	(-)	μ	population mean	(-)

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