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Authors

Liang, Chenjiyu

Guo, Fangzhou

Kim, Donghun

et al.

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Virtual Refrigerant Charge Sensing Method for Next-Generation Refrigerant in Residential Heat Pumps

Chenjiyu Liang, PhD
Non-member

Fangzhou Guo, PhD
Non-member

Donghun Kim, PhD
Member ASHRAE

Bo Shen, PhD
Member ASHRAE

ABSTRACT

The charge level of refrigerant in heat pump systems significantly affects their operational performance. Virtual refrigerant charge (VRC) sensing technology has been well-established for traditional refrigerants (HFCs and HCFCs) for its low cost compared to physical sensors. However, other than traditional refrigerants, HFOs are increasingly used in next-generation heat pumps; whether these conventional VRC sensing methods remain applicable for heat pump systems utilizing next-generation refrigerants requires further investigation. To address these issues, this study develops a low-cost VRC sensing method for next-generation refrigerant heat pumps used in residential buildings. The developed algorithm is evaluated by using simulation models to evaluate the accuracy, considering an R454B heat pump with a nominal heating capacity of 51K Btu/hr (14.95 kW) as an example, and compared with those of the two reference VRC sensing algorithms. Though the developed VRC sensing algorithm and the two reference methods can accurately predict the charge level for the R454B heat pump system (with mean absolute percentage error for various cooling and heating conditions less than 7%), the developed VRC sensing algorithm uses fewer sensors and improves the overall accuracy for heating conditions by 7.1%, and the accuracy for undercharge cooling conditions 14.2%, compared with a mainstream algorithm. This technology will complement physical leakage detectors, and promote the adoption of next-generation heat pump systems, along with reducing wasted energy and maintenance costs.

INTRODUCTION

Heat pumps are vital in modern heating, ventilation, and air conditioning (HVAC) systems and are widely adopted. The performance of a heat pump heavily depends on its refrigerant charge level. An undercharged system can lead to reduced heating or cooling capacity and increased energy consumption, while an overcharged system can cause excessive pressure, reduced efficiency, and potential system failures. Thus, maintaining the correct charge level is crucial for optimal heat pump operation, ensuring efficiency, reliability, and longevity.

However, directly measuring the refrigerant charge level in a heat pump system is challenging; thus, virtual refrigerant charge (VRC) sensor technology has been proposed (Li and Braun 2009), which uses a linear regression model to predict the

Chenjiyu Liang is a postdoc researcher in the Department of Building Technology, Lawrence Berkeley National Laboratory, Berkeley, California. **Fangzhou Guo** is a postdoc researcher in the Department of Building Technology, Lawrence Berkeley National Laboratory, Berkeley, California. **Donghun Kim** is a research scientist in the Department of Building Technology, Lawrence Berkeley National Laboratory, Berkeley, California. **Bo Shen** is research and development Scientist in the Building Technologies Research and Integration Center, Oak Ridge National Laboratory, Oak Ridge, Tennessee

refrigerant charge level in the system based on subcooling and superheat temperatures as the features, as shown in Eq. (1), achieving a certain degree of accuracy for constant speed heat pump (Braun and Li 2009).

$$m_{charge} = c_0 + c_1 T_{sc} + c_2 T_{sh} \quad (1)$$

For variable-speed heat pumps, however, the accuracy of the aforementioned method decreases as the compressor speed changes. Therefore, Kim and Braun (2015) added two additional features—refrigerant quality at the evaporator inlet and discharge superheat temperature, as shown in Eq. (2). This improvement reduced the prediction error of the charge level in heating mode from over 10% to 7% for eight heat pumps using R22 and R410A as refrigerants. These two mainstream algorithms have been widely studied and used (Kim and Lee 2021; Kim and Braun. 2020; Huet al. 2023; Li et al. 2016; Zhu et al. 2019).

$$m_{charge} = c_0 + c_1 T_{sc} + c_2 T_{sh} + c_3 x_{ei} + c_4 T_{shd} \quad (2)$$

In addition to the aforementioned features affecting the charge level, other factors can also have an impact. For example, Boahen et al. (2019) found that the evaporating temperature and condensing temperature of the heat pump system also influence the charge level. However, this algorithm is not based on a linear regression method, making it complex in form and inconvenient to apply.

From the above observations, it is evident that the charge level is related to multiple factors, and the factors suitable for predicting the charge level vary depending on the type of refrigerant used. Hydrofluoroolefins (HFOs) are increasingly being adopted in next-generation heat pumps due to their lower environmental impact. For instance, R454B, a blend of R32 and R1234yf, is gradually replacing hydrofluorocarbons (HFCs) like R410A in heat pump applications. Despite the growing use of R454B, there is a notable research gap in the application of VRC algorithms for these systems. Most studies have focused on refrigerants R410A and R507C (Kim and Lee 2021; Kim and Braun. 2020; Huet al. 2023; Li et al. 2016; Zhu et al. 2019; Li et al. 2022). While some VRC techniques have been studied for next-generation heat pumps, such as CO₂ heat pumps (Janecke et al. 2017), specific investigations into their effectiveness and optimization for R454B heat pumps remain scarce despite having a wide range of equipment available on the market.

Thus, this study evaluates whether the two mainstream VRC algorithms are suitable for R454B heat pumps' charge level prediction. Additionally, a feature selection method for VRC sensing, developed and applied for R410A heat pumps, demonstrated improved accuracy in charge level prediction (Guo et al 2024). This study applies that feature selection method to identify the appropriate features for VRC sensing in R454B heat pumps, and compares the accuracy of this algorithm with the two reference VRC sensing algorithms.

METHODOLOGY

To test the capabilities of the mainstream algorithm and develop an algorithm for the R454B heat pump charge level prediction, this study uses a calibrated heat pump performance simulation model for an R454B heat pump to generate the heat pump performance under various heating and cooling conditions and splits them as training and testing sets. Using the training sets, the developed algorithm is achieved by selecting the appropriate features for predicting charge level, and the mainstream algorithms are also obtained based on their empirical equations as shown in Eqs. (1) and (2). Then the testing sets are used for evaluating the adaptation ability of the algorithms for the R454B heat pump and comparing their accuracies for predicting the charge level under different conditions, as shown in Figure 1.

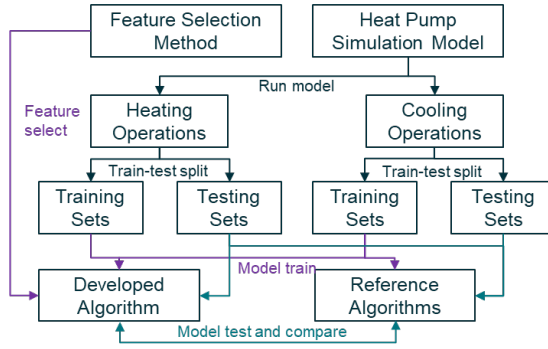


Figure 1 Methodology.

The following two sections will introduce how to select appropriate features for predicting the charge level based on the characteristics of the R454B heat pump, and how to use a calibrated heat pump model to generate evaluation methods that can be used for training and testing the algorithms.

Feature selection method

Because the mainstream methods typically determine the predictive charge level based on empirical knowledge, and different refrigerants present different properties, the most suitable features of the algorithm for predicting the R454B heat pump charge level still require investigation. Based on the previous researchers' experiences, the possible features are subcooling temperature, superheat temperature, refrigerant quality at the evaporator inlet, discharge superheat temperature, discharge saturation temperature, and suction saturation temperature (Guo et al. 2024), as shown in Eq. (3). This study uses a stepwise procedure to select the best set of features for the regression model.

$$m_{charge} = c_0 + c_1 T_{sc} + c_2 T_{sh} + c_3 x_{ei} + c_4 T_{shd} + c_5 T_c + c_6 T_e \quad (3)$$

The feature selection method starts with a linear regression model without any features and gradually adds one feature at a time. For each newly added feature, its p-value is calculated based on the training dataset to determine whether the new feature is significant for the charge level prediction and whether the coefficients (i.e., c_1 to c_6 in Eq. (3)) obey the physical rules of the heat pump system (c_1 , c_5 , and c_6 should be positive); thus selecting features that have a significant impact on the charge level and make sure that the selected features are all representative enough.

Performance evaluation method

The heat pump simulation model is used to generate different operation performances to develop and evaluate the performance of the algorithms. This study uses the Heat Pump Design Model (HPDM) developed by Oak Ridge National Laboratory (Rice 1997) as the simulation tool to generate different heating and cooling operation conditions of a calibrated two-speed R454B heat pump for residential application, with a nominal heating capacity of 51K Btu/hr (14.95 kW).

Based on AHRI Standard 210/240 (2020), the heating and cooling conditions below are chosen for the R454B heat pump performance simulation and the algorithm training and testing, as shown in Tables 1 and 2, respectively. Under each heating and cooling condition, both the superheat and subcooling temperatures are chosen from 0 to 30 °F (0 to 16.7 °C) as the input parameters to operate the HPDM model, thus generating different charge levels in the heat pump cycle correspond to the chosen superheat and subcooling temperatures. There are 1024 data sets for heating (512 sets for training and testing, respectively), and 1280 data sets for cooling (640 sets for training and testing, respectively) generated by the HPDM model, in which the training and testing data sets are randomly selected.

Table 1. Heating Conditions Chosen for Calculation

Condition	Condenser Air Inlet Temp (°F/°C)	Condenser Air Inlet Wet Temp (°F/°C)	Evaporator Air Inlet Temp (°F/°C)	Evaporator Air Inlet Wet Temp (°F/°C)	Compressor speed (rpm)
H0	70/21.1	60/15.6	62/16.7	56.5/13.6	2345
H1Full	70/21.1	60/15.6	47/8.3	43/6.1	3500
H1Low	70/21.1	60/15.6	47/8.3	43/6.1	2345
H2Full	70/21.1	60/15.6	35/1.7	33/0.6	3500
H2Low	70/21.1	60/15.6	35/1.7	33/0.6	2345
H3Full	70/21.1	60/15.6	17/-8.3	15/-9.4	3500
H3Low	70/21.1	60/15.6	17/-8.3	15/-9.4	2345
H4Full	70/21.1	60/15.6	5/-15	3/-16.1	3500

Table 2. Cooling Conditions Chosen for Calculation

Condition	Condenser Air Inlet Temp (°F/°C)	Condenser Air Inlet Wet Temp (°F/°C)	Evaporator Air Inlet Temp (°F/°C)	Evaporator Air Inlet Wet Temp (°F/°C)	Compressor speed (rpm)
AFull	95/35	75/23.9	80/26.7	67/19.4	3500
BFull	82/27.8	65/18.3	80/26.7	67/19.4	3500
BLow	82/27.8	65/18.3	80/26.7	67/19.4	2345
CFull	82/27.8	58/14.4	80/26.7	67/19.4	3500
CLow	82/27.8	58/14.4	80/26.7	67/19.4	2345
DFull	82/27.8	58/14.4	80/26.7	67/19.4	3500
DLow	82/27.8	58/14.4	80/26.7	67/19.4	2345
FLow	67/19.4	53.5/11.9	80/26.7	67/19.4	2345
GLow	67/19.4	58/14.4	80/26.7	67/19.4	2345
ILow	67/19.4	58/14.4	80/26.7	67/19.4	2345

Using the R454B heat pump performances under various heating and cooling conditions calculated by the HPDM model, this study trained and compared the accuracy of the developed algorithm with that of two reference algorithms: reference algorithms 1 and 2 are presented in Eqs. (1) and (2), respectively. The root mean square error (RMSE) and mean absolute percentage error (MAPE) are used to evaluate the accuracy.

RESULTS

This section presents the selected features for the developed algorithm and tested accuracy comparison for the three algorithms.

Heating condition

By using the feature selection method mentioned in the Methodology section under different heating conditions for training, the discharge saturation temperature and subcooling temperature are determined as the selected features. Then, During the process of training the algorithm, we found that superheat temperature is also an important feature, which has a significant impact on the accuracy of the results. Since the refrigerant is mainly distributed in the condenser and the evaporator, and the discharge saturation temperature and subcooling temperatures affect the charge level in the condenser, while the superheat temperature affects the charge level in the evaporator, this algorithm can accurately reflect the charge level throughout the heat pump cycle. Therefore, the developed algorithm contains three features and is shown in Eq. (4).

$$m_{charge} = c_0 + c_1 T_c + c_2 T_{sc} + c_3 T_{sh} \quad (4)$$

Based on Eq. (4), the algorithm was trained under various heating conditions with different subcooling, superheat temperatures, and charge levels. The training RMSE was 0.367 lb (0.166 kg), the MAPE was 0.0439, and the testing RMSE and MAPE were 0.363 lb (0.165 kg) and 0.0429, respectively, as shown in Figure 2.

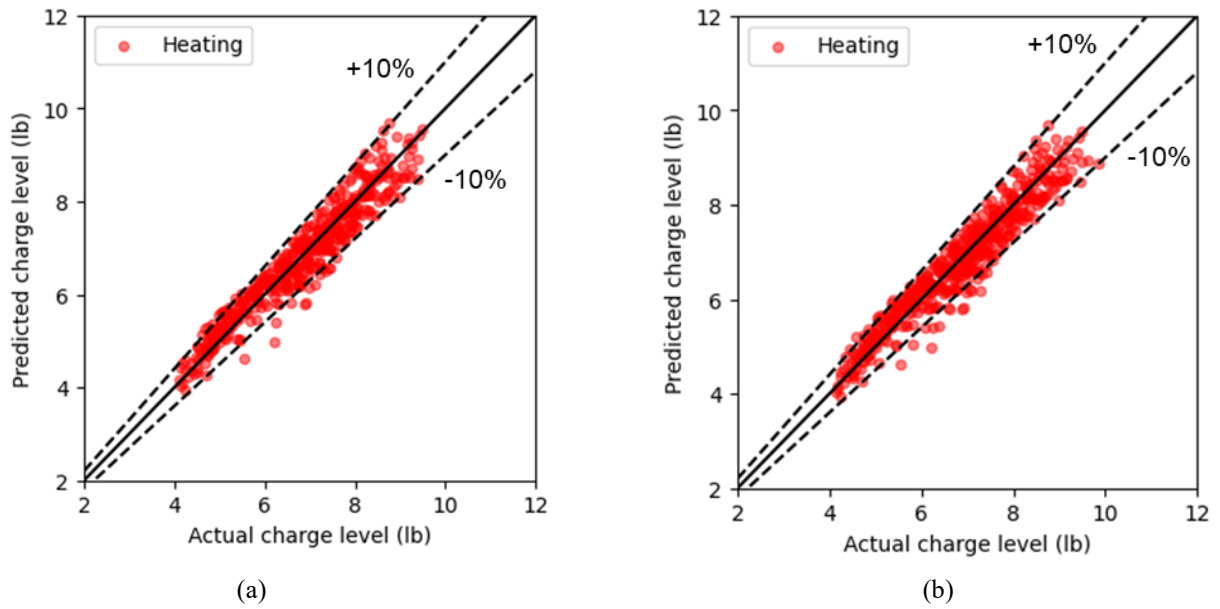


Figure 2 Developed algorithm's performance for heating conditions: (a) training; (b) testing.

Under various heating conditions, for reference algorithm 1 (Li and Braun 2009), the training RMSE and MAPE were 0.406 lb (0.184 kg) and 0.0491, respectively, and the testing RMSE and MAPE were 0.388 lb (0.176 kg) and 0.0462, respectively. For reference algorithm 2 (Kim and Braun 2015), the training RMSE and MAPE were 0.392 lb (0.178 kg) and 0.0484, and the testing RMSE and MAPE were 0.383 lb (0.174 kg) and 0.0462, respectively, as shown in Figure 3.

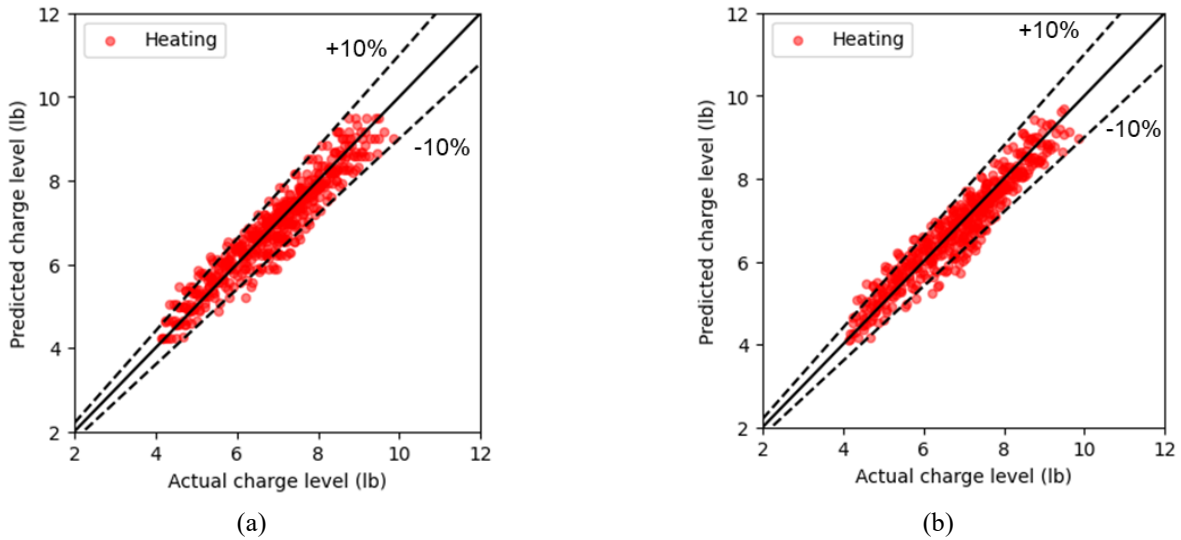


Figure 3 Reference algorithms' performance for heating conditions: (a) reference algorithm 1 (Li and Braun 2009); (b) reference algorithm 2 (Kim and Braun 2015).

The tested MAPEs were compared for the three algorithms, as shown in Table 3. All three algorithms perform well to

the R454B heat pump, with acceptable charge level prediction errors. However, the developed algorithm performs better than the two reference algorithms, with improvements of 7.1% compared to both reference algorithms 1 and 2. Especially, the developed algorithm uses fewer features and achieves better accuracy compared with the reference algorithm 2. This is because the features of the developed algorithm were selected using feature selection methods, which avoided the issue of redundant selection due to inter-correlation between features. As a result, the developed algorithm better conforms to physical principles and is thus more accurate.

Table 3. Algorithm Comparison For Cooling Conditions

Algorithm	MAPE in testing	Improvement
Developed	0.0429	/
Reference 1: Li and Braun (2009)	0.0462	7.1%
Reference 2: Kim & Braun (2015)	0.0462	7.1%

Cooling Condition

After feature selection, the selected features for cooling conditions are suction saturation temperature and subcooling temperature, thus the algorithm is shown below. Though they are different from the features selected in the heating conditions, this algorithm still reflects the refrigerant charge level in the evaporator and condenser through the suction saturation temperature and subcooling temperature, respectively. Additionally, the suction saturation temperature reflects the operating status of the indoor unit under cooling conditions.

$$m_{charge} = c_0 + c_1 T_e + c_2 T_{sc} \quad (5)$$

Based on Eq. (5), the algorithm was trained under various cooling conditions. The training RMSE and MAPE were 0.819 lb (0.371 kg) and 0.0614, respectively, and the testing RMSE and MAPE were 0.811 lb (0.368 kg) and 0.0584, respectively, as shown in Figure 4.

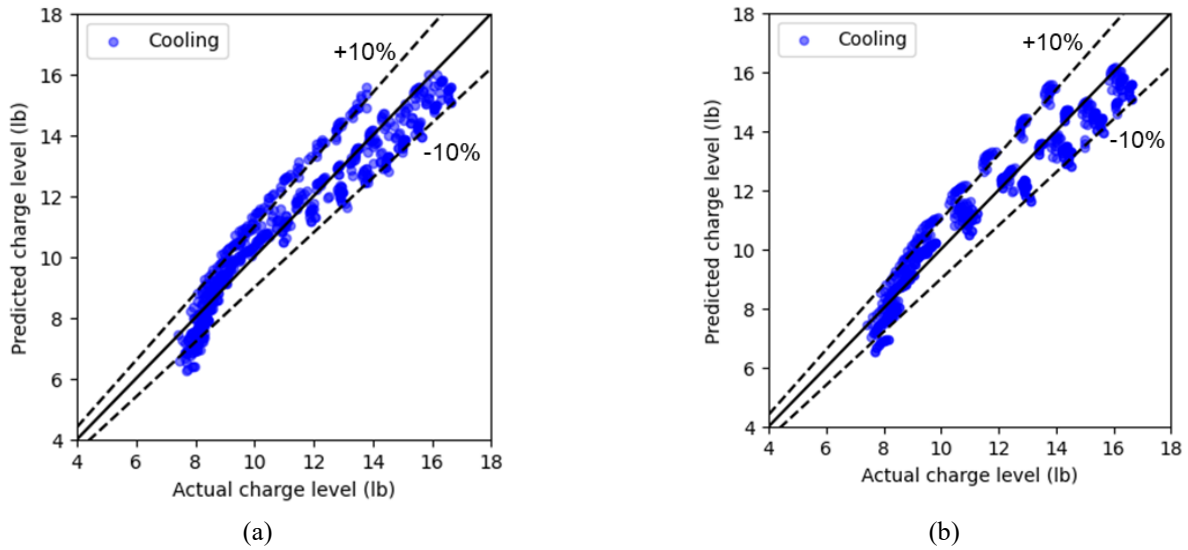


Figure 4 Developed algorithm's performance for cooling conditions: (a) training; (b) testing.

Under various cooling conditions, for reference algorithm 1 (Li and Braun 2009), the training RMSE and MAPE were 0.929 lb (0.421 kg) and 0.0727, respectively, and the testing RMSE and MAPE were 0.919 lb (0.417 kg) and 0.0688, respectively. For reference algorithm 2 (Kim and Braun 2015), the training RMSE and MAPE were 0.717 lb (0.325 kg) and

0.0587, and the testing RMSE and MAPE were 0.675 lb (0.306 kg) and 0.0543, respectively, as shown in Figure 5.

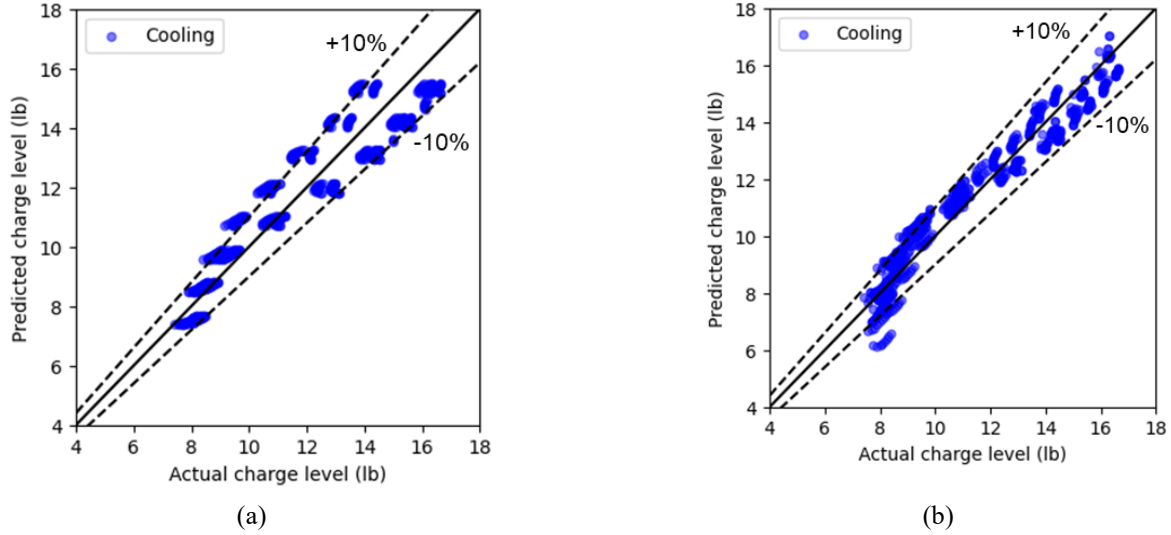


Figure 5 Reference algorithms' performance for cooling conditions: (a) reference algorithm 1 (Li and Braun 2009); (b) reference algorithm 2 (Kim and Braun 2015).

The tested MAPEs of the three algorithms are presented in Table 4. Though the MAPEs for cooling conditions are larger than those for heating conditions, the three algorithms can perform acceptably when applied in the R454B heat pump. The developed algorithm significantly performs better than the reference algorithm 1, both using two features. Although the overall performance is not as strong as that of reference algorithm 2, it saves two features and performs better during the undercharge conditions.

Table 4. Algorithm Comparison For Cooling Conditions

Algorithm	MAPE in testing	Improvement
Developed	0.0584	/
Reference 1 (Li and Braun 2009)	0.0688	15.1%
Reference 2 (Kim and Braun 2015)	0.0543	-7.6%

For the undercharge cooling conditions, all three algorithms do not perform well compared with the undercharge heating conditions. However, the developed algorithm uses fewer sensors and improves the charge level prediction accuracy for undercharge cooling conditions by 14.2%, compared with reference algorithm 2. This is because the features selected by reference algorithm 2 are inter-correlated, leading to redundancy, and thus it performs poorly under undercharge conditions.

Table 5. Algorithm Comparison For Under-charge Cooling Conditions

Algorithm	MAPE in testing	Improvement
Developed	0.0617	/
Reference 1 (Li and Braun 2009)	0.0634	2.7%
Reference 2 (Kim and Braun 2015)	0.0719	14.2%

Although the algorithm in this paper is validated based on simulated data, the model used to generate this simulated data is based on an actual heat pump unit and has been calibrated and validated, ensuring its accuracy. Although this study only validated a single heat pump system, future work will focus on the application of different next-generation refrigerants

(such as R290 and R1234yf) and heat pump units of varying capacities. Additionally, the presence of lubricating oil in the heat pump system affects the thermodynamic properties of the refrigerant and the efficiency of the heat exchanger, altering the discharge saturation temperature, subcooling, and superheating. This issue will also be addressed in future research.

CONCLUSION

Virtual refrigerant charge (VRC) sensing technology has been successfully applied for traditional refrigerant heat pumps. However, there is still a lack of research on whether they are capable of being applied to heat pumps using next-generation refrigerants currently being promoted. This study takes a residential heat pump system using R454B as an example to explore the feasibility of two mainstream reference algorithms and to investigate the appropriate features for predicting charge levels under different heating and cooling conditions. The prediction accuracies are calculated and compared. The main research conclusions are as follows:

- 1) All three algorithms can be applied to R454B HP charge level prediction, with acceptable mean absolute percentage errors for both cooling and heating conditions.
- 2) The developed VRC sensing algorithm uses one fewer sensor but improves the overall accuracy for heating conditions by 7.1%, compared with a mainstream algorithm.
- 3) The developed VRC sensing algorithm uses two fewer sensors and improves the accuracy for undercharge cooling conditions by 14.2%, compared with a mainstream algorithm.

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NOMENCLATURE

c_0 to c_6	=	coefficients of the regression equation
m_{charge}	=	charge level in the heat pump cycle
T	=	temperature
X_{ei}	=	refrigerant quality at evaporator inlet
HCFCs	=	hydrochlorofluorocarbons
HFCs	=	hydrofluorocarbons
HFOs	=	hydrofluoroolefins
HPDM	=	heat pump design model
HVAC	=	heating, ventilation and air conditioning
MAPE	=	mean absolute percentage error
RMSE	=	root mean square error
VRC	=	virtual refrigerant charge

Subscripts

c	=	discharge saturation
e	=	suction saturation
sc	=	subcooling
sh	=	superheat
shd	=	discharge superheat

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