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Deep learning-based refrigerant charge fault detection method of air-source heat pump system

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Abstract

Energy demands grow every year, and a significant amount of energy consumption is used for buildings cooling and heating. Since heat pump systems have high efficiency and can be utilized for buildings cooling and heating, they are commonly used around the world. Many studies show heat pumps have the best COP at the optimal refrigerant charge. Therefore, it is imperative to monitor the current refrigerant charge of the system and maintain it optimally in view of energy saving. However, some researches show that many heat pumps in the field have refrigerant leakage fault or overcharge fault. The refrigerant charge error can cause energy waste and thermal discomfort. Hence, many researchers have conducted studies for refrigerant charge fault detection (RCFD) method. In recent years, RCFD methods based on deep learning technology have been developed actively. This paper suggests a novel and efficient RCFD strategy using convolutional neural network (CNN). The CNN based multiple outputs regression model shows excellent results for predicting power consumption, cooling capacity (heating capacity), and the refrigerant charge amount simultaneously with a single model.

Keywords: heat pump; refrigerant charge fault detection; deep learning;multiple outputs regression; energy saving;

1. Introduction

The US Energy Information Administration presented that 39.7% of US total energy consumption in 2015 was used in commercial and residential buildings, and about 40% of it was spent on buildings heating and cooling [1]. Since heat pumps have high efficiency and can be utilized for buildings cooling and heating, heat pump systems are widely used all over the world. Therefore, many researchers have conducted studies to increase the efficiency of heat pump systems for energy saving.

Optimum refrigerant charge is essential in vapor compression systems [2-4]. However, Jacob et al. [5] found that 46% of HVAC systems installed in 75 buildings in California did not have an appropriate refrigerant amount, reducing performance and consuming unnecessary energy. Therefore, in terms of energy, a technique for detecting undercharge or overcharge of refrigerant is essential, and many studies for RCFD methods have been conducted so far [6-8]. Recently, due to the improved computational power of computers and big data, data-driven researches such as an artificial neural network (ANN) are trendy in refrigerant charge prediction techniques [9-12].

However, there are some limitations to the conventional ANN-based RCFD method. First, due to simple classification such as undercharge and overcharge, it was not possible to provide a quantitative refrigerant amount. Second, many conventional ANN-based RCFD methods only took one operation mode (cooling or heating mode) into consideration. Finally, many ANN-based RCFD articles provided only information on the refrigerant charge amount. However, the essential things that we want to know are the cooling or heating capacity and the efficiency of the heat pump systems according to the change of the refrigerant charge amount.

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The predictive ability for these three attributes can help determine the urgency of whether or not current refrigerant fault needs repairing right now.

In order to improve these limitations, this paper proposes a novel RCFD technique using CNN based multiple outputs regression model. Since the refrigerant charge amount, power consumption, and cooling capacity (heating capacity) of the heat pump system are substantially real numbers, the prediction for the three targets is a multiple outputs regression task [13-14]. The contributions of this proposed method are as follows. First, it provides quantitative information about the current amount of refrigerant in the heat pump system. Second, it also predicts the current heating capacity (cooling capacity) and the power consumption of the heat pump quantitatively. Thus, the current COP of the system can be calculated. In addition, the prediction for these three attributes can give information on the severity of the refrigerant charge fault. Third, both heating and cooling modes were considered, and a single model was used.

Briefly describing the results, including both cooling and heating mode, the refrigerant amount prediction error is within RMS error of 4.9%, the power consumption prediction error is within RMS error of 3.8%, and the cooling capacity (heating capacity) is below RMS error of 3.4% with a single model.

2. Methodology

2.1. Convolutional neural network (CNN)

The basic structure of CNN, one of the deep learning technologies, is composed of a convolutional layer, a pooling layer, and a fully-connected layer.

The convolutional layers and the pooling layers extract the features from the original raw data together [15]. After the input images and several filters perform a convolutional operation, the convolutional layer extracts a feature map by applying an activation function.

The pooling layer plays a role to reduce the size of the extracted feature map and to alleviate the sensitivity according to the location. Among the pixel values in the region of interest of the feature map, acquiring the largest value is called max-pooling, and calculating the average value is called average-pooling. Generally, max-pooling is widely used for CNN. Therefore, it is used for the RCFD model in this study.

The convolutional layers and the hidden layers of the fully-connected layers require a nonlinear function as the activation function. Mainly the rectified linear unit (ReLU) function is used.

The fully-connected layers have a similar structure to the existing ANN. All pixel values of the feature map after the pooling layer are connected to the input nodes of the fully-connected layer. After going through several hidden layers, the predicted value for each output node in the output layer is calculated using a linear activation function instead of the softmax function. In this study, the output layer has three output nodes to predict power consumption, cooling capacity (heating capacity), and the refrigerant charge amount.

The architecture of the CNN-based RCFD regression model used in this article is described in Table 1.

Table 1. The architecture of CNN-based RCFD multiple outputs regression model

Layer name	Input size	Filter size	Filter number	Stride	Output size	Activation function
Input	29×30×1	-	-	-	-	-
Convolutional 1	29×30×1	3×3	8	1	27×28×8	ReLU
Convolutional 2	27×28×8	3×3	8	1	25×26×8	ReLU
Max-pooling 1	25×26×8	2×2	-	2	12×13×8	-
Convolutional 3	12×13×8	3×3	8	1	10×11×8	ReLU
Convolutional 4	10×11×8	3×3	8	1	8×9×8	ReLU
Max-pooling 2	8×9×8	2×2	-	2	4×4×8	-
Flatten 1	4×4×8	-	-	-	128×1	-
Fully-connected 1	128×1	-	-	-	50×1	ReLU
Output	50×1	-	-	-	3×1	Linear

Since the proposed model was a CNN-based regression model, we used a linear activation function instead of the softmax function at the output layer and a mean squared error as a loss function. A loss function using a mean squared error is depicted as follows.

$$E(\boldsymbol{w}) = \frac{1}{2N}\sum_{n=1}^{N}\sum_{k=1}^{K}(y_{nk} - d_{nk})^2 \tag{1}$$

where $\boldsymbol{w}$ is the weight of a neural network, N is the total number of samples, K is the total number of output nodes, d_{nk} is the correct answer of the k_{th} output node in the n_{th} sample, and y_{nk} is the output value of the k_{th} output node in the n_{th} sample.

The learning process is to update the weights of each layer so that the value of the loss function is minimized. Stochastic gradient descent and backpropagation methods are widely used. We shuffled the training data randomly, and the shuffled data for learning was divided by mini-batch size. Since early stopping is widely utilized to prevent overfitting that deteriorates the generalization of a learned model [16], the early stopping algorithm was considered in this research.

2.2. Time-domain data to 2-D image data conversion method

Generally, CNN uses 2-D image data as input. Therefore, It is needed a process of converting time-series data of various sensors installed in the heat pump into 2-D image data. Although there are many conversion methods, in this study, the values of multiple sensors measured at fixed time intervals were stacked in chronological order and were converted to the 2-D image data [17]. Twenty-nine features were collected at two-second intervals and converted to one image data using the dataset obtained for 60 seconds. Therefore, one 2-D data sample size is 29×30.

Data normalization is essential for convergence and performance in neural network methods. In general, the min-max scaling method and the standardization method are used widely. In this study, training, validation, and test data were preprocessed with the min-max scaling method.

3. Experimental setup

3.1. Experimental setup and conditions

Experiments were carried out using a commercial 30 kW heat pump system with two indoor units and one outdoor unit. The heat pump is equipped with a variable-speed scroll compressor, three inverter fans, multiple EEVs, and a 4-way valve. Fig. 1 shows a schematic of the experimental setup [18].

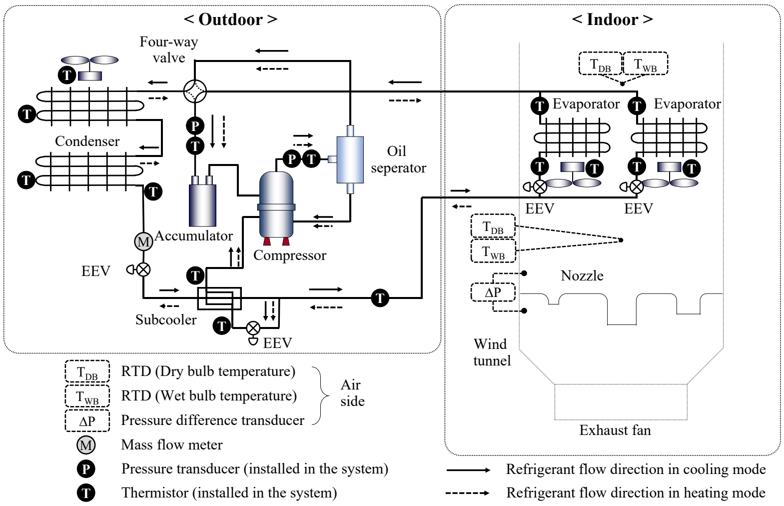

Fig. 1. Schematic of an experimental setup [18]

The sensors in black circles are initially installed sensors by the manufacturer. A pressure difference transducer, mass flow sensor, and RTD sensors are installed additionally for this research. However, it was noted that the measured values acquired from the additional sensors were not utilized for learning the CNN-based models. The nominal charge amount of refrigerant is 6 kg in heating mode and 9 kg in cooling mode. The outdoor unit was installed in the chamber to simulate the outdoor temperature and humidity conditions, and the two indoor units were installed in the chamber to create the indoor temperature and humidity conditions.

The experiments were carried out in both the cooling and heating mode. In the heating mode, the experiments started with 3 kg of refrigerant charge. After obtaining experimental data while changing the DSH for at least two hours in each refrigerant charge, an additional 1 kg of refrigerant charge was added. This process was repeated until the final refrigerant amount reached 8 kg. In cooling mode experiments, the refrigerant charge was added step by step from 6 to 11 kg, as mentioned above. When the target DSH was changed, or the refrigerant of 1 kg was added, the heat pump system became a transient state for about five minutes. This transient-state data was included in the training and test data with the steady-state data together.

The operation mode, various air conditions, compressor rotating speed, and target DSH were variables for the validation of this new RCFD method under various experimental conditions. The fan RPM in the outdoor unit was fixed at all experimental conditions, and two indoor units were always operated. In heating mode, the EEVs of both indoor units were fully opened, and the EEV of the outdoor unit was activated with the manufacturer's control logic.

In contrast, in cooling mode, the EEVs of the two indoor units were controlled, and the EEV of the outdoor unit was fully opened. Considering ANSI / AHRI standard 1230 [19], four air temperature conditions for cooling mode, and two air temperature conditions for heating mode were chosen. The experiment test conditions are described in detail in Table 2.

Table 2. Experimental conditions for cooling and heating mode

Variables	Value					
Refrigerant	R410A					
Lubricant	Polyvinyl ether(PVE) type					
Lubricant charge amount (kg)	3					
Operation mode	Cooling mode				Heating mode	
Refrigerant charge amount (kg)	6 - 11 (Δ=1)				3 - 8 (Δ=1)	
Target DSH (K)	5, 10, 15 (or maximum EEV opening)				5, 10 (or maximum EEV opening)	
Air condition (ANSI/AHRI 1230)	Rating	Low temp.	Condensate	Max load	Rating (low temp.)	Rating (high temp.)
ID inlet DB (˚C)	26.7	19.4	26.7	26.7	21.1	21.1
ID inlet WB (˚C)	19.4	13.9	23.9	19.4	15.6 (max)	15.6 (max)
OD inlet DB (˚C)	35.0	19.4	26.7	46.1	-8.3	8.3
OD inlet WB (˚C)	23.9	13.9	23.9	23.9	-9.4	6.1
Compressor speed (Hz)	60, 100	60	60, 100	60, 100	60, 100	60

The 29 features were selected based on previous studies [6-8], experimental conditions, and the attributes required to analyze the thermodynamic properties of the heat pump system. All the features utilized in the development of the model in this research can be acquired from the monitoring variables that the manufacturer provides.

3.2. Splitting of training, validation, and test data

In general, three datasets, such as the training data, the validation data, and the test data are required to improve the prediction performance of machine learning-based models. The total number of two-second interval data in this study is 223,590. To estimate the generalization error of this proposed model, experimental data, including refrigerant charges of 8 kg and 9 kg at condensation condition in cooling mode, were previously separated into test data. Besides, experimental data with the refrigerant charge of 4.5 kg, 5.5 kg, 6.5 kg, and 7.5 kg at rating conditions (high temperatures) under heating mode were added into test data in advance. The number of previously prepared test data mentioned above is 31,140. The number of rest data is 192,450. The rest of the data were split into three groups as 7 vs. 2 vs. 1. So, there were 134,700 for training data, 38,670 for validation data, and 19,080 for testing. Therefore, the number of training data is 134,700, the number of validation data is 38,670, and the number of final test data is 50,220. Finally, the number of 2-D converted training data is 4,490, the number of 2-D validation data is 1,289, and the amount of 2-D test data 1,674.

4. Results and discussion

The quantitative prediction of refrigerant levels is essential for proper monitoring and management of heat pump systems. Besides, if the power consumption and cooling capacity of the system can be predicted, it is possible to know the effect of the refrigerant charge fault on the heat pump system. This prediction can help determine the urgency of repairing a refrigerant fault. In this paper, we suggest a novel method that can predict power consumption, cooling capacity (heating capacity), and the refrigerant charge amount quantitatively and simultaneously using a single model.

Fig. 2 shows the prediction results for the power consumption values and cooling capacity (heating capacity), and the refrigerant charge amount of the heat pump systems. From Fig. 2 (a), the performance of power consumption prediction is within an RMS error of 3.8%. The error in the prediction of cooling capacity and heating capacity is an RMS error of 3.4% from Fig. 2 (b). Fig. 2 (c) shows that the CNN-based model achieved the predictive performance on the refrigerant charge amount with an RMS error of 4.9%.

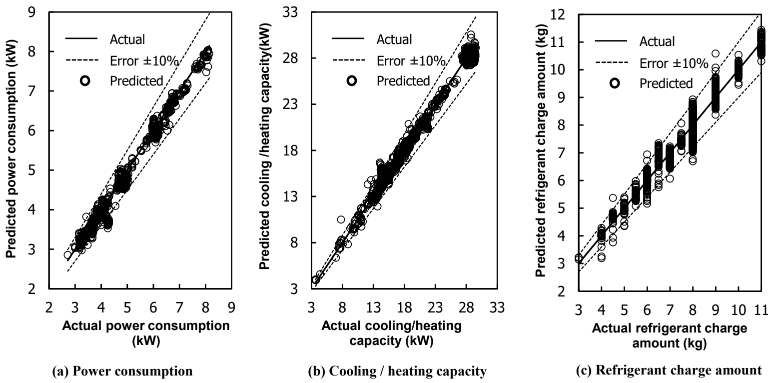

Fig. 2. Actual and predicted power consumption, cooling/heating capacity, and refrigerant charge in CNN-based regression model

The COP of a heat pump can be calculated because power consumption and cooling capacity are predicted according to the refrigerant amount change.

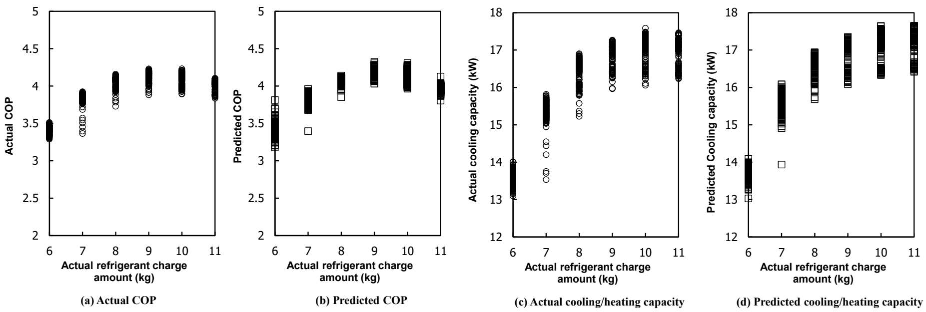

Fig. 3. Actual and predicted COP and cooling/heating capacity at the rating condition in the cooling mode

Fig. 3 (a) and (b) show the COP change of the system according to the amount of refrigerant at the rating condition in the cooling mode. They show that the predicted COP is similar to the actual COP. From Fig. 3 (c) and (d), it can be known that the cooling capacity of the heat pump with the refrigerant charge amount of 8 kg is reduced by about 2.4% compared to the nominal refrigerant charge amount of 9 kg. However, the cooling capacity in the refrigerant charge amount of 7 kg is reduced by about 8.8%. In this case, consumers may feel thermal discomfort due to reduced cooling capacity. When the refrigerant charge is 7 kg, the urgency of repairing the fault is much higher than 8 kg.

5. Conclusions

This research proposes a novel CNN-based RCFD multiple outputs regression method which has excellent quantitative prediction accuracy. This multiple outputs regression model can predict power consumption, cooling or heating capacity, and the refrigerant charge amount with a single model quantitatively. Therefore, it can provide helpful information for the severity of the refrigerant charge fault to the manufacturer or the service engineer. This comprehensive information can help manufacturers or maintenance engineers decide whether to fix a refrigerant charge defect urgently. In addition, this suggested model can predict three target variables in both the cooling and heating mode. The prediction errors for power consumption, cooling or heating capacity, and refrigerant charge amount are RMS errors of 3.8%, 3.4%, and 4.9%, respectively.

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