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ABSTRACT

Virtual sensors have previously been developed and demonstrated that can provide a low cost and relatively accurate estimation of the refrigerant charge contained in packaged (rooftop) air conditioners. One particular virtual refrigerant charge sensor approach uses four surface-mounted temperature measurements to determine suction superheat, liquid-line subcooling and evaporator inlet quality that are inputs to an empirical model for charge. The empirical parameters of the model are determined using linear regression applied to laboratory data collected from the system. In previous studies, extensive psychrometric chamber testing was required at different refrigerant charge levels and ambient conditions to obtain sufficient data for the regression. This testing is expensive for equipment manufacturers and it can be difficult to find available test facilities. The current work describes the development of an automated open lab training kit for calibrating a virtual refrigerant charge level sensor in an open laboratory space. The developed automated training kit algorithm has the ability to modulate the condenser and evaporator fans to simulate the effects of different ambient conditions and automatically add different amounts of refrigerant. The charge level is automatically adjusted and monitored using solenoid valves and a digital weighing scale. This approach reduces the human involvement to a great extent and eliminates the need for psychrometric chambers. An optimal set of test conditions has been determined using optimal experimental design techniques and implemented as a Python application. An Arduino microcontroller is used to continuously send data from the sensors to a personal computer which is used to supervise the process, including determining when the system has reached steady-state. The training kit has been applied to several different rooftop units in an open lab space. A comparison of the virtual refrigerant charge sensor accuracy and time/cost for calibration determined using the automated system and using psychrometric chamber test facilities has been presented.

1. INTRODUCTION

Previous studies (Jacobs 2003; Cowan 2004) indicate that more than 50% of the packaged air conditioning systems in the field (also called rooftop units, RTUs) are improperly charged. Systems over time tend to become undercharged due to slow refrigerant leaks that may go unnoticed with infrequent inspection or scheduled maintenance. Conversely, systems may become overcharged because of imperfect maintenance practices or unskilled technicians. This has helped fuel the motivation to develop fault detection and diagnostics (FDD) tools for RTUs in order to reduce annual energy consumption in commercial buildings. In one previously developed methodology, virtual sensors have been demonstrated that can provide a low cost and relatively accurate estimation of the amount of refrigerant charge contained in RTUs (Li and Braun 2009, Kim and Braun 2013). One particular virtual refrigerant charge (VRC) sensor approach uses four surface-mounted temperature measurements to determine suction superheat, liquid-line subcooling and evaporator inlet quality that are inputs to an empirical model for charge. The empirical parameters of the model are determined using linear regression applied to laboratory data collected from the system.

In previous studies, extensive psychrometric chamber testing at different refrigerant charge levels and ambient conditions has been used to obtain sufficient data for determining the empirical parameters of the VRC model. This testing is expensive for equipment manufacturers and it can be difficult to find available test facilities. This, along with additional sensor and instrumentation costs, is a major hurdle for equipment manufacturers looking to incorporate FDD technologies in new equipment.

In this work, the development of an automated methodology to calibrate the empirical parameters of the VRC sensor using data collected from operating the unit in an open laboratory space is described. The automated training kit modulates the condenser and evaporator fans to simulate the effects of different ambient conditions. The system is also able to automatically add different amounts of refrigerant to an RTU using a suction-side solenoid valve and a digital weighing scale. This approach reduces the human involvement significantly and eliminates the need for psychrometric chambers for tuning the VRC sensor.

The following work details the development and implementation of the automated VRC sensor training kit. In Section 2, a brief background about the VRC sensor and a description of the underlying algorithm used by the training kit are presented. In Section 3, implementation details and the initial system prototype are described. In Section 4, the automated VRC sensor training kit is applied to four different RTU configurations and psychrometric chamber testing results are presented.

2. VRC SENSOR MODELING AND VALIDATION

2.1 VRC sensor model

Li and Braun (2009) describe a virtual sensor for predicting the amount of refrigerant in an air conditioner using an empirical model based on suction superheat, ΔT_{sh}, and liquid-line subcooling, ΔT_{sc}. Kim and Braun (2013) suggested some improvements to the model by adding an empirical term considering the thermodynamic quality of the refrigerant entering the evaporator, x_{eri}. Using simple algebraic manipulation, an equivalent definition of the VRC sensor described by Kim and Braun (2013) is given by Equation (1):

$$\frac{m_{actual} - m_{rated}}{m_{rated}} = k_{sh}(\Delta T_{sh} - \Delta T_{sh,rated}) + k_{sc}(\Delta T_{sc} - \Delta T_{sc,rated}) + k_x(x_{eri} - x_{eri,rated}) \qquad (1)$$

where $\Delta T_{sh,rated}$ is the compressor suction superheat, $\Delta T_{sc,rated}$ is the liquid-line subcooling and $x_{eri,rated}$ is the evaporator inlet quality at some rating condition. Additionally, the VRC sensor model defined in Equation (1) has three empirically determined regression parameters: k_{sh}, k_{sc}, k_x. In previous work, these empirical parameters were determined by collecting psychrometric chamber data for a specific RTU at several different charge levels and ambient conditions (Li and Braun 2009; Kim and Braun 2013). This is very time consuming, especially considering the exhaustive combinations of ambient conditions and charge levels tested – no formal optimization of the testing requirements was considered.

2.2 Open Laboratory Training Approach

In order to reduce the psychrometric chamber testing requirements, an alternative methodology to determine the empirical parameters of the VRC sensor model was proposed (Vasudeven 2015). The methodology operates by reducing airflow across each of the heat exchangers in the RTU, summarized by Figure 2. At a given ambient temperature, reducing the airflow across the condenser causes the high-side refrigerant pressure to increase. Similarly, reducing the evaporator airflow causes the low-side refrigerant pressure to decrease. Overall, the effect of reducing the airflow, and manipulating the low- and high-side pressure, simulates how the refrigerant charge would be distributed in the RTU at different ambients. This results in different combinations of superheat, subcooling and evaporator inlet quality that are used as inputs to tune the empirical VRC parameters.

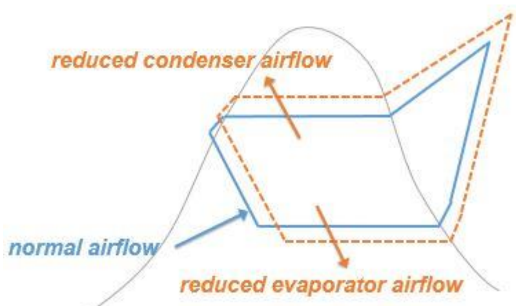

Figure 2: By reducing airflow across the condenser and evaporator coil, the charge distribution in the RTU at different ambient conditions can be simulated in an open laboratory space.

In order to determine the number and control combinations required to tune an accurate VRC sensor model for a given system, an exhaustive set of reductions in airflow rates and charge levels were collected for an RTU in an open lab space (Vasudeven 2015). Statistical design of experiment was used to minimize the information matrix of the linear regression problem in order to analyze the impact of using subsets of test cases.

3. AUTOMATED VRC SENSOR TRAINING KIT DESIGN

While the open laboratory training approach yielded a methodology that eliminated the need for psychrometric chambers, it still required significant human interaction. The next step was to automate the open laboratory training approach using electronics in order to reduce the amount of human intervention necessary. An overall schematic of the RTU components, the sensor measurements, the control variables, and the information flow of the system design is shown in Figure 3. The hardware selected for the training kit is generally considered to be typical and relatively low-cost when compared to similar data acquisition applications within the HVAC market.

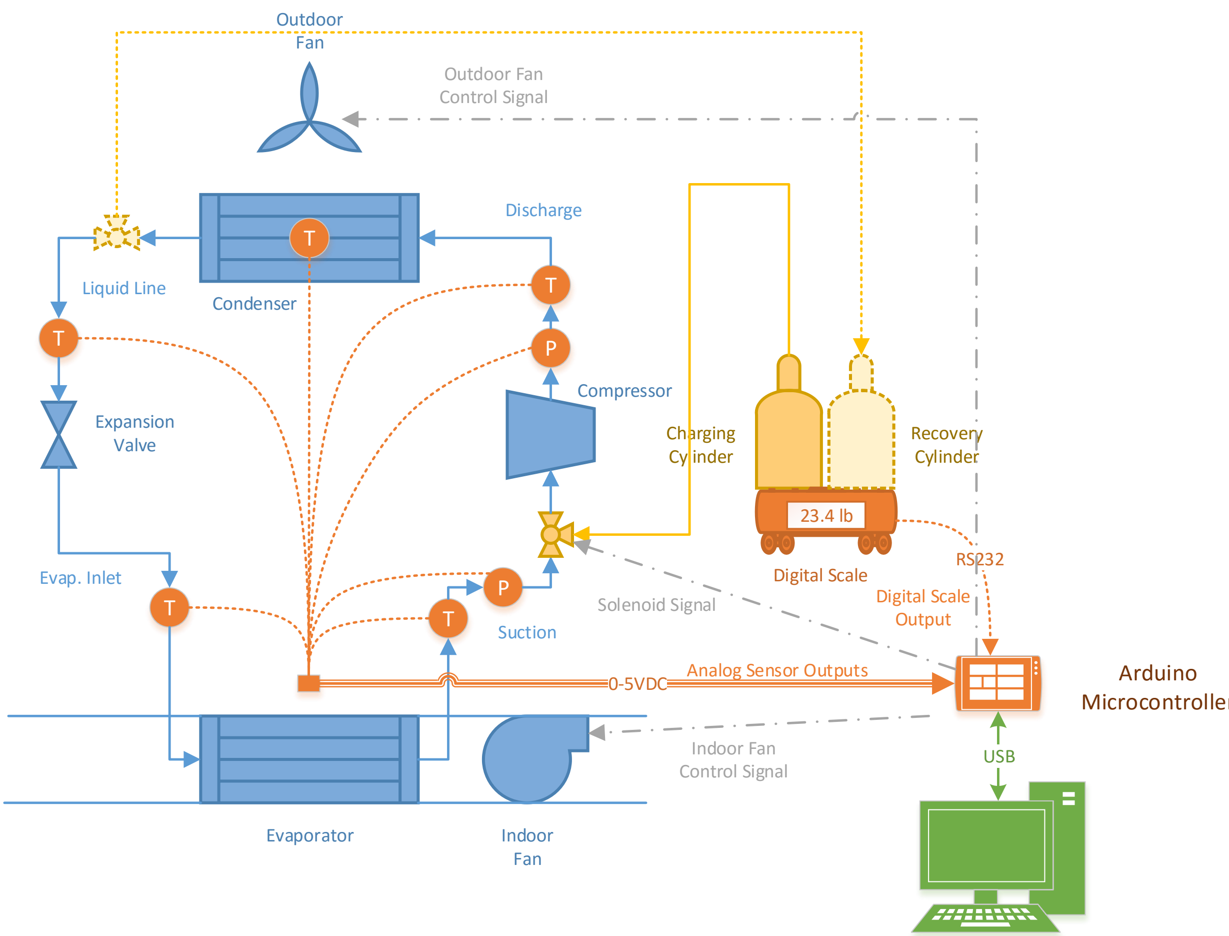

Figure 3: Schematic of automated VRC sensor training kit

3.1 Hardware Implementation

An Arduino Mega2560 microcontroller was used to interface with the sensors and control interfaces required to implement the automated training algorithm. Compared to other microcontrollers, the Arduino development environment makes interfacing with sensors and digital outputs relatively easy and with little configuration. To enable this, the Arduino designers have developed an extension of the C++ programming language with built-in functions that can be used to easily read and write to the digital and analog input and outputs found on the microcontroller.

In order to implement the VRC training algorithm, several refrigerant-side temperature and pressure measurements are required. Using these sensors, the empirical parameters used in the VRC sensor can be tuned using the training algorithm. It should also be noted that pressure measurements can be used to calculate the evaporator refrigerant inlet temperature and condenser refrigerant saturation temperature since the refrigerant at these points is a two-phase fluid. Systems that already have these pressure sensors installed for control purposes do not need to install additional temperature sensors which reduces instrumentation costs. Pressure sensors may be required for systems with microchannel condensers since locating a reliable saturation temperature point is not trivial.

To measure these refrigerant-side temperatures, low-cost thermistor circuits were designed. The thermistors selected for the application have to be surface-mounted to the RTU refrigerant circuit in the locations required. Compared to other types of temperature sensor types (thermocouples, RTDs, etc.) thermistors offer the best combination of accuracy, reliability, and cost. Pressure transducers have also been installed on the system considered in this study to measure the low- and high-side pressures. The high-side pressure is important for the RTU being tested since it has a microchannel condenser. This makes measuring the condenser saturation temperature nearly impossible or unreliable with surface-mounted temperature sensors.

The hardware implementation also incorporated components used to control the operational mode of the RTU and the control set-points of the indoor fan and outdoor fan. The operational mode of the unit (controlling the system to stand-by, fan-only, low-stage cooling, or high-stage cooling mode) is controlled using three relays. The relays were connected to the G, Y1, Y2 thermostat signals and are sequenced using the software implementation. Conventional control of the indoor and outdoor fans has been overridden using electronically commutated (EC) motor controllers producing a 0-10 VDC pulse-width-modulated output. The duty cycle was controlled via the software implementation for each fan. The motor controlling the indoor fan provides a constant torque output so the PWM output provides the torque set-point of the motor. The outdoor fan was driven by a constant speed motor, thus the PWM output provides the speed setting to the motor.

Refrigerant charge addition was automatically controlled using a suction-side solenoid valve and an electronic weighing scale with a digital output. A relay was used to control the solenoid valve position from the microcontroller using a digital 5 VDC output. When the solenoid is open, refrigerant charge is able to enter the refrigerant circuit of the RTU. The refrigerant charging bottle is placed on the electronic scale in order to measure the mass of refrigerant that has left the cylinder and entered the refrigerant circuit. The personal computer interfaces with the digital output of the scale via a USB serial data connection.

The last component of the automated VRC sensor training kit is a personal computer that is used to run the Python software implementation of the automated training algorithm. A USB serial data connection is use to interface the personal computer and the microcontroller. The software on the personal computer uses logic to determine the control outputs and collects the required sensor outputs used for tuning the empirical VRC parameters.

3.2 Microcontroller Implementation

An implementation of the VRC sensor training algorithm has been created using open-source software packages. As previously noted, the training kit is comprised of one microcontroller and one personal computer each performing different functions. The software embedded on the microcontroller is implemented using the Arduino variant of the C++ programming language. The software used on the personal computer is implemented using the Python programming language. These two systems communicate between one another via a USB data connection.

On the microcontroller side, the software is implemented so that when a control input sequence is received, the following sequence is performed:

1. Receive the control inputs – compressor mode, indoor and outdoor fan set-points, solenoid valve positions for adding/removing charge
2. Update cooling mode – run the system in fan only, low stage or high stage cooing
3. Update fan control set-points
4. Update the charge valve positions
5. Read analog temperature and pressure values
6. Read digital weighing scale output
7. Send updated measurement values via serial connection

This procedure is repeated by the microcontroller indefinitely while the training algorithm is being executed. Whenever the control input message is sent from the training kit algorithm (which is once per second) the procedure on the microcontroller is executed and the measurements are sent back in response.

3.3 Software Implementation

An object-oriented implementation of the VRC sensor training algorithm has been implemented and tested. At a high level, the algorithm controls the state of the RTU to a sequence of tests and collects steady-state data that can be used to tune the empirical parameters used by the VRC sensor.

On initialization, the training algorithm receives some configuration parameters as inputs and sets up some data connections between the microcontroller and SQLite database used to store the sensor measurements. The serial data connection is initialized by designating the port the microcontroller is connected to and setting the baud rate between the devices. The database connection is simply created by specifying a file path. The schema for storing the data is automatically generated by the training kit object on creation.

Also during initialization, the test sequence is loaded from the configuration file. The test sequence is stored as a list where each element is a list of the desired set-points used for each test. These set-points include the refrigerant charge level, the cooling mode, the indoor fan torque setting, and outdoor fan speed setting. As the algorithm progresses, test scenarios are popped off the list until all the scenarios have been exhausted. At this point, the algorithm has finished testing the system and the RTU is shutdown.

After executing the training algorithm, the software transitions from test scenario to test scenario by applying this sequence of steps. First, the system determines whether the current charge level is at the desired set-point value. If the current charge level is not at the set-point level, the system enters a charge adjustment sequence. In this sequence, the low-side and high-side valves are open or closed in order to add or remove charge, respectively. In the initial hardware implementation, only the low-side solenoid valve to add charge was installed. This means that only the addition of charge can be performed, though the logic in the software implementation is the same. This process continues until the charge level reaches the set-point level.

Once the refrigerant charge level has reached the set-point value, the system enters into a steady-state detection state. In this state, the system applies a steady state filter to a fixed length first in, first out (FIFO) buffer of data points. The steady state detector consists of fitting a simple linear regression model to determine the current slope of the sensor measurements in the FIFO buffer. The data contained in this buffer are the sensor outputs and the steady state detector filters each sensor individually. Thus a total of 8 simple linear regression models are determined and the 8 slope estimations are each compared to a threshold value. When the absolute value of the slopes are less than the threshold, and the variance of each sensor data is lower than another threshold, the data are deemed to be steady-state. When the data are not determined to be steady, the process simply waits for more data to enter the FIFO buffer.

When the samples are determined to be steady, the algorithm enters into the steady-state data collection process. This process simply collects steady state data points for a fixed amount of time in order to be used later in the parameter tuning procedure. Currently, 5 minutes' worth of data is collected at a sampling interval of 1 second. Once 300 samples have been collected, the algorithm exits the current test scenario and begins the process again for the next test scenario.

4. PSYCHROMETRIC CHAMBER TEST RESULTS

In order to test the performance of the automated VRC sensor training algorithm and virtual sensor implementation, a series of tests were performed. The test plan had two primary considerations in mind: evaluate how well the open laboratory training algorithm tunes the empirical VRC parameters and how well the VRC sensor performs for different types of systems. To do this, combinations of different expansion valves and condenser coils were used in a 5-ton RTU as described in Table 1. The RTU has two cooling stages, a variable speed indoor blower, and a variable speed outdoor fan.

Table 1. System configurations and testing environments planned to evaluate automated virtual sensor training algorithm and virtual charge sensor performance.

ID	Expansion Device[2]	Condenser Coil	Test Environment
A2	TXV	Microchannel	Psychrometric Chamber Testing
A1	TXV	Microchannel	Automated Open Lab Training
B1	FXO	Microchannel	Automated Open Lab Training
B2	FXO	Microchannel	Psychrometric Chamber Testing
C1[1]	FXO	Finned-Tube	Automated Open Lab Training
C2	FXO	Finned-Tube	Psychrometric Chamber Testing
D1[1]	TXV	Finned-Tube	Automated Open Lab Training
D2	TXV	Finned-Tube	Psychrometric Chamber Testing

[1] Testing for C1 and D1 was performed inside the psychrometric chambers simulating an open laboratory space. This was done in order to accelerate the tests by not having to remove the RTU from the psychrometric chamber facility once it has been installed.
[2] TXV = thermostatic expansion valve; FXO = fixed orifice expansion device

In order to test the performance of the automated VRC training system as well as the accuracy of the VRC sensor applied to different equipment, the RTU was operated under a range of operating conditions, described in Table 2. This included both wet coil and dry coil tests under outdoor ambient conditions ranging from 20.56 °C (69 °F) to 42.22 °C (108 °F). Additionally, reduced condenser and evaporator airflow rates were tested for the test cases as well.

Table 2. Test conditions for RTU with finned-tube condenser and fixed orifice expansion device for low stage cooling operation in psychrometric test chambers.

Test Variable		Test Values	
Compressor Stage	[-]	LOW	HIGH
Indoor Dry Bulb	[°C]	26.67	26.67
Indoor Wet Bulb	[°C]	13.89, 20.56	13.89, 20.56
Outdoor Dry Bulb	[°C]	20.56, 27.78, 35.00, 41.22	20.56, 27.78, 35.00, 41.22
Charge Level[1]	[%]	60, 70, 80, 90, 100, 110, 120	60, 70, 80, 90, 100, 110, 120
Indoor Fan Torque[2]	[%]	30, 60	50, 90
Outdoor Fan Speed[3]	[%]	40, 70	70, 100

[1] Charge is measured relative to the recommended charge according to the manufacturer's nameplate data.
[2] Indoor fan torque is set according to a nominal flow rate of 1350 CFM for low stage operation; 2000 CFM for high stage operation.
[3] Outdoor fan speed is set using the manufacturer's default value for low and high stage operation.

The first system tested in the psychrometric chamber test facilities was System A (microchannel condenser, thermostatic expansion valve). The empirical parameters of the VRC model were determined using the automated open laboratory training kit. The RTU was installed in the psychrometric chamber test facilities and was tested for both stages of cooling. The resulting accuracy of the VRC sensor models trained in the open laboratory space and applied to the psychrometric chamber test data collected over the range of ambient conditions is shown for both cooling stages in Figure 4. The results show that the VRC sensor outputs for low-stage cooling tests were less accurate than those for high-stage cooling operation. This trend was observed for the other systems as well. At low charge levels, the performance of the VRC sensor during low-stage operation was worse. It can be seen that even the training data were less accurately predicted at low charge levels. This was not the case for high stage cooling operation; the accuracy was relatively the same at all charge levels tested. It should be noted that the root-mean-squared error (RMSE) was less than 10% for both stages of operation. This indicates that the predictions from the VRC sensor could be used as part of an automated FDD system with relative confidence.

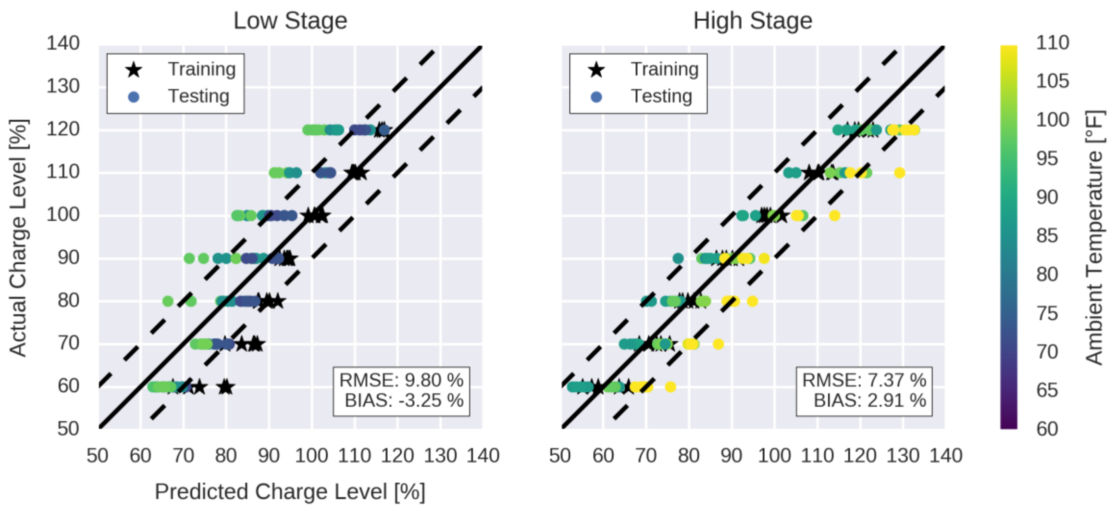

Figure 4. VRC sensor prediction accuracy for RTU with microchannel condenser and thermostatic expansion valve (System A) applied to both stages of operation under different ambient conditions.

After the completion of testing and evaluating the data collected from System A, the thermostatic expansion valve (TXV) was replaced by a fixed orifice expansion device. The orifice size and design was selected with the help of the original equipment manufacturer to ensure that the performance of the unit was representative of actual units. After the replacement of the expansion device, the RTU was referenced as System B.

The automated open laboratory training kit was applied to System B in an open laboratory space in order to collect data used to determine the empirical parameters of the VRC sensor model. At the conclusion of this process, the RTU was installed in the psychrometric chambers and tested over a range of ambient conditions. The accuracy of the VRC sensor models for System B trained using open laboratory data and applied to the psychrometric chamber test data collected over the range of ambient conditions is shown for both cooling stages in Figure 5. The results show that the low-stage cooling test VRC predictions were less accurate than those for high-stage cooling operation. This is especially true when the amount of refrigerant charge was above 90%. After analysis of the experimental data, it was determined that for these cases, the system operated with zero superheat or subcooling. One explanation for this is the diameter of the fixed orifice was too large for the low-stage operation. This is understandable since the orifice must be designed for the high stage operation in order to maximize design point performance. Because there was no superheat or subcooling for these conditions, the VRC model must rely entirely on the evaporator refrigerant quality term (which is essentially a function of condensing pressure). With this in mind, the performance of the VRC sensor is rather respectable considering the system performance information available. The RMSE error for the low stage operation was on par with the results obtained for System A. The accuracy during high stage operation was actually better than System A at 6.68%.

Following the testing and evaluation of the data collected from System B, the microchannel condenser coil originally installed on the unit was replaced by a finned tube condenser coil received from the original equipment manufacturer. This coil was designed for the RTU and can be ordered as a lower efficiency option. After the replacement of the condenser coil, the RTU was referenced as System C.

Because the system was already installed in the psychrometric chambers at this point, the open laboratory training kit was applied with the system installed in the psychrometric chambers rather than the open laboratory space. Open laboratory space conditions were simulated by controlling the air entering the evaporator and condenser coils to be equal at typical indoor conditions. One advantage of this was that the environmental conditions used to train the VRC sensor could be analyzed and its impact on the accuracy of the VRC model assessed.

The accuracy of the VRC model designed for System C for each stage of operation is shown in Figure 6 over the range of ambient conditions tested. The performance of the VRC sensor applied to System C was better than System A or System B, which may indicate that a system having a finned tube condenser may be modeled more easily. In both stages of operation, the RMSE was approximately 6.20%. Additionally, the accuracy observed over the range of charge levels was relatively constant.

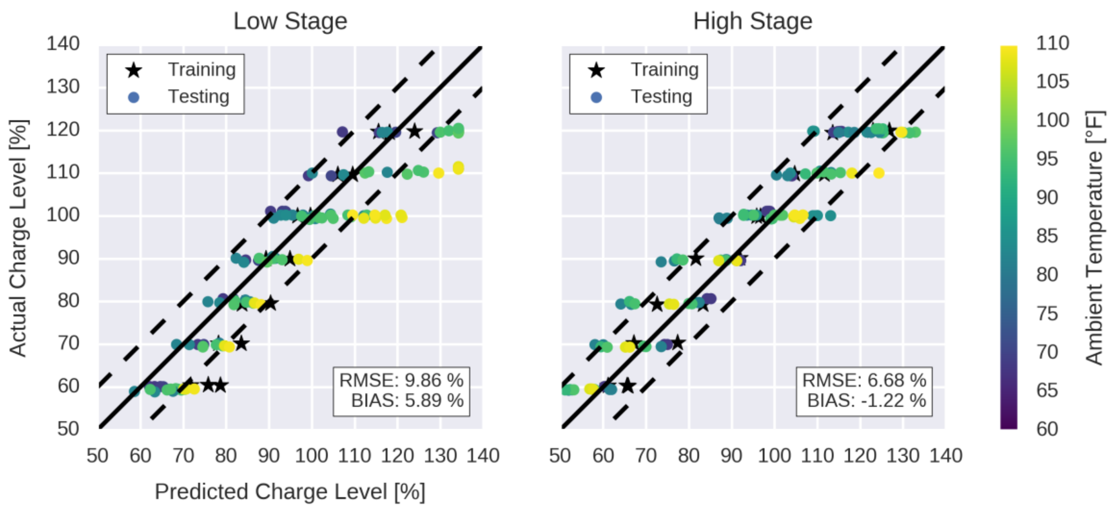

Figure 5. VRC sensor prediction accuracy for RTU with microchannel condenser and fixed orifice expansion device (System B) applied to both stages of operation under different ambient conditions.

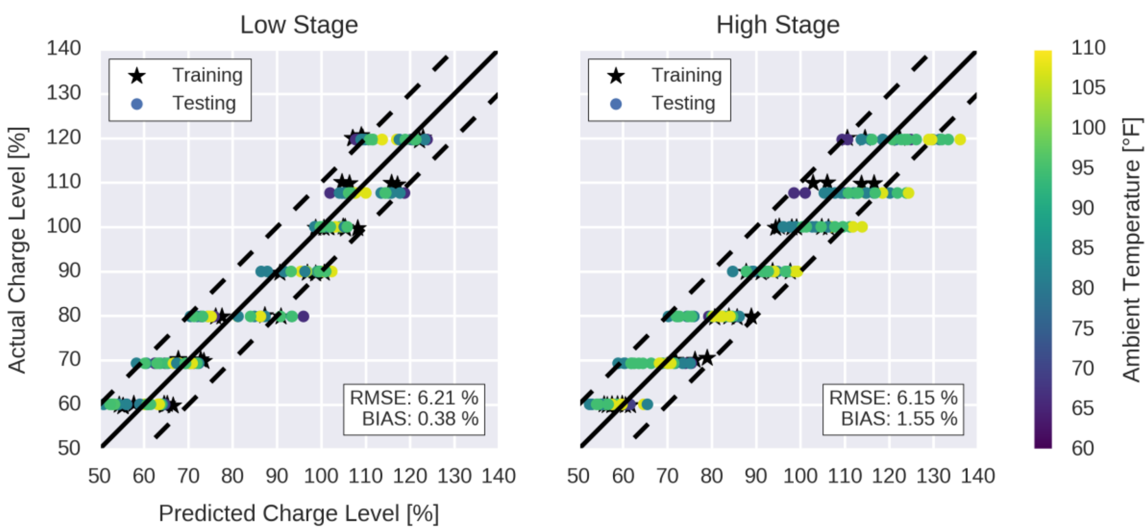

Figure 6. VRC sensor prediction accuracy for RTU with finned tube condenser and fixed orifice expansion device (System C) applied to both stages of operation under different ambient conditions.

After testing and evaluating the data for System C, the fixed orifice valve was replaced by a thermostatic expansion valve (TXV). The new system is referenced as System D. Again, as the unit was already inside the Psychrometric chamber, open laboratory space conditions were simulated by controlling the air entering the evaporator and condenser coils to be equal at typical indoor conditions. After the training, System D was tested and data was collected at all conditions similar to those of System C. The accuracy of the VRC model designed for System D for each stage of operation is shown in Figure 7 over the range of ambient conditions tested. The RMSE was approximately 6.66% for low stage operation, while for the high stage it was around 5.71%.

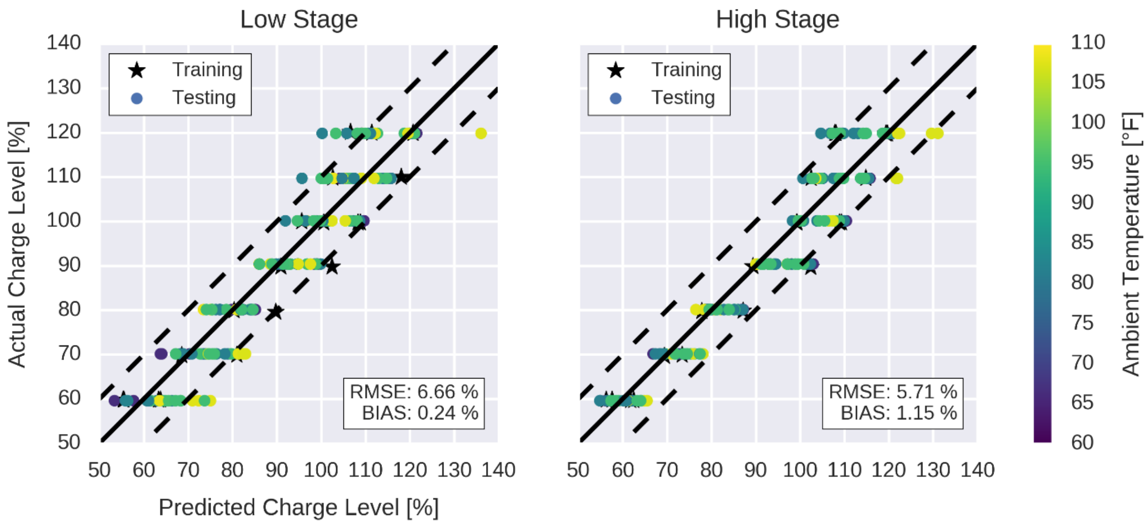

Figure 7. VRC sensor prediction accuracy for RTU with finned tube condenser and thermostatic expansion valve (System D) applied to both stages of operation under different ambient conditions.

The accuracy of the VRC models developed for the four systems tested are shown together in Table 3. For all systems, both the RMSE at each stage and the overall accuracy were less than the goal of 10%. For the microchannel units, the VRC sensor is less accurate during low stage operation. For these systems, the subcooling was very sensitive to the charge level. This often led to zero subcooling at many test conditions. Furthermore, when these systems were overcharged, superheat was driven to zero. This made estimating the refrigerant charge level problematic using the proposed model. The results also show that the open laboratory training algorithm provides experimental data that can be used to design VRC models without extensive testing in psychrometric chamber test facilities.

Table 3. Summary of the prediction accuracy of the VRC sensor applied to the different systems tested during this study.

			RMSE (%)		
System	**Expansion Device**	**Condenser Coil**	**Low Stage**	**High Stage**	**Overall**
A	TXV	Microchannel	9.80	7.37	8.56
B	FXO	Microchannel	9.86	6.68	8.27
C	FXO	Finned-Tube	6.21	6.15	6.18
D	TXV	Finned-Tube	6.66	5.71	6.19

While it is important to show that automated open laboratory VRC sensor training methodology can be used develop accurate models, the savings in both time and development cost are significant as well. Table 4 shows a comparison between the testing requirements and costs for training the VRC sensor using psychrometric chambers and with the automated open laboratory methodology. In previous studies, psychrometric chambers were used to collect data representing different operational states and ambient conditions for RTUs at different charge levels. To do this, approximately 110 test combinations were used lasting about 160 total hours. It is estimated that this testing could be performed by a third-party laboratory ratings agency, costing $1,100 USD per 8-hour shift. Therefore, the total cost of testing the RTU to determine the empirical parameters of the VRC sensor is approximately $22,000 USD.

In comparison, the automated open laboratory system was able to reduce the total test combinations from 110 to 34. Moreover, control of the ambient conditions was no longer needed, eliminating the need for psychrometric chambers. The total time requirement to complete the entire VRC sensor training was approximately 14 hours, or approximately two 8-hour shifts. Using the same facility and labor costs, the total cost to train the VRC sensor using the automated system is approximately $2,200 USD. The true cost could be even less since the same facility and labor cost for both training methodologies was used in the calculation. Using the automated open laboratory methodology, facility costs should be greatly reduced since psychrometric chambers are not needed. Labor costs should be reduced as well since the system is automated and little human labor is required once the system is installed and configured on the RTU.

Table 4. Comparison of testing requirements and cost of the traditional methodology using psychrometric chambers and the automated open-laboratory methodology used to tune the empirical parameters of the VRC sensor.

	Psychrometric Chamber Methodology	**Automated Open Laboratory Methodology**
Total Test Combinations	110	34
Test Variables	• Charge Level • Indoor Fan Speed • Compressor Stage • Ambient Temperature	• Charge Level • Indoor Fan Speed • Outdoor Fan Speed • Compressor Stage
Approximate Test Duration	160 hours (4 weeks, 8 hours/day)	14 hours
Approximate Training Cost	$22,000 USD	$2,200 USD

6. CONCLUSIONS

A methodology and system have been implemented for rooftop units to automatically tune the empirical parameters of a virtual sensor for estimating the amount of refrigerant in a system. This system reduces engineering time and costs associated with the virtual sensor by reducing the amount of tests required in a psychrometric chamber test facility and testing the system in an open laboratory space instead. In order to assess the accuracy of this methodology, the system was applied to four different RTUs (with varying types of components) to tune the model. This model was then compared with data collected for the units collected using psychrometric chamber test facilities over a wide range of ambient conditions. The results showed that the overall accuracy of each of the virtual refrigerant charge sensor models had root-mean-square errors less than 10%. This shows that the automated open laboratory training system results in accurate sensors for many types of RTUs. In addition, it was found that the time and cost associated with training a VRC sensor using the automated approach can be reduced by about a factor of 10.

After analyzing the data, it was observed that the VRC sensor tends to be less accurate when applied to systems with microchannel condensers. While the reasons for this loss of accuracy are somewhat unclear, it may be caused by the much smaller condenser volume in comparison to systems with conventional finned tube condensers. The systems that were tested with microchannel condensers tended to have lower levels of subcooling as well, especially for low charge levels. Since subcooling is an essential input to the VRC sensor, accurate prediction of charge levels is much more difficult when subcooling is zero at undercharged conditions. Further investigation of systems with microchannel heat exchangers would provide more evidence and possibilities for improvement in the VRC sensor model.

REFERENCES

Cowan, A. (2004). *Review of Recent Commercial Roof Top Unit Field Studies in the Pacific Northwest and California*. New Buildings Institute [NBI] for Northwest Power and Conservation Council [NPCC] and Regional Technical Forum [RTF].

Jacobs, P. (2003). *Small HVAC Problems and Potential Savings Reports*. California Energy Commission [CEC].

Kim, W. & Braun, J. E. (2013) Performance evaluation of a virtual refrigerant charge sensor. *International Journal of Refrigeration*, 36(3), 1130-1141.

Li, H., Braun, J. E., (2009). Development, evaluation and demonstration of a virtual refrigerant charge sensor. *HVAC&R Research*,15(1), 117-136.

Vasudevan, J. (2015). *Training and Evaluation of Virtual Sensors for Rooftop Units*, Master's Thesis. Purdue University, West Lafayette, IN.