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Low Refrigerant Algorithm Detection for Cooling Systems Relying on Trending and Data Analysis

Fadi M. Alsaleem
Wichita State University, United States of America, fadi.alsaleem@wichita.edu

Amro Quedan
Wichita State University, United States of America, amquedan@wichita.edu

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Fadi ALSALEEM[1]*, Amro QUEDAN[2]

[1]Wichita State University, Department of Mechanical Engineering,
Wichita, Kansas, USA
Contact Information (316-719-0450, fadi.alsaleem@wichita.edu)

[2]Wichita State University, Department of Electrical Engineering,
Wichita, Kansas, USA
Contact Information (940-595-4627, amquedan@wichita.edu)

* Corresponding Author

ABSTRACT

A hybrid algorithm of an enhanced version of Mann-Kendall trending and data analysis is proposed to solve the limitations of current technology in detecting and diagnosing cooling system refrigerant faults in general and refrigerant leakage specifically. A data abstraction mechanism is applied over feed of temperatures and power measurement to calculate and store only the significant information for further analysis. Next, an enhanced version of Mann-Kendall trending is applied periodically over the stored data to calculate the trend strength (upward or downward) for each measurement. Finally, a harmonic mean is utilized to balance the trends contribution and evaluate the result against a threshold value for potential faults. Such an algorithm is expected to have an important positive impact, because it is designed to accurately detect low refrigerant at an early stage. This should help in the following ways: (a) to reduce the impact of refrigerant emissions on climate, and (b) to potentially reduce the U.S. energy use by more than 0.1–.02 quad per year. This algorithm is a robust first step towards leveraging the latest technology advancements, especially in computer science and mathematics, in order to vertically advance the field of cooling systems.

1. INTRODUCTION

Refrigerant leakage is one of the most common problems with cooling systems, causing, for example, supermarket refrigeration systems to lose up to 25% of their nominal refrigerant per year (David Cowan et al., 2010) and 60% of existing cooling systems and one-third of new cooling system installations (Rossi, 2004), (Mowris, 2004), and (Piotr et al., 2014) to be inefficient mostly due to low charge (David Cowan et al., 2010). Refrigerant leakage is one of the dangers responsible for climate change, creating a double adverse effect due to the increase in direct emissions as well as indirect CO2 emissions. In addition to climate impact, refrigerant leakage creates a negative snowball financial impact (David Cowan et al., 2010), as shown in Figure 1. In the early stages, leakage affects energy cost, whereby the system runs longer to satisfy the cooling load and the repair cost is fairly constant. The repair and energy costs rise exponentially as the system persists in losing refrigerant. At a certain low refrigerant level, catastrophic system failures may occur. These failures, such as compressor failure due to high discharge temperature or food damage in the case of a reach-in cooler at a supermarket, dramatically increase the financial burden of refrigerant leakage.

There are two major components for the low refrigerant detection model; the processes to initiate the need for refrigerant evaluation (processes) and the method /algorithm to detect and diagnose low refrigerant (method). Next, we review the major limitations of these two components.

1.1 Refrigerant-Leakage Detection Process

For the past decades, most refrigerant-leakage detection processes were limited to on-site, expensive, and time-consuming diagnosis, with less attention on cost and flexibility. The on-site diagnosis may occur during a regular maintenance check-up or after an emergency call. Both scenarios have major drawbacks. Although regular maintenance schedules tend to be proactive and usually detect refrigerant leakage in the early stages, the cost of regular check-up is high and its reoccurrence is inconvenient, especially when the cooling system itself is fine. Moreover, repetitive refrigerant checking using a pressure measurement, during these checkups, results in lowering the refrigerant level. Emergency visits are usually initiated by users, and by that time, leakage is very severe and has already impacted the environment and the energy bill.

1.2 Refrigerant-Leakage Detection Method

Different methods were proposed in the literature to detect refrigerant leakage (Katipamula and Brambley, 2005a). Some of these methods rely on the underlying physics of HVAC systems (Quantitative methods). Others are rule-based methods that were developed based on prior knowledge of the system (Qualitative methods). In addition, if the system operation data are available, during normal operation and under fault condition, a learned relationship (black or gray box models) is used. Each of these methods suffers from a certain type of weakness. For example, the quantitative-based methods are complex and computationally intensive and may require input measurement that may not be readily available. The qualitative methods, on the other hand, are specific to a system type and rely on rules and thresholds values that will be difficult to be used for other systems. Finally, the history learned-based models require a huge amount of training data and may fail in dealing with data that are beyond that training data.

Most refrigerant leakage-detection methods require intrusive sensing of the refrigerant's pressure. One exception is the work of Li and Braun who they invented the application of virtual sensor concept in the HVAC domain to replace the intrusive expensive pressure measurements by the cheap temperature sensors (Li and Braun, 2006). This concept was further enhanced and evaluated in recent research work (Li and Braun, 2009) and (Kim, W.H and Braun, 2013). Different methods were suggested to estimate the temperature to pressure correlation parameters. However, most of these methods (i) require technical data that are provided by manufacturers and (ii) the temperature sensors are required to be mounted at a specific location to provide accurate estimation (Li and Braun, 2009) and (Kim, W.H and Braun, 2013).

Due to the above shortcoming, most of the current leakage detection methods are not accurate or can't be widely applied over majority of HVAC systems (Yuill, 2014). To assess current cooling system fault diagnostic methods and algorithms, including refrigerant leakage detection, recently a team of researchers at Purdue University conducted a rigorous study and developed an evaluation protocol. Applied over thousands of faulty cooling systems data, the protocol concluded that current generic cooling system fault diagnostics algorithms and hand-held FDD tools are ineffective. For example, their study shows that the protocol of California's Title 24 for HVAC fault diagnostics for refrigeration and air conditioning (RAC) has produced more than 50% false positive faults and has missed 32% of the real faults (Yuill and Braun, 2013), (Yuill et al., 2014), and (Yuill, 2014).

Form the aforementioned literature review, we first note that while there are a lot of work on improving the methods of detecting and diagnosing refrigerant-leakage fault, less attention has been given to advance the processes for applying these methods. It is noted that also most of the refrigerant-leakage detection methods are not accurate or not general or practical enough to cover wide range of systems. In this work, we are exploring a new processes of refrigerant-leakage ,online -monitoring, benefiting from recent advances in computing technology that can facilitate detecting refrigerant leakage in the early stages, similar to a regular check-up but without the need to check the system on site. Also, the new processes demonstrably reduces the need for expensive emergency calls. Utilizing this new processes, a hybrid algorithm of an enhanced version of Mann-Kendall trending and data analysis is proposed to solve the limitations of current methods in accurately detecting and diagnosing refrigerant leakage.

1.3 Paper Scope and Organization

In this work we highlight the use of online monitoring and cloud computing platform described in (Alsaleem, et al., 2014) in providing continuous refrigerant leakage detection capabilities for residential vapor compression systems. Specifically, a data abstraction mechanism is applied over a feed of temperatures and power measurement to calculate and store only the significant information for further analysis. Next, a sample size adjusted version of Mann-Kendall trending is applied over the stored data to calculate the trend strength (upward or downward) for each measurement. Finally, a harmonic mean is utilized to aggregate the rate trends contribution and this result is evaluated against a threshold value to determine whether to signal for potential faults. The organization of this paper is as follows. In section 2, we introduce the new refrigerant detection model, the processes and the method. In section 3, we present initial result for applying the new model over hundreds of real filed HVAC systems. In section 4, we summarize the paper and give some conclusions.

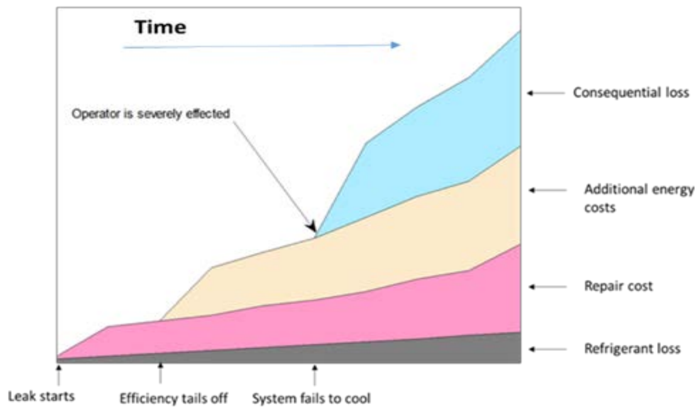


Figure 1: Financial impact of refrigerant leak over time, (David Cowan et al., 2010)

2. THE REFRIGERANT LEAKAGE DETECTING MODEL

The complete hardware for this new diagnostics model is described in (Alsaleem et al., 2014) and is shown in Figure 2. Few key points are to be mentioned here. (1) The hardware consists of an indoor kit that is equipped with voltage and current sensors as well as temperature sensors to track air supply, air return, indoor liquid line, and suction line temperatures. The outdoor kits measure the aggregate outdoor current and voltage. (2) the data for each system run is transmitted in chunks, each of maximum of fifteen minutes and at sampling rate of one sample per five seconds (0.2 HZ),(3) a cloud structure is built to host the low charge algorithms to receive and processes the data from the indoor and outdoor kits.

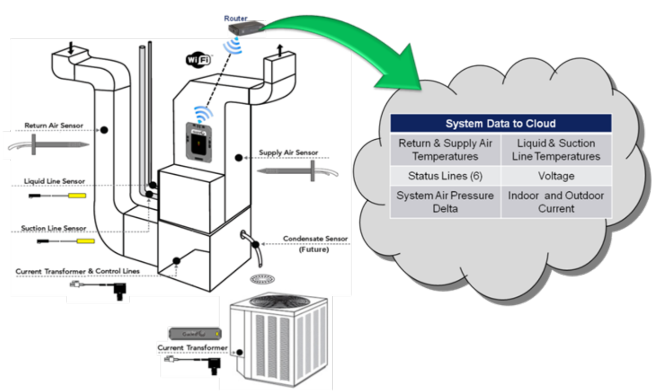


Figure 2: Hardware shows the indoor and outdoor kits to gather and send sensors data to the cloud

1.2 Mann-Kendall Trending Test

The purpose of the Mann-Kendall test is to assess for a given data if there is a monotonic trend over time. It has been used in many applications, such as water quality monitoring (McLeod et al., 1990) and more recently for weather trending and prediction (Soltani et al., 2013). Its advantages over linear regression analyses includes: it does not require a normal distribution for the data, it is independent of the data magnitude, and it can deal well with missing or irregularly spaced data. The trending test compares each data point to all subsequent values. If the data from newer values is greater than earlier data, then the Mann-Kendall statistics value *S* is increased by *1*; otherwise, it decreased by *1*. In mathematical terms, this could be described as:

$$S = Sign\left(\sum_{i=1}^{m-1} \sum_{j=i+1}^{m} \begin{cases} 1 \; if \; (T_j - T_i) > 0 \\ 0 \; if \; (T_j - T_i) = 0 \\ -1 \; if \; (T_j - T_i) < 0 \end{cases} \right) \tag{1}$$

where T_i,T_j are the daily average values for a given measurement at a given day where j > i. A very high positive *S* value indicates an increasing trend, whereas a very low negative value indicates a decreasing trend. The sign function, introduced by the authors, adjusts the sign of the *S* value to always indicate a positive value if the measurement trend direction support the fault. To account for sample size, the magnitude of *S* was adjusted by the following scale (assuming sample data are not similar) as follow *(*HydroGeoLogic, 2004*)*:

$$S_N = \frac{S \mp 1}{g(S)^{1/2}} \tag{2}$$

where, $g(S) = \frac{1}{18}[n(n-1)(2n+5)]$, and *n* is the sample size.

2.2 Mann-Kendall Trend Calculation

Here we discuss the use of trending analysis to track and warn of capacity degradation due to refrigerant leakage over time. As a HVAC system loses it is capacity, it is expected that some measurements (such as split temperature: return air minus supply air, and averaged total power) to trend down and others (such as suction temperature) to trend up, as shown in Figure 3. These trend directions uniquely characterize capacity drop and are different for other faults such as evaporator fouling, in which the split temperature is expected to trend up. In such a situation, it is rational to design an algorithm that watches the trend of each measurement over time and use the trends conurbation that aligns with a capacity drop behavior to generate a confident decision about the status of system capacity.

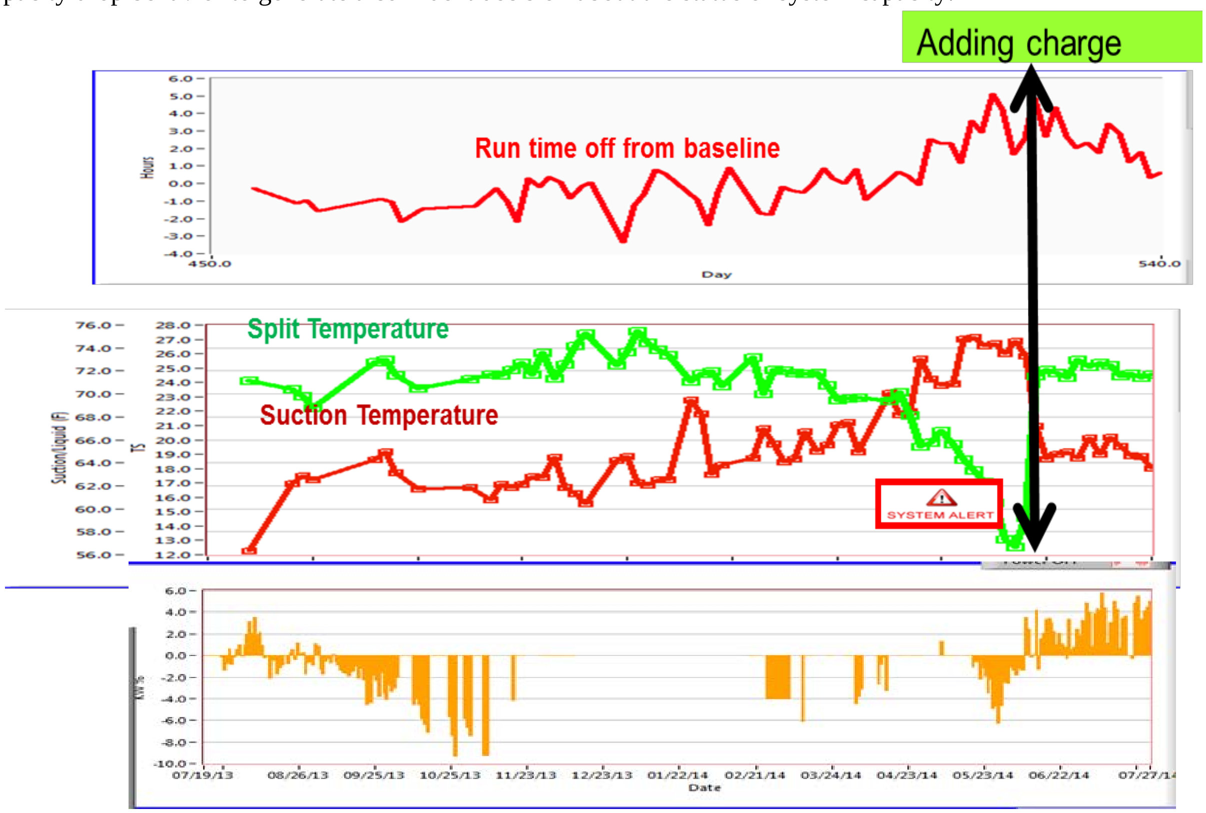


Figure 3: HVAC capacity drop, due to refrigerant leakage, impact on split temperature, suction temperature, run time, and power. First upper plot shows the run time in hour's deviation from baseline data. Middle plots are; red for suction and green for split temperatures in F°, and bottom plot is the daily average power deviation from baseline. The figure shows that as system loses refrigerant over time, run time deviation from baseline and the suction line temperatures increase while the split temperature and power deviation from baseline decrease.

Figure 4 shows a schematic for the proposed algorithm. Here, the average temperatures, power, and total run time deviation from a bassline of each day are accumulated and stored in a database. The Mann-Kendall is then applied weekly to calculate the trend strength/sum of each component, the Mann-Kendall application detail over one measurement is described in (Alsaleem et al., 2016). It is worth to mention that (2) is modified to include the normalized difference between the recent measurement and the average of this measurement for all monitored systems as follows:

$$S_{NA} = \frac{S \mp 1}{VAR(S)^{\frac{1}{2}}} + sign \times \frac{T_m - \overline{T}.}{\overline{T}} \qquad (3)$$

where $\overline{T}$ is the average of a measurement under consideration for all systems, T_m is the current measurement value for a given system. The sign is positive for a measurement that a decreasing trend supports a fault and is negative for a measurement that an increasing trend supports the fault.

Equation 3 represents one of the major contribution of this paper, that is to come up with an adaptive approach to customize a measurement threshold to trigger a certain fault based on knowledge from the big data of monitored systems (second term) and a specific signature from the monitored system itself (first term). This solution is in contrast with most of the current HVAC systems fault diagnostics methods that were built around comparing a HVAC system measurements to fixed thresholds values. These thresholds were either chosen wide enough to cover system variations in the field (threshold 2 in Figure 5) at the expense of missing real faults or chosen very tight range at the expense of producing false alerts (system 1 using threshold 1).

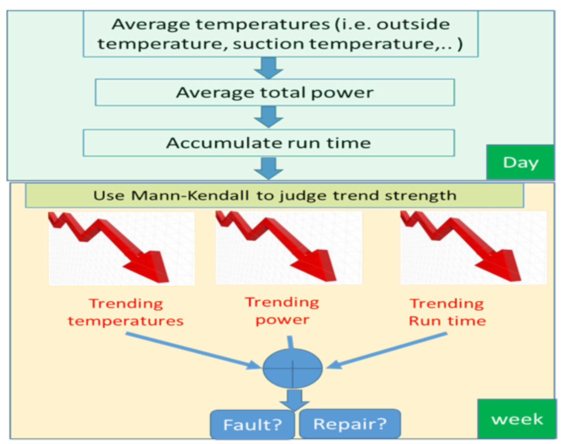


Figure 4: Algorithm schematic for detecting low charge using trending analysis

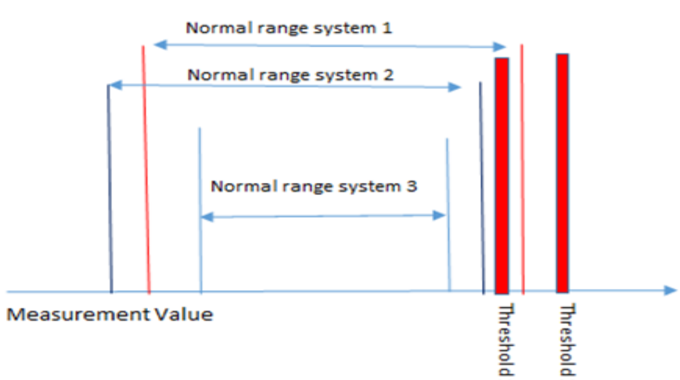


Figure 5: Fault threshold variation in typical HVAC systems

The importance of adding the normalized difference term to (3) can be understood easily considering the following scenarios; a strong decrease trend for the split temperature might exist for a cooling system, as a sign of continuous loss of refrigerant, while its current value is around the average split temperature of all monitored cooling systems. This should have less impact on triggering a low-refrigerant fault, compared to another system with the same trend strength but with a lower split temperature. The contribution of the calculated trends sum is averaged using a harmonics mean approach that is explained in the next section.

2.3 Mann-Kendall Trends Accumulation

Multiple trends algorithms are needed to capture the measurements behavior effected by capacity degradation. The combined effect of these trends is averaged using the F-measure, borrowed from the information retrieve science (Rijsbergen, 1979). The F-measure, given in (4) for two inputs values X, Y, calculates the harmonic mean of two values. The harmonic mean differs from the traditional arithmetic mean by keeping an equal influence of the two values, especially when their difference is high. Using the capacity degradation problem as an example, if the trend for split temperature is very strong decreasing (0.9 confidence level out of 1.0) but suction temperature has poor increasing up trend (0.1 confidence out of 1.0). The arithmetic mean of these trends is 0.5. However, the harmonic mean for the same trends is 0.18. As the system suction temperature doesn't strongly support capacity degradation, the 0.18 measure is more physically realistic measure to infer low capacity fault.

$$F = \frac{2XY}{X+Y} \qquad (4)$$

A slight modification to *(4)* is done by introducing β:

$$F_\beta = \frac{(\beta^2+1)XY}{\beta^2 X + Y} \qquad (5)$$

β, is a parameter to control the balance between the two inputs variable X and Y. for example, when β>1 then F becomes more influenced by Y value. In the capacity drop calculation, it is a good practice to weight the split temperature higher compared to suction temperature. This is true as split temperature is the one observed directly by homeowner and it is a stronger indicator for capacity drop. Equation *5* can be generalized so it could be used for n variable inputs:

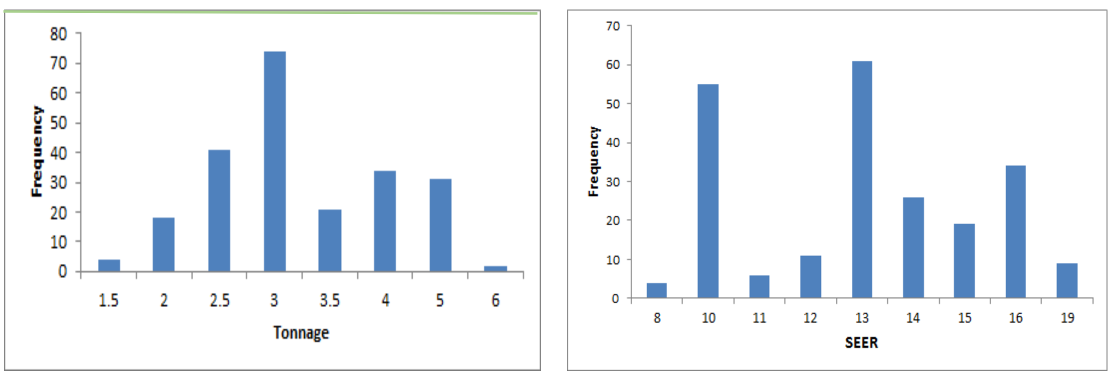
$$F = \frac{n}{\frac{1}{x_1}+\frac{1}{x_2}\dots+\frac{1}{x_n}} = \frac{n}{\sum_{i=1}^{n}\frac{1}{x_i}} = \frac{n.\prod_{j=1}^{n}x_j}{\sum_{i=1}^{n}\frac{\prod_{j=1}^{n}x_j}{x_i}} \qquad (6)$$

The use of the multiple trends with the harmonic mean for capacity degradation detection is as follows: at the end of each week, if the harmonic mean of the confidence level of the measurement trends sum is greater than a specific threshold value, then a low-refrigerant fault is declared.

3. RESULT AND DISCUSSION

A sample of 225 HVAC systems installed in real homes were used in this investigation. Of these systems, 118 were charged with R410A refrigerant and the rest were charged with R-22 refrigerant. The tonnage size and SEER information for this sample size is given in Figure 6. The Pie charts in Figure 7 captures the low refrigerant alerts status statistics in a two years period. The pie chart to the left, divides the alerts to: valid not sent alerts, invalid alerts, and sent alerts. The chart shows 0.0% invalid alerts. The pie chart to the right, classifies the valid sent alerts to two groups; fixed and not fixed alerts. Alerts are considered to be valid only if a fix was performed after sending the alert or, in the case of no fix was reported, if the capacity drop was confirmed by noticeable increase of power consumption for at least a week after declaring the fault at slimier environment conditions, refer to Figure 8 as an example. The chart in Figure 7 shows that 21.0% of the valid alerts were not sent. Alert is not severe enough and from past experience was not easy for on-site technician to confirm, or homeowner chose not to be notified about efficiency alerts are just few reasons for not sending this valid alert. An alert is considered to be a fixed alert only if the owner of the HVAC system received the alert and responded by calling a service technician, the technician showed up and confirmed the diagnostics, the homeowner agreed to pay for the fix, and finally the technician did the right fix!. If any of these conditions is not met, such as the homeowner chose not to acknowledge or to react on the alert, technician failed to confirm the diagnostics, technician confirmed the diagnostics but homeowner chose not to perform the repair due to cost issue, or technician confirmed the diagnostics, homeowner agreed on the fix cost and technician performed the fix, but it was not complete, then the alert considered to be a not fixed valid alert. In this study, only 44% of the valid alerts were fixed. This raise the difficult question on how to grantee the right fix to be performed for systems with valid alerts. We believe *understanding and accounting for the complex relationship between technician and homeowner, while designing the HVAC FDD algorithms is a key in answering this question*.

Work in progress is to establish a way to compare results obtained by this algorithm with results from other traditional generic HVAC FDD algorithms. Initial screening shows good signs that this new method of alerting refrigerant leakage is more accurate compared to the on-site checkup performed by an average experienced technician. The evidence came from multiple HVAC installs, where the new algorithm has trigged the low capacity drop due to refrigerant leakage and it took multiple on-site service visits to confirm these leakage using temperature and pressure measurements.



(a) (b)

Figure 6: The tonnage size (a) and SEER ratting (b) for the 225 HVAC systems used in this study

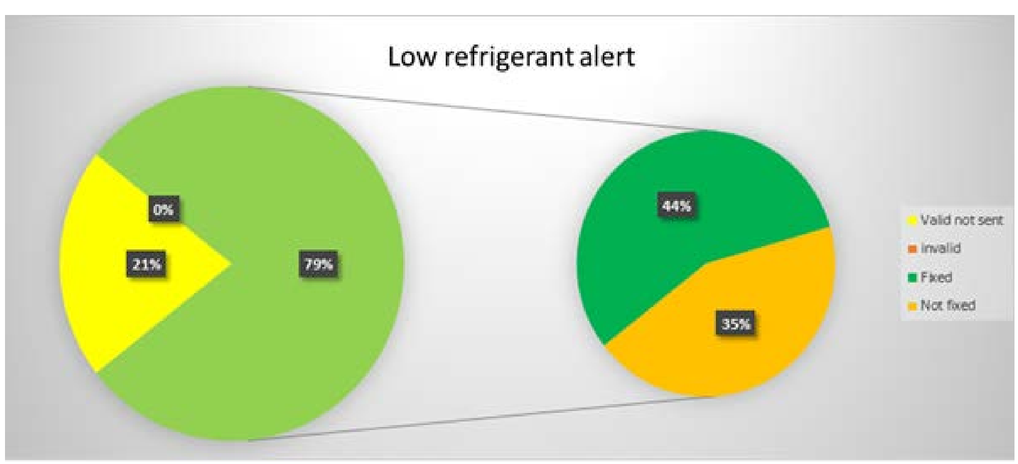


Figure 7: Trending low refrigerant alerts statistics

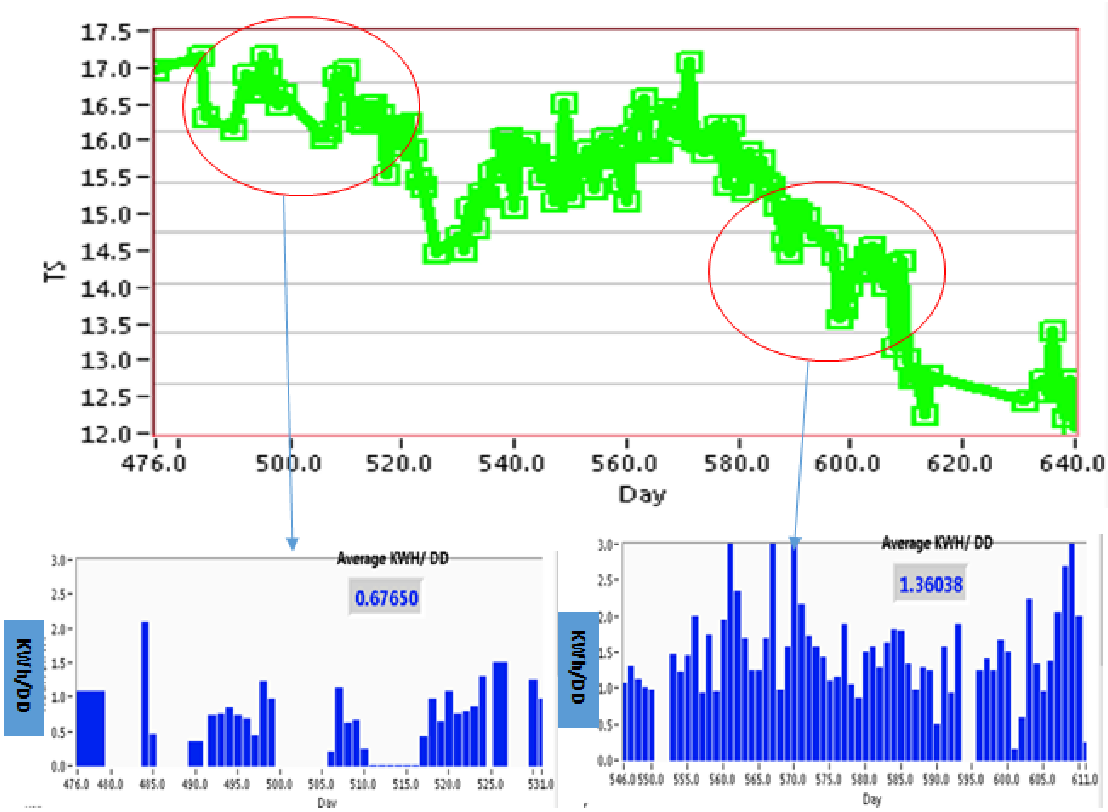


Figure 8: An example of using power consumption to confirm the generated low refrigerant alert for a system that an on-site diagnostics/fix was not performed. Top plot is the trend plot of split temperature, and bottom plots are the normalized KWh for the system before and after the alert was sent. In these plots, the KWh is normalized to the degree per day temperature index

4. CONCLUSIONS

The presented work attempts to bridge the research gap between a cost-effective, practical implementation, and an accurate and effective diagnostic model for HVAC systems by combining multidisciplinary fields of science: data analytics, cloud computing, and mechanical engineering. As an example, the use of modified trending analysis in addressing the challenging problems of refrigerant-leakage detection was presented. The application of this research may not only impact the fault detection and diagnosis within HVAC and other energy transporting system, but can also more generally inform innovation in other domains with fault phenomenology indicated by trends over time including medical, automotive, and economic policy fields.

Finally, the presented work touched on some of the HVAC systems FDD algorithms filed implementation issues. These issues such as, the complex relationship between a home owner and a service technician and the multiple possible scenarios and interactions that could result from sending even a valid alert, are hardly discussed in other research work. Future work is planned to explore further this complex relationship, benefiting from the cloud-based system flexibility to communicate, store, and analyze data, that can potentially feed and enhance the overall field of HVAC system FDD.

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