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Permalink

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Journal

Applied Thermal Engineering, 293

ISSN

1359-4311

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Publication Date

2026-05-01

DOI

10.1016/j.applthermaleng.2026.130290

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Research Paper

Virtual refrigerant charge sensor for variable-speed heat pumps based on feature selection

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ARTICLE INFO

Keywords:

Heat pump
Refrigerant charge
Fault detection and diagnosis
Virtual sensor
Energy efficiency

ABSTRACT

The refrigerant charge level in heat pump systems significantly impacts their energy efficiency. Virtual refrigerant charge (VRC) sensing technology has been comprehensively investigated and well-established due to its lower cost compared to physical sensors. However, the previous VRC research often relied on expert judgment and physical reasoning for their variable selection, which can potentially select redundant (or highly correlated) or insignificant features, and it is also primarily focused on single-speed systems. To address these challenges, this study proposes a VRC algorithm for variable-speed heat pumps that selects features through a rigorous feature selection method in combination with physical insights. We also propose a piecewise linear model structure segmented by subcooling temperature to accurately predict charge levels, particularly when subcooling temperatures are substantially low. The proposed algorithm was evaluated using experimental data of a residential R410A heat pump, and the performance was compared with two baseline VRC algorithms. The results are: (1) The proposed algorithm outperforms for the case with subcooling temperature less than 1 °C. (2) The proposed algorithm achieves a tested mean absolute percentage error (MAPE) of 4.23%, and improves the overall accuracy for cooling conditions by approximately 60%, compared with the two baseline algorithms. (3) The proposed algorithm uses two fewer features and improves the accuracy for undercharge cooling conditions by 68.0%, compared with baseline algorithm 2. These improvements enhance prediction accuracy and prevent overfitting, providing a more reliable refrigerant charge level prediction and helping improve the heat pump energy efficiency.

1. Introduction

Building energy consumption exceeds 30% of the entire global energy consumption [1,2]. Heat pumps play a crucial role in modern heating, ventilation, and air conditioning (HVAC) systems to decrease the energy consumption of buildings and are widely utilized [3,4]. The efficiency of a heat pump is significantly influenced by its refrigerant charge level [5–7]. An undercharge scenario can result in decreased heating or cooling capacity and higher energy usage; it was reported that a 25% reduction in refrigerant charge resulted in an average 15% decrease in energy efficiency and a 20% decrease in capacity [8]; whereas an overcharge scenario can lead to high pressure, reduced efficiency, and potential system malfunctions [9]. Therefore, maintaining the correct refrigerant charge is essential for optimal heat pump performance, ensuring efficiency, reliability, and longevity.

Direct measurement of the refrigerant charge level in a heat pump system poses significant challenges. Although physical sensors can detect refrigerant leakage in heat pumps, they are unable to accurately determine the remaining charge level in the system. Moreover, test results [10,11] indicate that the performance of these sensors is sensitive to their placement and entails relatively high installation costs. In addition to utilizing physical refrigerant leakage sensors, level sensors can also be used to monitor the charge in liquid receivers. However, for small-capacity systems, such measurements are often impractical and uneconomical. Furthermore, in heat pump systems, the refrigerant is distributed not only in the storage component (where it can be measured using level sensors) but also across various heat exchangers, making it difficult to measure accurately.

Several studies have shown that heat pump operating parameters are correlated with the refrigerant charge level, thereby enabling the use of these parameters to estimate the charge level and to identify over-

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Received 21 November 2025; Received in revised form 30 January 2026; Accepted 13 February 2026

Available online 18 February 2026

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Nomenclature

c_0	intercept
c_1 to c_6	coefficients
$list_{ex}$	list to store the excluded features
$list_{in}$	list to store the included features
m_{charge}	refrigerant charge level
$\hat{m}_{charge,i}$	predicted refrigerant charge level
$MAPE$	mean absolute percentage error
n	total number of data used for testing
$RMSE$	root mean square error
SE	standard error
t_{score}	t statistic
T_c	condensation temperature
T_{dis}	discharge temperature
T_e	evaporation temperature

T_{ll}	liquid line temperature
T_{sc}	subcooling temperature
$T_{sc,turn}$	subcooling temperature turning point
T_{sh}	superheat temperature
T_{shd}	discharge superheat temperature
T_{suc}	suction temperature
x_{ei}	refrigerant quality at the evaporator inlet

Greek symbols

α	significance level
ε	normally distributed random noise

Abbreviations

HVAC	heating, ventilation, and air conditioning
VRC	virtual refrigerant charge
VRF	virtual refrigerant flow

charged or undercharged operating conditions. Catrini and Piacentino [12] used experimental data to demonstrate that the refrigerant charge level is correlated with condensation pressure, subcooling temperature, and superheat temperature. In addition, Li et al. [13] reported that variations in refrigerant charge level also affect the evaporation pressure, suction temperature, and discharge temperature. Therefore, the original virtual refrigerant charge (VRC) sensor was proposed by Li and Braun (2009) [14,15]. This technology employs a regression algorithm to estimate the refrigerant charge level based on subcooling and superheat temperatures, as illustrated in Eq. (1) [14]. These two features calculate the charge level distributions in the condenser and evaporator, respectively. A higher subcooling temperature indicates a greater presence of high-density liquid phase in the condenser, while a higher superheat temperature signifies a larger quantity of low-density vapor phase in the evaporator. Therefore, these factors can be used to effectively predict the charge level.

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

where m_{charge} is the refrigerant charge level; T_{sc} and T_{sh} are subcooling and superheat temperatures, respectively; c_0 is the intercept; and c_1 and c_2 are the coefficients of T_{sc} and T_{sh} , respectively.

This algorithm with two features has been demonstrated for a variety of different vapor compression systems, including chillers, split-systems, packaged systems, heat pumps [16], and air conditioners, and for various combinations of thermal and electrical expansion valves, and with/without accumulators for both residential and commercial

applications. However, those have been primarily focused on the single-speed system. For variable-speed units, its accuracy deteriorates with the changes in compressor speed, as shown in Fig. 1(a). Only a limited number of studies have applied VRC to variable-speed systems [17]. Among them, Kim and Braun [18] were the first, to our knowledge, to introduce a VRC algorithm for such systems. They included two additional features—refrigerant quality at the evaporator inlet and discharge superheat temperature, as described in Eq. (2). Thus, two features represent the charge level (T_{sc} and T_{shd}) for condenser, while the other two (T_{sh} and x_{ei}) represent the charge level for evaporator.

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

where x_{ei} is the refrigerant quality at the evaporator inlet; T_{shd} is the discharge superheat temperature; and c_3 and c_4 are the coefficients of x_{ei} and T_{shd} , respectively. After incorporating two additional physical variables, this algorithm reduced the prediction error of the charge level under heating conditions from over 10% to 7% when applied to eight heat pumps using R22 and R410A refrigerants, compared to the algorithm presented in Eq. (1). The algorithm has been extensively studied and applied by many researchers [19–21]. For example, applying this method to rooftop air conditioners and direct expansion heat pumps using R410A and R22, the overall relative error in predicting the charge level is around 10%. Based on the structure of Eq. (2), a deep learning-based residual neural network method was employed to predict the refrigerant charge level in a variable refrigerant flow (VRF) system [22]. Furthermore, for heat pump systems using CO₂ as the refrigerant,

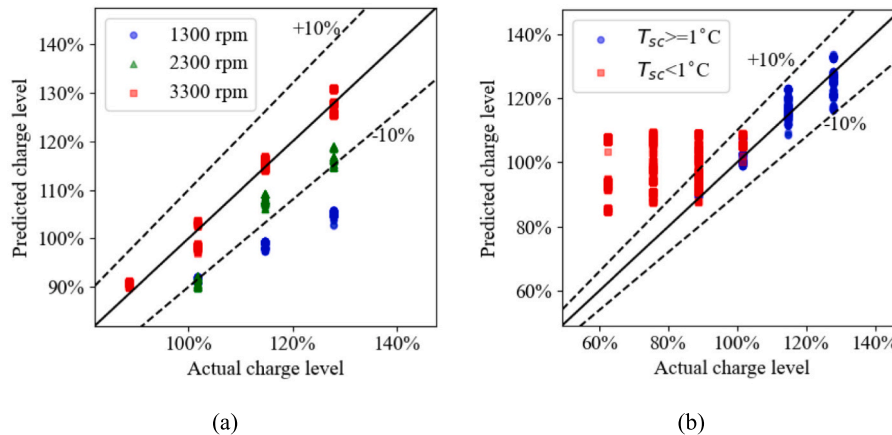


Fig. 1. Limitations of the previous VRC algorithms: (a) the two-feature algorithm cannot adapt to variable speed heat pump; (b) the four-feature algorithm cannot adapt to both overcharge and undercharge scenarios [25].

which operate under transcritical cycles and employ a gas cooler instead of a condenser, the subcooling temperature and discharge superheat temperature used in Eqs. (1) and (2) are no longer applicable. Accordingly, two recent studies [23,24] modified the structure of Eq. (2) by replacing the condenser-side variables with the refrigerant density at the gas cooler side to estimate the refrigerant charge level. In addition, the performance of the VRC sensor under other faulty conditions, such as heat exchanger fouling and compressor valve leakage, has been tested by some other researchers. The VRC sensor is very robust when these faults occur [14,19].

However, studies have also shown that the VRC approach can become inaccurate under significantly overcharged and undercharged scenarios. Ref. [26] shows the deviation of charge level prediction in overcharge conditions (high prediction errors, exceeding 30%), and Fig. 1(b) from our study shows similar issues under undercharge scenarios with the substantially low subcooling temperature ($< 1^\circ\text{C}$). It should be emphasized that the two-factor algorithm presented in Eq. (1) only presents the conditions when the subcooling temperature is greater than 1°C . In scenarios below 90% nominal charge level (subcooling temperature is smaller than 1°C), it exhibits performance similar to that shown in Fig. 1(b), meaning that this method not only fails to predict various compressor speeds, but also struggles to adequately account for both overcharge and undercharge situations, resulting in significant

features for VRC sensing based on experimental data for a residential R410A heat pump, and compares the accuracy with two baseline VRCs.

2. Proposed algorithm

Traditional algorithms typically determine the charge level by fitting the overcharge and undercharge conditions together based on empirical knowledge of feature selection, resulting in limited prediction performance for variable-speed heat pumps. Because the subcooling temperature of the heat pump is often closely related to the charge level, this study proposes an algorithm that divides the charge level prediction into two segments by using a subcooling temperature turning point ($T_{sc,turn}$), as shown in Eq. (3). It should be emphasized that the heat pump considered in this study is a residential system, which typically does not incorporate a liquid refrigerant receiver between the condenser and evaporator [31,32]. Compared to traditional algorithms, this approach more effectively addresses the inaccuracies by predicting undercharge and overcharge conditions separately. Thus, it can improve the accuracy of predicting both the overcharge and undercharge conditions. However, it is important to emphasize that Eq. (3) does not imply that all six physical variables are applied in the algorithm. The method for selecting the appropriate physical variables will be introduced in Section 2.2.

$$m_{charge} = \begin{cases} c_{0,1} + c_{1,1}T_{sc} + c_{2,1}T_{sh} + c_{3,1}x_{ei} + c_{4,1}T_{shd} + c_{5,1}T_c + c_{6,1}T_e & (T_{sc} > T_{sc,turn}) \\ c_{0,2} + c_{1,2}T_{sc} + c_{2,2}T_{sh} + c_{3,2}x_{ei} + c_{4,2}T_{shd} + c_{5,2}T_c + c_{6,2}T_e & (T_{sc} \leq T_{sc,turn}) \end{cases} \quad (3)$$

errors. Usually, when the subcooling temperature is low, the high-density liquid-phase refrigerant proportion cannot be maintained, thus resulting in an undercharge condition.

Besides those issues, the selection of features in VRC plays an important role in predicting the charge level. However, despite comprehensive VRC research, the feature selection approach remains in question and varies depending on VRC algorithms. For instance, Boahen et al. [27] identified that the evaporating temperature and condensing temperature of the heat pump system also correlate with the charge level. Zhu et al. [28] used the refrigeration pressure drop of the liquid line between the condenser outlet and the expansion valve inlet as a feature to predict the charge level. However, their algorithms are based on multivariate polynomial regression [27] with the pressure drop as a feature [28], making these algorithms complex and challenging to implement. Additionally, feature selection approaches for VRC algorithms vary significantly from existing literature and are highly customized, depending on factors such as the specific system and refrigerant used. This lack of standardized methodologies often necessitates a deep understanding of the unique characteristics of the system, and the process typically involves considerable trial and error. What's more, the physical variables related to refrigerant charge levels are always correlated with each other. When they are used to train a regression model, the statistical significance of some variables is prone to being affected. As a result, the trained regression model may not align with physical principles. This issue is known as "multicollinearity" in statistics [29,30], which can lead to high prediction errors on new datasets.

Thus, this study proposes a rigorous feature selection method based on a segmented VRC model for better prediction. Given the strong relationship between subcooling temperature and charge level, the prediction algorithm is divided into two segments depending on whether the subcooling temperature is above or below its turning point. In each segment, relevant features are selected based on physical principles and statistical significance to effectively predict the charge level. This paper applies the proposed algorithm to identify the appropriate

where T_c and T_e are condensation and evaporation temperatures, respectively; $T_{sc,turn}$ is the subcooling temperature turning point; and $c_{5,1}/c_{5,2}$ and $c_{6,1}/c_{6,2}$ are the coefficients of T_c and T_e , respectively.

In this study, linear regressions are considered because they have already demonstrated high accuracy in predicting the charge level. In these two segments, the study considers six physical variables affecting the charge level as possible features in the proposed algorithm, including subcooling temperature (T_{sc}), superheat temperature (T_{sh}), refrigerant quality at the evaporator inlet (x_{ei}), discharge superheat temperature (T_{shd}), condensation temperature (T_c), and evaporation temperature (T_e), as shown in Eq. (3).

However, as mentioned previously, not all of the aforementioned six physical variables are used for predicting the charge level, as this could lead to overfitting. This study first analyzes the influence of these six physical variables on the charge level from a thermodynamic perspective (Section 2.1). Subsequently, a feature selection method is proposed (Section 2.2). This method selects the physical variables that are theoretically relevant and significantly correlated with the charge level, based on the correlation signs (positive or negative) and the significance of their correlations. These selected physical variables are then used as features to predict the charge level.

2.1. Physical variables relationship

This section analyzes the positive and negative correlations between the six physical variables and the charge level. The five temperatures (except for refrigerant quality at the evaporator inlet) are presented in Fig. 2(a). Since the majority of the refrigerant in the heat pump system is present in the condenser and evaporator, and these six physical variables are related to the operating states of the condenser and evaporator, their influence on the distribution of refrigerant can be analyzed to calculate the refrigerant density distribution in the system and thus predict the refrigerant charge level. It is emphasized that the present study examines a residential heat pump with a basic vapor compression cycle without a liquid receiver (i.e., no receiver installed between the

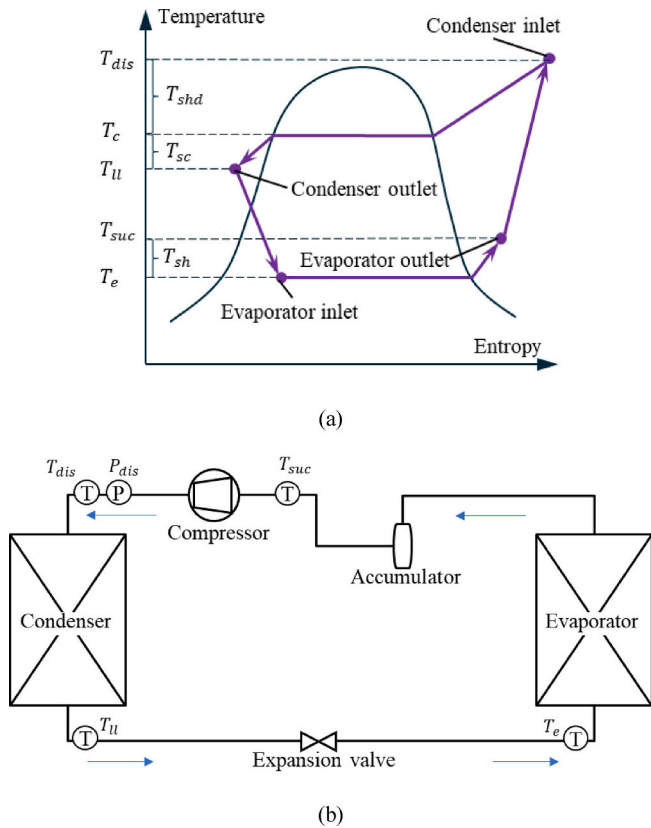


Fig. 2. Refrigerant charge level related physical variables: (a) on the temperature-entropy diagram; (b) on the system diagram.

condenser and the expansion valve), internal heat exchanger, flash tank, or ejector, as shown in Fig. 2(b). Moreover, because the evaporator-outlet refrigerant is treated as superheated vapor under the conditions investigated, the accumulator charge inventory is not considered.

- (1) Subcooling temperature (T_{sc}): The subcooling temperature typically has a positive correlation with the charge level. In the condenser, the refrigerant is distributed in gas, gas-liquid, and liquid phases. The higher the subcooling, the higher the proportion of subcooled liquid refrigerant in the condenser is. Since the liquid phase refrigerant has the highest density, a higher subcooling temperature indicates a higher charge level. Therefore, subcooling temperature is positively correlated with the charge level; in addition, the relationship between subcooling and charge level can be assumed to be linear because the density of the liquid-phase refrigerant is much greater than that of the gas-phase refrigerant and can be considered constant [14].
- (2) Superheat temperature (T_{sh}): The superheat temperature usually has a negative correlation with the charge level. In the evaporator, the refrigerant is distributed in gas-liquid and gas phases. The higher the superheat, the higher the proportion of superheated gas-phase refrigerant in the evaporator is. Since the gas-phase refrigerant has the lowest density (under normal temperature and pressure, the density of gas-phase R410A is approximately 6% of that of the liquid-phase R410A), a higher superheat temperature indicates a lower charge level. Therefore, superheat temperature is negatively correlated with the charge level.
- (3) Refrigerant quality at the evaporator inlet (x_{ei}): The refrigerant quality at the evaporator inlet usually has a negative correlation with the charge level. It refers to the ratio of the mass of the gas phase to the total mass of the refrigerant mixture (gas and liquid phases) at the inlet of the evaporator. A higher refrigerant quality

at the evaporator inlet indicates a higher proportion of gas-phase refrigerant entering the evaporator, indicating that the lower-density gas-phase refrigerant occupies more volume in the evaporator, thus leading to a lower charge level.

- (4) Discharge superheat temperature (T_{shd}): The discharge superheat temperature usually has a negative correlation with the charge level. Discharge superheat temperature refers to the temperature difference between the refrigerant discharge and its saturation temperature at the compressor outlet (i.e., the saturated condensation temperature). When the refrigerant charge level is insufficient, the refrigerant in the evaporator evaporates completely early, leading to more superheated gas-phase refrigerant entering the compressor, which in turn increases the discharge superheat temperature. Therefore, discharge superheat temperature is negatively correlated with the charge level.
- (5) Condensation temperature (T_c): The condensation temperature typically has a positive correlation with the charge level. When the refrigerant charge level is excessive, the amount of liquid refrigerant in the condenser increases, and the excess refrigerant increases the system pressure, further elevating the condensation temperature. In addition, the charge level change causes the variations in refrigerant flow rate, resulting in a change of refrigerant density at the compressor inlet. These variations in flow rate lead to different pressure drops across the expansion valve; thus influence condensation pressure and temperature. Therefore, the condensation temperature is positively correlated with the refrigerant charge level.
- (6) Evaporation temperature (T_e): The evaporation temperature typically has a positive correlation with the charge level. The increase in refrigerant charge level leads to an increase in the evaporation pressure, because the pressure increases with mass when the system volume is fixed. Since evaporation pressure is positively correlated with evaporation temperature, the evaporation temperature also rises accordingly. Therefore, evaporation temperature is positively correlated with the refrigerant charge level.

In summary, the correlations between the six physical variables and the refrigerant charge level are summarized in Table 1. Furthermore, under the same operating conditions, a comparison of the refrigeration cycles at the nominal refrigerant charge and at the reduced (under-charged) condition after refrigerant leakage is shown in Fig. 3. After a significant refrigerant leakage, the overall refrigeration cycle shifts rightward and on the temperature-entropy diagram (reflecting lower refrigerant density and reduced system pressure), exhibiting a higher degree of superheat and a lower degree of subcooling. In fact, there are

Table 1

Six physical variables' relationship with refrigerant charge level and required sensors.

Physical variables	Relationship with m_{charge}	Required sensors
T_{sc}	+	Condenser pressure and outlet temperature
T_{sh}	−	Evaporator inlet and outlet temperatures
x_{ei}	−	Condenser pressure and outlet temperature, evaporator inlet temperature
T_{shd}	−	Condenser pressure and inlet temperature
T_c	+	Condenser pressure
T_e	+	Evaporator inlet temperature

*Positive and negative correlations are represented as “+” and “−”, respectively. x_{ei} can be determined from the condenser pressure and outlet temperature, together with the evaporator inlet temperature, only when T_{sc} is greater than zero. Otherwise, the expansion valve inlet may contain two-phase refrigerant, in which case the inlet enthalpy cannot be uniquely determined based solely on condenser pressure and outlet temperature measurements.

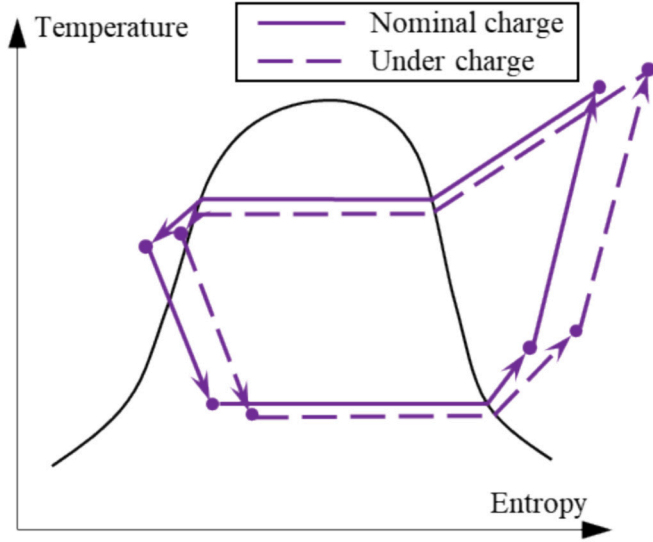


Fig. 3. Refrigeration cycle at nominal-charge and under-charge conditions.

certainly correlations among these six features. For example, the refrigerant quality at the evaporator inlet is associated with evaporating pressure, condensing pressure, and the temperature at the condenser outlet (subcooling temperature). Thus, it is necessary to use the proposed feature selection method to identify the most suitable features from them, which will be presented in Section 2.2.

Some researchers have also demonstrated a similar relationship between these physical variables and the charge level through theoretical analysis and experimental data: subcooling and superheat temperatures (T_{sc} , T_{sh}) [33]; evaporation and condensation temperatures, and subcooling temperature (T_e , T_c , T_{sc}) [34]; evaporation and condensation temperatures, and subcooling and superheat temperatures (T_e , T_c , T_{sc} , T_{sh}) [35,36]. The rigorous feature selection method proposed in Section 2.2 determines whether a particular physical variable should be included as an appropriate feature in the regression model for predicting

the charge level based on the positive or negative signs of the correlation. This ensures that the regression model is consistent with theoretical principles and avoids overfitting.

2.2. Feature selection method

Based on the analysis of the positive and negative correlations between each physical variable and the charge level in Section 2.1, this study proposes a feature selection method as part of the charge level prediction algorithm. This method selects features from the six physical variables that have the appropriate correlation signs and significant impacts on predicting the charge level. The specific process is illustrated in Fig. 4.

The feature selection method uses a sequential procedure for both cases when the subcooling temperature is larger than/equal to, or smaller than the subcooling turning point [as shown in Eq. (3)]. It starts with an empty list of physical variables ($list_{in}$), a list to store the excluded physical variables ($list_{ex}$) to be included that start with all six physical variables, and a linear regression algorithm without any features (i.e., physical variables). Then the linear regression algorithm applies all the physical variables in the $list_{in}$ plus a physical variable in $list_{ex}$ to perform regression for predicting the charge level. For each physical variable in the $list_{ex}$, its p -value is calculated to determine whether the physical variable is significant for the charge level prediction and whether the coefficients (i.e., c_0 to c_6 in Eq. (3)) obey the physical rules of the heat pump system (i.e., c_1 , c_5 , and c_6 should be positive; c_2 , c_3 , and c_4 should be negative). Then, the physical variable in $list_{ex}$ that aligns with the correlation signs and has the smallest p -value is added to $list_{in}$. This process is repeated until the p -values of all physical variables in $list_{ex}$ exceed the significance level, thereby determining the final $list_{in}$ as the selected features for the linear regression algorithm.

In this process, the regression t -test is used to identify if a physical variable is statistically significant for the linear model for charge level prediction:

$$m_{charge} = c_0 + c_1 T_{sc} + c_2 T_{sh} + c_3 x_{ei} + c_4 T_{shd} + c_5 T_c + c_6 T_e + \varepsilon \quad (4)$$

where ε is a normally distributed random noise. The regression t -test is

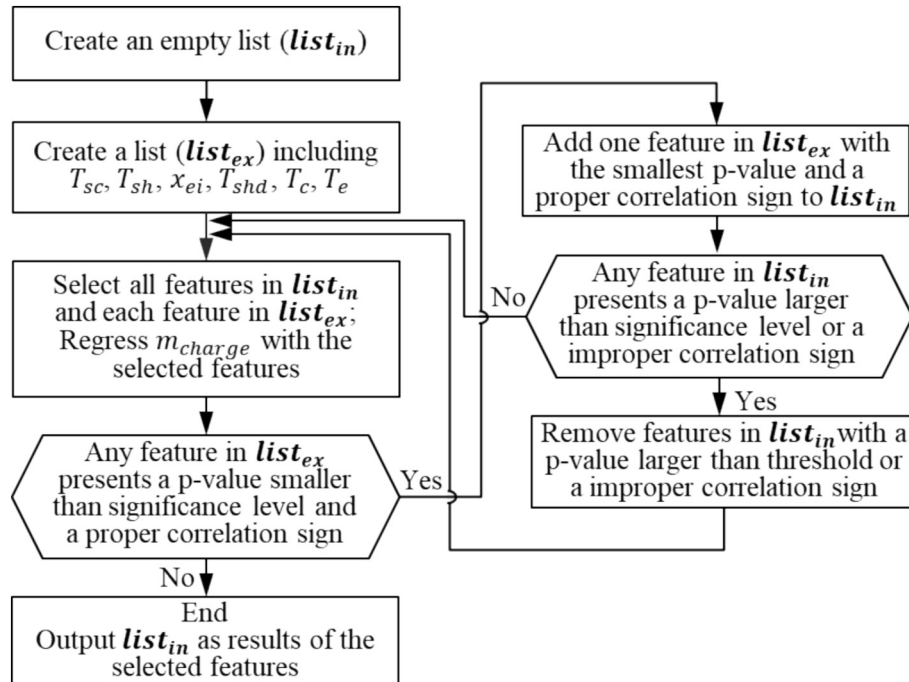


Fig. 4. Refrigerant charge level-related feature selection method.

applied to test whether the above six physical variables are useful for the prediction of the charge level. Take T_{sc} as an example, the null hypothesis (H_0) states that $c_1 = 0$, and the alternative hypothesis (H_1) states that $c_1 \neq 0$. If $\hat{c}_1$ represents the least squares estimator of c_1 and $SE(\hat{c}_1)$ represents the standard error of $\hat{c}_1$, then

$$t_{score} = \frac{\hat{c}_1}{SE(\hat{c}_1)} \sim t_{n-2} \quad (5)$$

follows a t-distribution with $n - 2$ degrees of freedom when H_0 is true (n represents the sample size). The p -value is calculated according to t_{score} and if it is smaller than the significance level (α) prespecified for the test, then H_0 is rejected. That is, it is $100 \bullet (1 - \alpha)\%$ confident that $c_1 \neq 0$ and T_{sc} is useful for the prediction of m_{charge} . In this study, the significance level (α) is considered as 0.05.

The feature selection method proposed in this study not only assesses the significance of each physical variable on the charge level based on its p -value but also takes into account the signs of their correlations according to physical principles. Due to potential multicollinearity among the physical variables, even a model with good accuracy might select too many features, leading to overfitting and reduced robustness. Therefore, this proposed feature selection method prevents selecting irrelevant or insignificant physical variables and ensures that the proposed algorithm has a more reasonable form compared to traditional algorithms.

3. Evaluation method

To apply and evaluate the proposed algorithm and feature selection method, this study uses the experimental results of an R410A heat pump under different cooling conditions, and splits them into training and testing sets. Although the production of R410A heat pump equipment may be discontinued in certain countries in the future, it is still widely used in most countries and possesses significant research value. The heat pump units tested in this study are also split-type heat pumps that are still utilized in the US market. The training set is used by the developed algorithm to select the appropriate features for predicting the charge level. Baseline algorithms are considered based on previously published empirical equations, as shown in Eqs. (1) and (2). Before training, the features were standardized (zero mean, unit variance) to improve numerical stability and ensure comparable feature scales. Then the testing set is used to evaluate the proposed and baseline algorithms for the R410A heat pump and compare their accuracies for the charge level prediction under different conditions, as shown in Fig. 5.

The following two sections will introduce the experiment's details and the indices to evaluate the algorithms' performances.

3.1. Experiment for evaluation

To apply and evaluate the proposed algorithm for charge level prediction and the corresponding feature selection method, experiments of

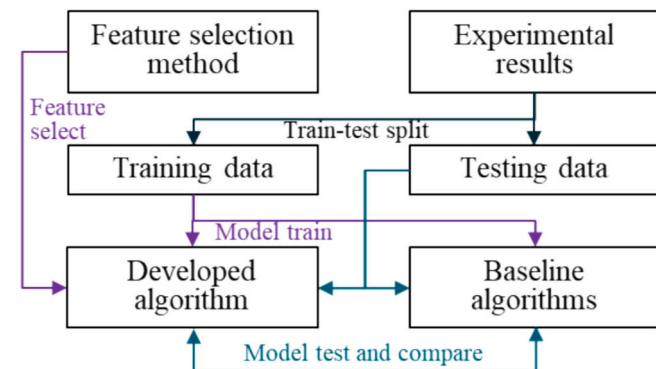


Fig. 5. Development and evaluation of virtual refrigerant charge sensor.

a variable-speed residential heat pump with a nominal refrigerant charge level of 6.1 kg were conducted in a psychrometric chamber at the University of Oklahoma [37]. This unit is available in the US market, with a nominal cooling capacity of 10.1 kW and a nominal power consumption of 2.43 kW. The experimental platform with the system diagram and sensor locations is shown in Fig. 6, and the uncertainties of the sensors are listed in Table 2.

The uncertainty of the charge level is obtained based on the formula of uncertainty propagation, as shown in Eq. (6).

$$u_f = \sqrt{\left(\frac{\partial f}{\partial x_1} u_{x_1}\right)^2 + \left(\frac{\partial f}{\partial x_2} u_{x_2}\right)^2 + \dots + \left(\frac{\partial f}{\partial x_n} u_{x_n}\right)^2} \quad (6)$$

where u_f is the total uncertainty of the output variable u_f , $\frac{\partial f}{\partial x_i}$ is the partial derivative of the function u_f with respect to each input variable x_i , and u_{x_i} is the uncertainty associated with each input variable x_i .

Two cooling conditions are chosen based on AHRI Standard 210/240 (2020) [38], for the algorithm training and testing, as shown in Table 3.

Under each cooling condition, different refrigerant charge levels (6 settings), compressor speeds (3 settings), and indoor fan speeds (2 settings) are selected. The specific parameter ranges are shown in Table 4. As a result, a total of $2 \times 6 \times 3 \times 2 = 72$ steady-state data points are obtained from the experiment.

Before conducting feature selection, the 72 experimental datasets are randomly split into a training set and a test set. This study randomly selected 80% of the steady-state data as training data, and all the other 20% of the data are in the test set. Typically, for linear models, the number of training samples should be approximately 10 times the number of features [39]. In our study, we consider 6 features; thus, 50 samples are generally sufficient.

3.2. Performance evaluation indices

Using the R410A heat pump operation data under various cooling conditions, this study trains and compares the performance of the developed algorithm with the two baseline algorithms: baseline algorithms 1 and 2 are presented in Eqs. (1) and (2), respectively. The root mean square error (RMSE) [40] and mean absolute percentage error (MAPE) [41] are used to evaluate the accuracy of the algorithms, as shown in Eqs. (7) and (8), respectively.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (m_{charge,i} - \hat{m}_{charge,i})^2} \quad (7)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{m_{charge,i} - \hat{m}_{charge,i}}{m_{charge,i}} \right| \quad (8)$$

where n is the total number of data points used for testing, $m_{charge,i}$ is the actual charge level, and $\hat{m}_{charge,i}$ is the predicted charge level.

4. Results and discussion

This section demonstrates the process and results of applying the proposed feature selection method to determine the refrigerant charge level prediction model form as described in Eq. (3). It also compares the accuracy of the determined algorithm with two baseline algorithms, thereby showing the advantages of the proposed method.

4.1. Feature selection results

The traditional refrigerant charge level prediction algorithms consider both the undercharge and overcharge conditions together and select features based on experience, and thus may not perform well when the subcooling temperature is excessively low or high. Therefore, this study proposes fitting piecewise linear equations segmented by the subcooling temperature, leading to a form presented in Eq. (3). Upon

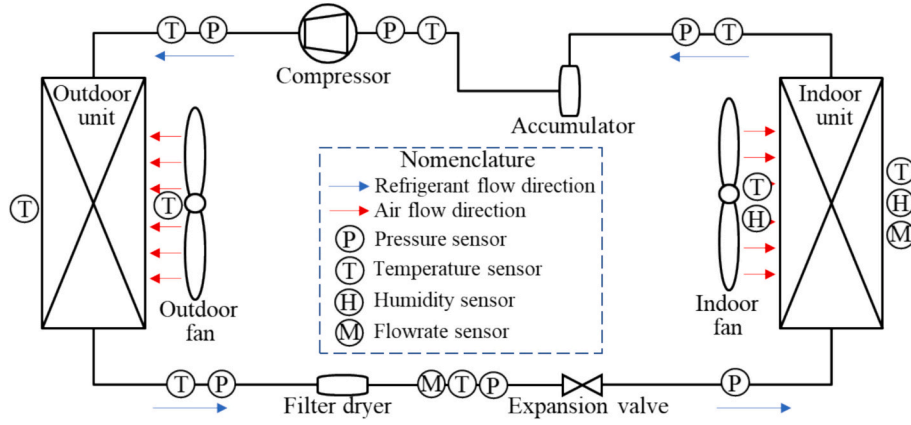


Fig. 6. Experimental platform.

Table 2
Sensors' uncertainties [37].

Sensor	Uncertainty
Power	$\pm 0.5\%$
Pressure	$\pm 0.25\%$ of the full scale
Temperature	$\pm 0.5\text{ }^{\circ}\text{C}$
Humidity	$\pm 1.5\%$
Flowrate	$\pm 2\%$ for air and $\pm 0.5\%$ for refrigerant
Charge	$\pm 10\text{ g}$

observation, this study found that the subcooling temperature turning point ($T_{sc,turn}$) should be around $1\text{ }^{\circ}\text{C}$ for the experimental heat pump. Consequently, the entire regression problem is divided into two cases: subcooling temperature larger than the switching point (Case 1: $T_{sc} > T_{sc,turn}$) and subcooling temperature smaller than or equal to the switching point (Case 2: $T_{sc} \leq T_{sc,turn}$). In each case, the proposed feature selection method is applied to determine the appropriate features for predicting the refrigerant charge level.

Fig. 7 shows the feature selection process in Case 1: $T_{sc} > T_{sc,turn}$. The algorithm starts with a model that has no features and sequentially adds the six physical variables from $list_{ex}$ to the regression model, and the regression model evaluates the correlation coefficients and the p -values for predicting the charge level of each physical variable. Firstly, among the six physical variables, the subcooling temperature has the lowest p -value and a positive correlation coefficient, which is consistent with the analysis in Section 2.1. Therefore, the subcooling temperature is added to $list_{in}$. Then, the algorithm continues to add each of the remaining five physical variables from $list_{ex}$ to the regression model, along with the already included subcooling temperature, to predict the charge level. The results show that the quality at the evaporator inlet has the lowest p -value and a negative correlation coefficient, which is consistent with the analysis in Section 2.1. Therefore, the quality of the evaporator inlet is then added to $list_{in}$. Further, the algorithm continues to screen the remaining four features from $list_{ex}$, but finds that the p -values of the remaining features do not meet the threshold for p -value (0.05). The process ends, with the two features of the algorithm being subcooling temperature and the quality at the evaporator inlet, and both features are statistically significant and follow physical principles; no more features can be added to the regression model.

Fig. 8 shows the feature selection process in Case 2: $T_{sc} \leq T_{sc,turn}$, and

the process is similar to that in Case 1. In the first step, among the six physical variables, subcooling temperature also has the lowest p -value and a positive correlation coefficient (though with its small variance), which is consistent with the analysis in Section 2.1. Therefore, the subcooling temperature is added to $list_{in}$. Then, the algorithm continues to add each of the remaining five physical variables from $list_{ex}$ to the regression model, and the superheat temperature shows the lowest p -value and a negative correlation coefficient, which is consistent with the analysis in Section 2.1. Further, after including the subcooling and superheat temperatures as the features, the method finds that the p -values of the remaining features do not meet the threshold for p -value (0.05). The process ends, with subcooling and superheat temperatures being the two features that are statistically significant and follow physical principles.

Thus, based on the above feature selection process, the developed algorithm is determined as Eq. (9).

$$m_{charge} = \begin{cases} c_{0,1} + c_{1,1}T_{sc} + c_{3,1}x_{ei} & (T_{sc} > T_{sc,turn}) \\ c_{0,2} + c_{1,2}T_{sc} + c_{2,2}T_{sh} & (T_{sc} \leq T_{sc,turn}) \end{cases} \quad (9)$$

where $c_{0,1}$, $c_{1,1}$, and $c_{3,1}$ are 7.08, 0.56, and -0.34 , respectively; $c_{0,2}$, $c_{1,2}$, and $c_{2,2}$ are 4.76, 0.53, and -0.27 , respectively.

Based on Eqs. (6) and (9), as well as the measurement uncertainties of the instruments presented in Table 2, the uncertainty in the charge level has been calculated. The uncertainties of T_{sc} , T_{sh} , and x_{ei} are derived from the direct measurement results of pressure and temperature. The uncertainties in the condensation temperature and the enthalpy at the condenser outlet are calculated, which are then used to further estimate their uncertainties. The calculation results indicate that the uncertainty in the charge level ranges from 0.3 to 0.5 kg.

It should be noted that in this study, when the subcooling temperature is very low, the proposed feature selection method still selects the subcooling temperature as one of the features. This demonstrates both

Table 4

Heat pump operation parameters under each experimental condition.

Contents	Parameters
Charge level (kg)	3.8, 4.6, 5.4, 6.2, 7.0, 7.8
Compressor speed (rpm)	1300, 2300, 3300
Indoor fan speed	60%, 100%

Table 3

Experimental conditions chosen for charge level predictions.

Condition	Indoor dry/wet bulb temperature [$^{\circ}\text{C}$ ($^{\circ}\text{F}$)]	Outdoor dry/wet bulb temperature [$^{\circ}\text{C}$ ($^{\circ}\text{F}$)]
A(Cooling)	26.7(80.0)/19.4(67.0)	35.0(95.0)/23.9(75.0)
E(Cooling)	26.7(80.0)/19.4(67.0)	30.6(87.0)/20.6(69.0)

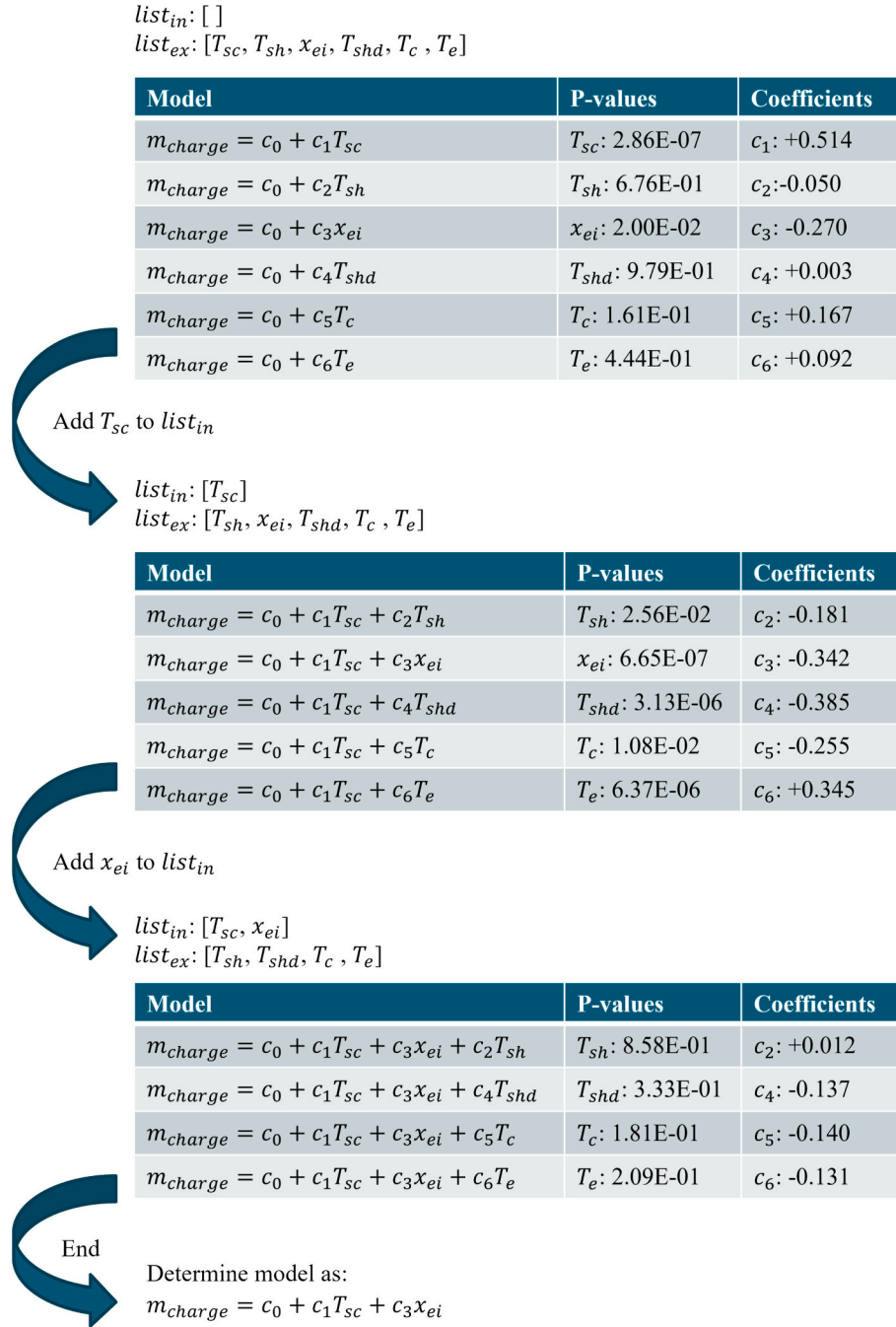


Fig. 7. Feature selection stepwise results when the subcooling temperature is larger than the turning point.

the significance of subcooling temperature in predicting the charge level and the objectivity of the proposed feature selection method. For different heat pumps, condenser capacities vary, and the significance of subcooling temperature may differ, but appropriate features can be selected for specific heat pump cases using the two-segment algorithm structure and feature selection method proposed in this study.

4.2. Algorithm performance

Based on Eq. (9), the developed algorithm was trained under various cooling conditions with different compressor speeds, indoor fan speeds, and charge levels. In addition, the remaining 20% of the experimental data is used for testing the algorithm. The training RMSEs are 0.317 and 0.257 kg, respectively, and the MAPEs are 3.49% and 4.46%,

respectively, for the cases when the subcooling temperature is larger than and smaller than/equal to the turning point. The testing RMSEs are 0.300 and 0.261 kg, respectively, and the MAPEs are 3.64% and 4.59%, respectively, for the cases when the subcooling temperature is larger and smaller than/equal than the turning point, as shown in Fig. 9. The majority of the errors are within 10%, and the positive and negative errors distribute along the symmetry axis, indicating acceptable accuracy of the developed algorithm. The proposed algorithm uses subcooling temperature as the criterion, and treats the case with subcooling temperature less than 1 °C separately from the case with larger subcooling temperature, to distinguish between overcharge and undercharge cases. In each case, appropriate algorithms are determined using feature selection methods. Therefore, the algorithm can accurately predict both overcharge and undercharge scenarios.

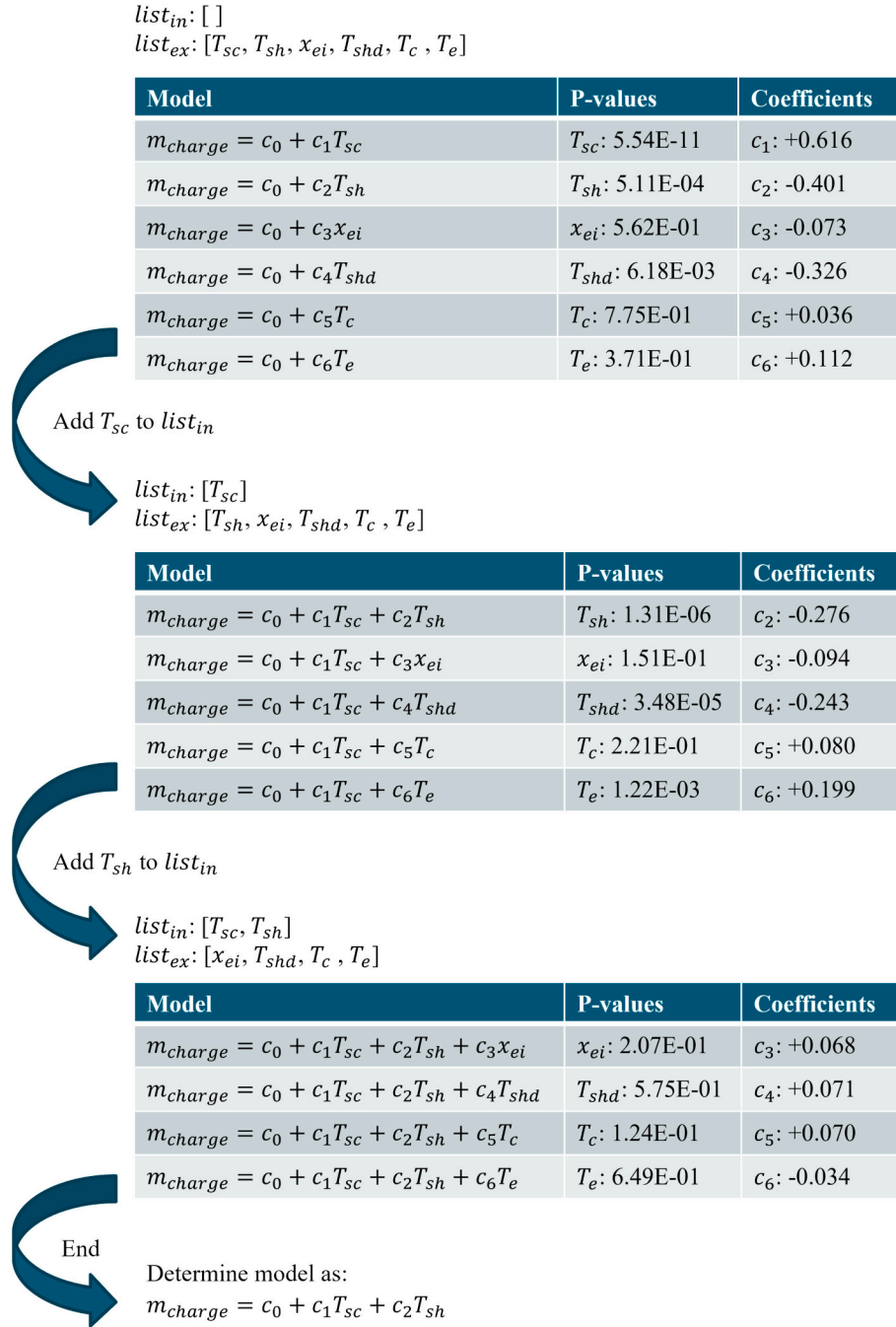


Fig. 8. Feature selection stepwise results when the subcooling temperature is smaller than the turning point.

Based on Eqs. (1) and (2), the two baseline algorithms are also trained using 80% experimental data under various cooling conditions, and are tested using the remaining 20% data. The coefficients of the two baseline algorithms, c_0 to c_2 for baseline algorithm 1 in Eq. (1) and c_0 to c_4 for baseline algorithm 2 in Eq. (2), are fitted using the same training dataset as the developed algorithm, and the test dataset is also the same. The test performance of the two algorithms is presented in Fig. 10. For baseline algorithm 1 [14], the testing RMSE and MAPE are 0.672 kg and 10.9%, respectively. For baseline algorithm 2 [18], the testing RMSE and MAPE are 0.667 kg and 10.95%, respectively. The two baseline algorithms do not separate the cases of low subcooling temperatures (less than 1 °C) from those with normal and higher subcooling temperatures. As a result, neither can achieve good predictions for some undercharge scenarios, usually resulting in the predicted charge level

being higher than the actual value; this phenomenon is similar to that reported in Ref. [26]. Even though baseline algorithm 2 uses more features, it does not result in an improvement in accuracy.

The testing MAPEs are compared for the three algorithms, as shown in Table 5. The proposed algorithm outperforms the two baseline algorithms, with significant improvements of 61.2% and 61.4% compared to baseline algorithms 1 and 2, respectively.

When focusing only on undercharge scenarios (when the charge level is less than the nominal charge of 6.1 kg), the proposed algorithm demonstrates more significant improvements, as shown in Table 6. The proposed algorithm performs 67.0% and 68.0% better compared to baseline algorithms 1 and 2, respectively. Especially, the developed algorithm uses two fewer features and achieves better accuracy compared with the baseline algorithm 2. The proposed algorithm takes into

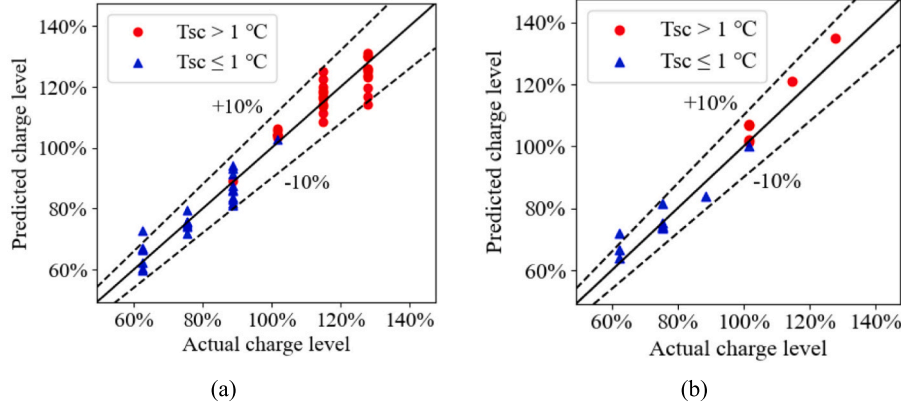


Fig. 9. Developed algorithm's performance: (a) training; (b) testing.

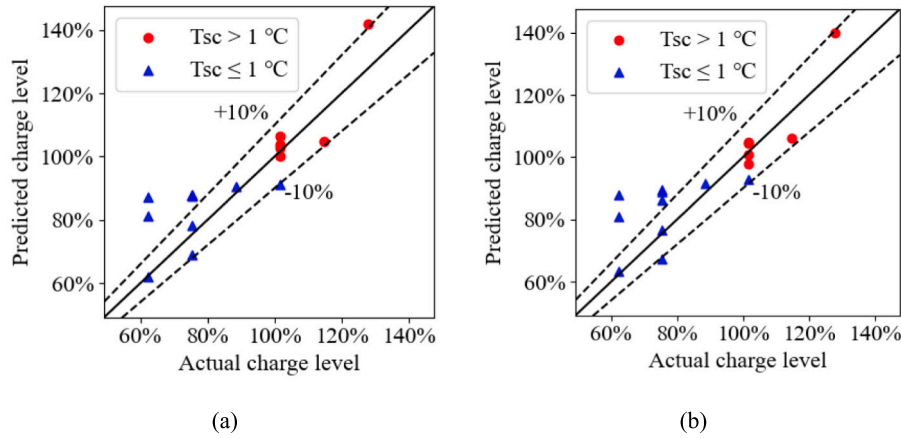


Fig. 10. Baseline algorithms' performance: (a) baseline algorithm 1 [14]; (b) baseline algorithm 2 [18].

Table 5
Algorithm comparison.

Algorithm	MAPE	Improvement
Proposed	4.23% (3.64% and 4.59% when T_{sc} greater and smaller than 1°C , respectively)	/
Baseline 1 [14]	10.90% (4.83% and 14.54% when T_{sc} greater and smaller than 1°C , respectively)	61.2%
Baseline 2 [18]	10.95% (4.57% and 14.77% when T_{sc} greater and smaller than 1°C , respectively)	61.4%

Table 6
Algorithm comparison when under charge: charge level < 100%.

Algorithm	MAPE in testing	Improvement
Proposed	4.94%	/
Baseline 1 [14]	14.99%	67.0%
Baseline 2 [18]	15.44%	68.0%

account the special cases of low subcooling ($T_{sc} < 1^{\circ}\text{C}$) and separates them from the general cases. Feature selection is performed separately for each case to determine the appropriate algorithms. Therefore, it is better suited to handle the undercharge scenario corresponding to low subcooling temperatures compared to the two baseline algorithms, which avoided the issue of redundant selection due to intercorrelation between features. As a result, the developed algorithm is significantly more accurate with fewer selected features.

Though the six candidate features are physically highly correlated, it

is impossible to make them completely independent in a vapor compression cycle. The proposed feature selection method determines the appropriate features based on physical laws rather than purely statistical criteria, and utilizes p -values to determine which features truly influence the charge level of the heat pump. Given that the characteristics of each heat pump differ, it is essential to select features based on the heat pump capacities, refrigerant, rather than relying on the empirical equation, as in the baseline algorithms, that the features are empirically determined. The latter approach carries a higher risk of selecting mutually correlated features, which may adversely impact the model's performance.

4.3. Discussion

This study uses a residential variable-speed heat pump operating with R410A as a case study to evaluate the adaptability of the proposed algorithm across diverse operating conditions, benchmarked against two baseline methods. The emphasis of this study is not on the training results of the coefficients and the value of the subcooling temperature turning point related to Eq. (9) in Section 4. Instead, the focus is on Eq. (3) in Section 2, which presents a segmented structure using the subcooling temperature as the turning point, along with a feature selection method to determine the signs of the coefficients and identify which features are significant. Therefore, interested readers are encouraged to replicate the approach outlined in Section 2 using their own heat pump testing data. Relative to conventional approaches that treat undercharge and overcharge jointly, the proposed method more effectively mitigates prediction inaccuracies, thereby improving accuracy for both regimes.

However, the heat pump unit examined is a residential configuration; consequently, the algorithm may not directly generalize to systems with receivers or other charge-management components (e.g., accumulators, flash tanks, ejectors). Moreover, the present analysis focuses on R410A, and extension to other next-generation refrigerants, such as R410A's substitute as R454B, natural refrigerant as R290, and transcritical cycle of CO₂, requires further investigation. We plan to address these limitations by broadening the dataset and operating envelope, evaluating additional refrigerants and schematics, and conducting out-of-sample validation on independent units.

5. Conclusion

VRC sensing technology has been widely applied for a variety of vapor compression systems. However, most VRC algorithms may select too many features, leading to algorithm redundancy and could fail to accurately predict refrigerant charge levels in both undercharge and overcharge scenarios. Therefore, we proposed a systematic feature selection method to choose minimal variables and a segmented modeling approach to cover a wide range of charge conditions, including substantially low subcooling temperature cases ($T_{sc} < 1$ °C). This study takes a residential variable-speed heat pump system using R410A as an example to investigate the adaptability of the proposed algorithm under different operating conditions, and compares it with two baseline algorithms.

The main research conclusions are as follows:

- (1) The proposed VRC sensing algorithm treats the case with subcooling temperature less than 1 °C separately, thus presenting better accuracy to predict under both undercharge and overcharge scenarios.
- (2) The proposed VRC sensing algorithm can achieve tested MAPES of 4.23%, and improves the overall accuracy for cooling conditions by 61.2% and 61.4%, compared with the two baseline algorithms.
- (3) The proposed VRC sensing algorithm uses two fewer features and improves the accuracy for the undercharge scenario by 68.0%, compared with baseline algorithm 2.

The proposed algorithm divides the charge level prediction into two segments, thus adapting well to both undercharge and overcharge scenarios. Additionally, a rigorous feature selection method is employed to ensure that the physical variables chosen in each segment not only align with physical principles but also exhibit statistical significance. These improvements not only enhance the model's prediction accuracy but also prevent overfitting caused by selecting too many physical variables, providing a more reliable solution for accurate refrigerant charge level prediction and helping improve the heat pump operation efficiency.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This research was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Office of Building Technologies and Industrial Efficiency and Decarbonization Office of the U.S. Department of Energy, under Contract No. DE-AC02-05CH11231, through project "Virtual Sensor-based FDD and Control Suite for Widespread Adoption of Residential Embedded-FDD Heat Pumps".

Data availability

Data will be made available on request.

References

- [1] F. Zha, Y. Wang, C. Liang, W. Shi, X. Li, D. Guo, S. Mao, Utilizing multi-connected three-fluid heat exchangers in indoor units to improve the low load-ratio performance of variable refrigerant flow systems, *J. Build. Eng.* 103 (2025) 112150.
- [2] C. Liang, X. Li, W. Shi, Humidity grade-matched fresh air dehumidification system with adjustable treating stages, *J. Clean. Prod.* 423 (2023) 138822.
- [3] C. Liang, X. Li, X. Meng, W. Shi, J. Gu, B. Wang, Y. Lv, A year-round efficient air source heat pump with separate and distant heat extraction for non-decaying heating capacity during defrosting, *Energy* 315 (2025) 134404.
- [4] M. Song, S. Deng, C. Dang, N. Mao, Z. Wang, Review on improvement for air source heat pump units during frosting and defrosting, *Appl. Energy* 211 (2018) 1150–1170.
- [5] J. Choi, Y.C. Kim, The effects of improper refrigerant charge on the performance of a heat pump with an electronic expansion valve and capillary tube, *Energy* 27 (4) (2002) 391–404.
- [6] H. Cho, C. Ryu, Y. Kim, H.Y. Kim, Effects of refrigerant charge amount on the performance of a transcritical CO₂ heat pump, *Int. J. Refrig.* 28 (8) (2005) 1266–1273.
- [7] Y.H. Eom, J.W. Yoo, S.B. Hong, M.S. Kim, Refrigerant charge fault detection method of air source heat pump system using convolutional neural network for energy saving, *Energy* 187 (2019) 115877.
- [8] W. Kim, J.E. Braun, Evaluation of the impacts of refrigerant charge on air conditioner and heat pump performance, *Int. J. Refrig.* 35 (7) (2012) 1805–1814.
- [9] J.-H. Chae, J.M. Choi, Evaluation of the impacts of high stage refrigerant charge on cascade heat pump performance, *Renew. Energy* 79 (2015) 66–71.
- [10] S. Tassou, I. Grace, Fault diagnosis and refrigerant leak detection in vapour compression refrigeration systems, *Int. J. Refrig.* 28 (5) (2005) 680–688.
- [11] H. Rasmussen, S. Thorud, Using a refrigerant leak detector to monitor waste gases from halogenated anesthetics, *J. Am. Assoc. Lab. Anim. Sci.* 46 (5) (2007) 64–68.
- [12] P. Catrini, A. Piacentini, Experimental analysis of the effects of condenser fouling and refrigerant charge faults on the performance of variable-speed rooftop units, *Appl. Therm. Eng.* 279 (2025).
- [13] G. Li, J. Deng, D. Wang, C. Dai, W. Kuang, L. Zhang, C. Xiong, Experimental study of heat exchangers fouling and improper refrigerant charges on the variable refrigerant flow air conditioning system, *Energ. Buildings* 343 (2025).
- [14] H. Li, J.E. Braun, Development, evaluation, and demonstration of a virtual refrigerant charge sensor, *Hvac&R Res.* 15 (1) (2009) 117–136.
- [15] H. Li, J.E. Braun, Decoupling features and virtual sensors for diagnosis of faults in vapor compression air conditioners, *Int. J. Refrig.* 30 (3) (2007) 546–564.
- [16] Y. Hu, D.P. Yuill, Multiple simultaneous faults' impacts on air-conditioner behavior and performance of a charge diagnostic method, *Appl. Therm. Eng.* 215 (2022) 119015.
- [17] M. Jounay, O. Cauret, C. Teuillieres, C.T. Tran, A novel on-board method for quantifying refrigerant charge in residential heat pumps, *Int. J. Refrig.* 177 (2025) 263–272.
- [18] W. Kim, J.E. Braun, Extension of a virtual refrigerant charge sensor, *Int. J. Refrig.* 55 (2015) 224–235.
- [19] W. Kim, J.E. Braun, Development, implementation, and evaluation of a fault detection and diagnostics system based on integrated virtual sensors and fault impact models, *Energ. Buildings* 228 (2020) 110368.
- [20] Y. Hu, Y. Zhang, X. Liu, H. Li, Development and demonstration of a method to detect refrigerant charge level for variable refrigerant volume systems, *Appl. Therm. Eng.* 235 (2023) 121354.
- [21] W. Kim, J.-H. Lee, Fault detection and diagnostics analysis of air conditioners using virtual sensors, *Appl. Therm. Eng.* 191 (2021) 116848.
- [22] Y. Zheng, H. Han, J. Xiong, H. Zhang, X. Cao, B. Gu, W. Dai, X. Gao, W. Yi, Improvements and intelligence integration of virtual refrigerant charge (VRC) sensor, *Int. J. Refrig.* 182 (2026) 456–468.
- [23] C. Zhang, B. Hou, M. Li, C. Dang, H. Tong, X. Li, Z. Han, Refrigerant charge estimation method based on data-physic hybrid-driven model for the fault diagnosis of transcritical CO₂ heat pump system, *Energy* 309 (2024) 133144.
- [24] W. Shao, T. Yang, L. Zhao, H. Zou, K. Smierciw, S. Zhang, M. Huang, Online monitoring and estimating of refrigerant charge in automotive transcritical CO₂ heat pump systems, *Appl. Therm. Eng.* 278 (2025).
- [25] F. Guo, D. Kim, P. Hlanze, J. Cai, Rigorous feature selection of the virtual refrigerant charge sensor for variable-speed heat pumps, in: *International Refrigeration and Air Conditioning Conference*, 2024, p. 2661. Paper.
- [26] G. Li, Y. Hu, H. Chen, L. Shen, H. Li, J. Li, W. Hu, Extending the virtual refrigerant charge sensor (VRC) for variable refrigerant flow (VRF) air conditioning system using data-based analysis methods, *Appl. Therm. Eng.* 93 (2016) 908–919.
- [27] S. Boahen, K.H. Lee, J.M. Choi, Refrigerant charge fault detection and diagnosis algorithm for water-to-water heat pump unit, *Energies* 12 (3) (2019) 545.
- [28] X. Zhu, Z. Du, Z. Chen, X. Jin, X. Huang, Hybrid model based refrigerant charge fault estimation for the data Centre air conditioning system, *Int. J. Refrig.* 106 (2019) 392–406.
- [29] A. Alin, Multicollinearity, *wiley interdisciplinary reviews: computational statistics* 2 (3) (2010) 370–374.

- [30] Y. Haitovsky, Multicollinearity in regression analysis: comment, *Rev. Econ. Stat.* (1969) 486–489.
- [31] A. Hepbasli, Y. Kalinci, A review of heat pump water heating systems, *Renew. Sust. Energ. Rev.* 13 (6–7) (2009) 1211–1229.
- [32] Z. Wang, M.B. Luther, M. Amirkhani, C. Liu, P. Horan, State of the art on heat pumps for residential buildings, *Buildings* 11 (8) (2021) 350.
- [33] Y. Hu, D.P. Yuill, Effects of multiple simultaneous faults on characteristic fault detection features of a heat pump in cooling mode, *Energ. Buildings* 251 (2021) 111355.
- [34] M. Kim, M.S. Kim, Performance investigation of a variable speed vapor compression system for fault detection and diagnosis, *Int. J. Refrig.* 28 (4) (2005) 481–488.
- [35] B. Chen, J.E. Braun, Simple rule-based methods for fault detection and diagnostics applied to packaged air conditioners/discussion, *ASHRAE Trans.* 107 (2001) 847.
- [36] Y. Hu, D.P. Yuill, A. Ebrahimifakhar, A. Rooholghodos, An experimental study of the behavior of a high efficiency residential heat pump in cooling mode with common installation faults imposed, *Appl. Therm. Eng.* 184 (2021) 116116.
- [37] P.G. Hlanze, J. Cai, D. Kim, Experimental assessment of the effect of refrigerant charge levels on variable-speed heat pump performances, in: *International Refrigeration and Air Conditioning Conference*, 2024, p. 2635. Paper.
- [38] A. Standard, Performance rating of unitary air-conditioning & air-source heat pump equipment, *AHRI Standard 210*, 2020, p. 240.
- [39] G.T. Knofczynski, D. Mundfrom, Sample sizes when using multiple linear regression for prediction, *Educ. Psychol. Meas.* 68 (3) (2008) 431–442.
- [40] T.O. Hodson, Root mean square error (RMSE) or mean absolute error (MAE): when to use them or not, *Geosci. Model Dev. Discuss.* 2022 (2022) 1–10.
- [41] A. De Myttenaere, B. Golden, B. Le Grand, F. Rossi, Mean absolute percentage error for regression models, *Neurocomputing* 192 (2016) 38–48.