Development of a Remote Refrigerant Leakage Detection System for VRFs and Chillers

Shunsuke Kimura

Michio Moriwaki

Manabu Yoshimi

Shohei Yamada

Takeshi Hikawa

See next page for additional authors

Authors

Shunsuke Kimura, Michio Moriwaki, Manabu Yoshimi, Shohei Yamada, Takeshi Hikawa, and Shinichi Kasahara

Development of a Remote Refrigerant Leakage Detection System for VRFs and Chillers

Shunsuke KIMURA[1]*, Michio MORIWAKI[2], Manabu YOSHIMI[3]
Shohei YAMADA[4], Takeshi HIKAWA[5], Shinichi KASAHARA[6]

[1-6]Daikin Industries, Ltd., Nishi-Hitotsuya, Settsu, Osaka, 566-8585, Japan
Phone: +81-6-6195-7264,
E-mail: [1]shunsuke.kimura@daikin.co.jp, [2]michio.moriwaki@daikin.co.jp,
[3]manabu.yoshimi@daikin.co.jp, [4]shouhei.yamada@daikin.co.jp,
[5]takeshi.hikawa@daikin.co.jp, [6]shinichi.kasahara@daikin.co.jp

* Corresponding Author

ABSTRACT

Reducing refrigerant leakage from refrigeration and air-conditioning equipment is one of the essential issues to solve the global warming problem. Many countries are enacting laws requiring owners of large refrigeration and air-conditioning equipment such as VRFs, chillers, and large rooftops to carry out regular inspections for refrigerant leaks and to repair any leaks that are found. There are two methods of regular inspections: direct inspections using visual checks or a gas sensor leak detector, and indirect inspections using equipment operating data to detect leakages. However, large equipment has many inspection points, and manual inspection using the direct method is very time-consuming and labor-intensive, placing a heavy burden on both the equipment owner and inspector. On the other hand, in many cases, there are incentives such as exemption from inspections or halving the number of inspections by installing a permanent leak detection system. The authors are developing a highly accurate refrigerant leakage detection system that meet incentive requirements using machine learning techniques. This paper reports on the details of the technology and the detection accuracy evaluated with on-site VRFs and chillers.

1. INTRODUCTION

The 2016 Kigali Amendment to the Montreal Protocol requires ratifying countries to phase down their production and consumption of HFCs, but the United States has not yet ratified it. However, based on the AIM Act passed in 2020, the EPA has issued a rule to phase down approximately 85% of HFCs production and consumption by 2036, using 2011-2013 as the base year, similar to the Kigali Agreement. Currently, allocations for HFC production and consumption after 2024 and to promote conversion to low-GWP refrigerants are under discussion, and measures to utilize recycled refrigerants and to prevent refrigerant leakage when equipment is in use are also being considered. Specifically, EPA Order 608 establishes annual refrigerant leakage limits for each type of equipment, imposes periodic leak inspections on repaired equipment, and provides penalties for noncompliance. California has taken measures such as setting GWP limits for refrigerants used depending on the type of equipment, ahead of other states. These measures are expected to spread to the entire United States.

These trends have stimulated the development of leak detection systems. Conventional leak detection has been mainly based on systems that require special detection operations [1]. However, with the recent advances in big data analysis technology, many refrigerant leak detection systems have been proposed that use machine learning techniques to process normal operating data, without special detection operations. According to Hosseini *et. al.* [2], 82 papers were published worldwide between 2016-2020 on air conditioner failure detection systems using machine learning, 10 of them are on leakage detection. In addition, 6 of these 10 papers are for VRFs. In Japan, Wakui *et. al.* [3] reported on the simulation of a leakage detection system for VRFs using machine learning.

However, most of these papers are validated using simulations or experimental data acquired in laboratories, and only a few have been validated using on-site operating data. Therefore, a leakage detection system during cooling using machine learning that operates on a remote monitoring system for VRF equipment was developed and its detection accuracy was validated using a large amount of on-site data [4-5]. The technology was also applied to a detection system for chillers [6-7], which has been launched in Europe. Furthermore, a leak detection function during heating operation for VRFs has also been developed [7] and validated with on-site data. This paper reports a summary of the developed leakage detection system for heat pump VRFs and for cooling chillers, and the newly developed leakage detection system for heat recovery VRFs.

2. METHODOLOGY

2.1 Overview of The Detection System

The leakage detection system estimates changes in refrigerant charge amount from the operating data acquired from VRF and chiller equipment and automatically detects leakages. Figure 1 shows the overview of the developed system. This shows the detection flow for cooling, and the algorithm for heating is almost the same except for the refrigerant leak index ("*RLI*" in Figure 1). The *RLI* and other indices are described in detail in sub-section 2.2.

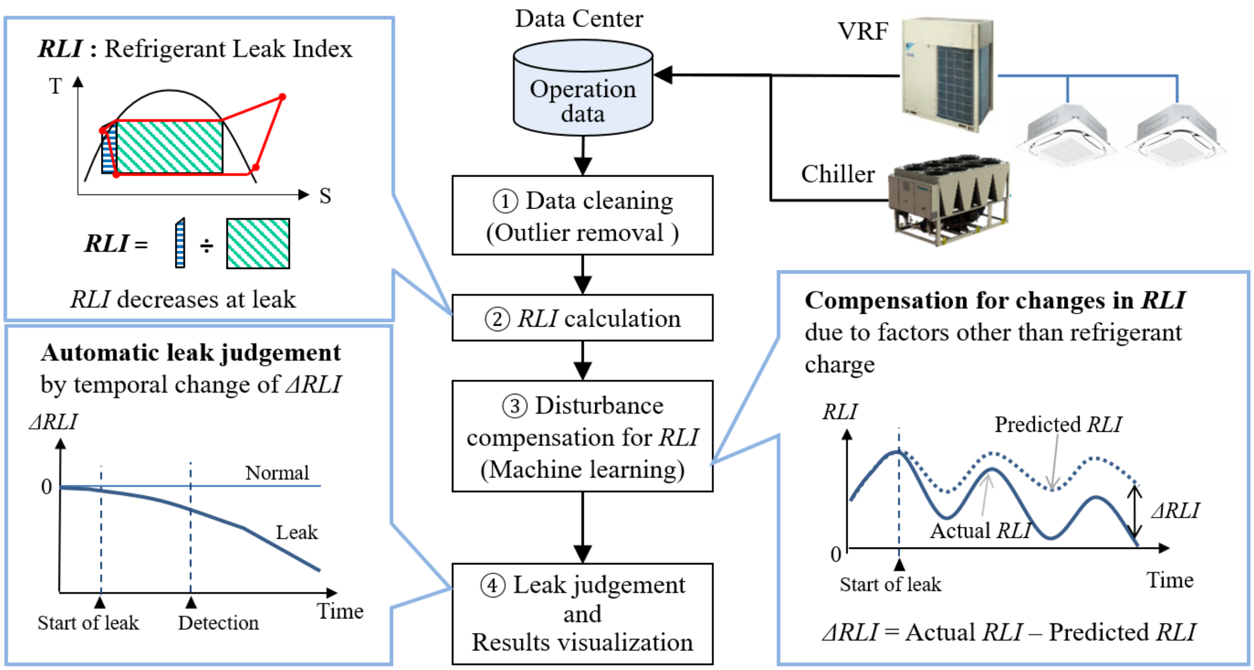

Figure 1: Overview of the leakage detection system

2.2 Refrigerant Leak Index (*RLI*)

The leakage detection system calculates the *RLI* (Refrigerant Leak Index), an index strongly correlated with the refrigerant charge amount, from the operating data and detects leakages based on changes in this value. The *RLI* used in VRF and chiller cooling operations is a dimensionless value defined as the area ratio of the liquid region to the saturated region on the *T-S* diagram, as shown in Figure 1, and can be calculated using sensor values provided in common VRF. As the refrigerant charge amount decreases due to leaks, the *RLI* also decreases.
Figure 2 shows an example of piping diagrams for VRF and chiller. In case of VRF, the *RLI* calculation method is slightly different between heat pump (HP: all indoor units switch between cooling and heating simultaneously) equipment and heat recovery (HR: each indoor units provide cooling or heating individually) equipment: HP equipment uses the temperature sensor at the outlet of the outdoor heat exchanger ("Thx" in Figure 2), whereas HR equipment uses the temperature sensor at the outlet of the subcooled heat exchanger ("Tsc" in Figure 2). This is due to the difference in control methods during normal operation.
During heating operations of VRF equipment, the degree of superheat of the compressor discharge temperature (*DSH*) is used instead of the above *RLI*. When the refrigerant charge amount decreases due to leaks, the discharge temperature rises and so does the *DSH*. The reason why *RLI* is not used during heating is that VRF operates multiple indoor units as condensers during heating, as shown in Figure 2. The number and types of connected indoor units vary from one VRF equipment to another, and a machine learning model using the *RLI* obtained for each of these indoor units would

make the logic very complicated. As a result, the amount of calculation increases, and implementation becomes difficult. Therefore, this VRF-specific issue was solved by using *DSH* as an index for heating.

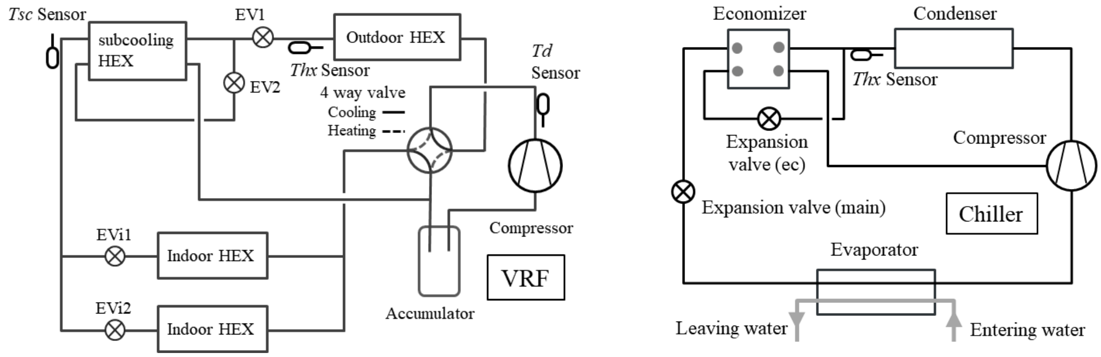

Figure 2: Example of piping diagrams for VRF and chiller

2.3 Disturbance Compensation for *RLI*

The *RLI* changes not only due to the refrigerant leaks, but also due to external disturbances such as outdoor temperature and compressor speed. Therefore, even though there is no refrigerant leak, the *RLI* may drop due to the disturbances and the detection algorithm may misjudge it as a leak. To prevent this, the disturbances from *RLI* is removed and the index *ΔRLI*, which represents only the changes in the refrigerant charge amount, is calculated. As shown in Figure 1, *ΔRLI* is the difference between the actual *RLI* calculated directly from the operating data and the predicted *RLI* under normal conditions. This predicted *RLI* is calculated by a prediction model created using machine learning (ML) from past normal operating data. The disturbances for *DSH*, which is an index for heating, is removed in the same way as above, and *ΔDSH* is calculated as an index of the changes in only the refrigerant charge amount.

To create the *RLI* and the *DSH* prediction models for VRFs and the *RLI* prediction model for chillers, ML methods were used according to the characteristics of the respective training data. The specific ML methods and training data acquisition methods for each prediction model are described in sub-section 2.4.

2.4 Method for Creating *RLI* Prediction Models for VRFs

Since VRFs have enough operating data stored in the data center, it is possible to create an *RLI* prediction model for normal conditions using these as training data. However, the stored data contain both normal data and anomalous data. Normal data means that all functions are normal, and the refrigerant charge amount is appropriate. Anomalous data may be due to malfunctioning components or sensors, or insufficient or excessive refrigerant charge amount.

Therefore, in the process of data cleaning, only normal data were extracted from the stored data as training data for the creation of *RLI* prediction models. The extraction was carried out in the following two stages.

First, the data of equipment without failure records and equipment with completed failure repairs were extracted.

Next, the mean value of *RLI*, an index of refrigerant charge amount, was then calculated for each extracted equipment. The relative frequency distribution of these values is close to the black line of normal distribution curve shown in Figure 3; the *RLI* value, in other words, the refrigerant charge amount, varies even in equipment without failure as shown in Figure 3. This variation is due to the accuracy of refrigerant charge amount at installation, refrigerant recovery and recharge before and after component replacement.

The equipment with values near the center of the distribution curve (“Appropriate charge” area in Figure 3) is charged with the appropriate amount of refrigerant, and its operating data is determined to be available for training.

Using the training data extracted in this way, the prediction models of normal *RLI* were created by LightGBM [8]. In the case of HP equipment model, the explanatory variables were outdoor temperature, compressor speed, compressor current, and opening of the expansion valve for subcooling heat exchanger control (“EV2” in Figure 2). In the case of HR equipment model, they were compressor speed, evaporating temperature, condensing temperature, opening of main expansion valve ("EV1" in Figure 2), and opening of expansion valve for subcooling heat exchanger control ("EV2" in Figure 2). Note that the training data used were not only the data from the target VRF system itself, but also the data acquired from several different units of the same VRF type. This is for reducing the operating cost. Therefore, the prediction model will be a common model for that type.

The normal *DSH* prediction model for heating was also created in the same way: the explanatory variables in the case of the *DSH* prediction model were outdoor temperature, compressor speed, total capacity of indoor unit in operation and opening of the expansion valve for subcooling heat exchanger control.

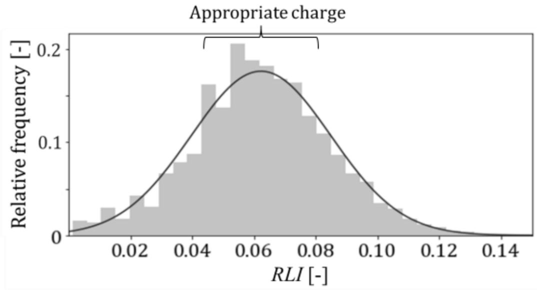

Figure 3: Distribution of *RLI* mean value

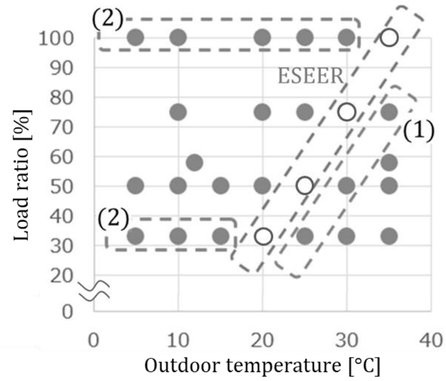

Figure 4: Combination of outdoor temperature and compressor load factor set for the test

The data with leaks or other failures found in the first process were labelled according to the failure and used as the anomaly data for the validation of leakage detection accuracy.

2.5 Method for Creating *RLI* Prediction Models for Chillers

The prediction model for chillers was created in a different way from that for VRFs. For chillers, the stored data could not be used as training data because there was almost no data of units mounted a temperature sensor to measure the condenser outlet temperature used for *RLI* calculation. Therefore, a chiller mounted with a sensor for measuring the condenser outlet temperature was installed in a climate chamber, and tests were carried out under various conditions simulating actual operations to obtain training data.

Four test conditions were varied: outdoor temperature, compressor load ratio, leaving water temperature (*LWT*) and refrigerant charge amount as leak condition. In order to create a highly accurate prediction model while reducing the number of test man-hours, the test conditions were chosen from frequently occurring operating conditions from the on-site data stored in the data center.

First, the variation range of the outdoor temperature was set to be between 5 and 35°C, taking into account the European climate. The compressor load ratio was set to vary between 33% and 100%, according to the specifications of the chiller to be tested. Figure 4 shows the combination of test conditions set with the range of variation of outdoor temperature and compressor load ratio. The 27 test conditions sets were chosen by focusing on the ESEER condition and its lower load area (1), which appears frequently in air conditioning applications, and the area (2), which appears frequently in process temperature control applications. *LWT* are generally distributed in the range of 2 to 20°C, depending on the application and load ratio. The four conditions of 5, 7, 11, and 13°C were selected as the most frequently occurring on-site conditions.

The data obtained from the tests carried out based on the above test conditions were used as training data, and a normal *RLI* prediction model was developed using random forest regression. The six explanatory variables used in the prediction are outdoor temperature, compressor load ratio, *LWT*, main expansion valve opening ("main" in Figure 2), economizer expansion valve opening ("ec" in Figure 2) and compressor current. The training data for the *RLI* prediction model was obtained from a random sampling of 70% of the operating data with 100% refrigerant charge amount. The remaining data with 100% refrigerant charge amount and the data with 120, 90, 85, 80% refrigerant charge amount were used as test data for the validation of leak detection accuracy.

2.6 Automatic Leakage Detection Logic

In the case of cooling, the automatic leakage detection logic outputs judgement results of leakage based on the decrease in *ΔRLI*. Figure 5 shows the overview of the automatic detection logic of refrigerant leakage. The detection logic consists of the moving window with N terms, the planar mapping section, the anomaly calculation section and the judgement section. The planar mapping section obtains the data of two arbitrary adjacent points, *ΔRLI*(t-1) and *ΔRLI*(t), from the time series of ΔRLI in the moving window and plots them at the coordinates (*ΔRLI*(t-1), *ΔRLI*(t)) in the mapping plane.

The mapping plane is pre-classified into normal, undercharged, and overcharged areas based on the decision boundaries plotted by ML. The undercharged area is in the third quadrant and the overcharged area is in the first quadrant. The anomaly calculation section calculates the anomaly score (*ANS*) defined by Equation (1) when the *N*-1 points created from the *N* data in the moving window have been plotted to the mapping plane.

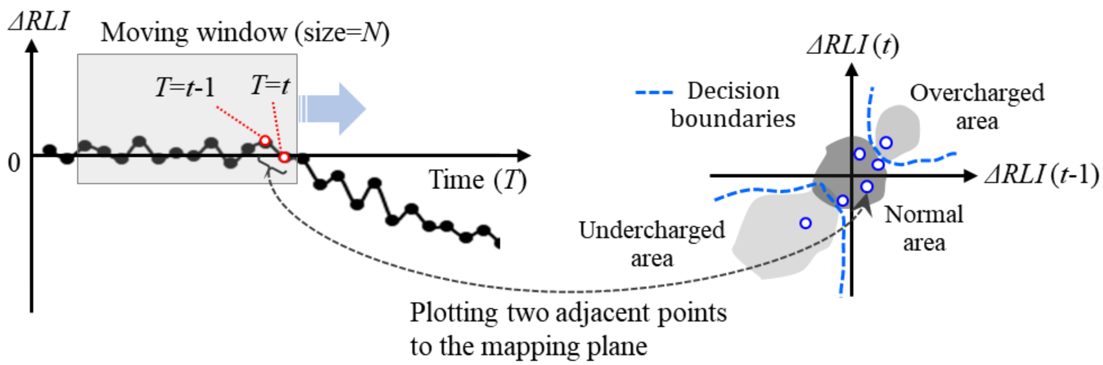

Figure 5: Overview of the automatic leakage detection logic

$$ANS = \frac{Number\ of\ points\ in\ undercharged\ region}{N-1} \tag{1}$$

ANS is the ratio of the number of points mapped in the undercharged area to the *N*-1 points mapped from the moving window. If this value exceeds a predetermined threshold, the judgment section determines that there is a leak. If the distribution of points is mapped in the undercharged or overcharged areas from the beginning of operation, it is judged to be initially undercharged or overcharged, respectively.
In the case of heating, the leakage index is *ΔDSH*, which increases opposite to *ΔRLI* during leakage, thus the undercharged area is distributed on the first quadrant**.**

3. RESULTS and DISCUSSION

3.1 VRF Data Validation Result

The responses of *ΔRLI* and *ΔDSH* in VRF equipment were evaluated. All the following results are for HR equipment. The results for HP equipment are described in our previous paper [7] and will be skipped here. Figures 6 and 7 show the examples for cooling and heating operation, respectively. In both figures, the left plots show the data of a normal equipment with the appropriate refrigerant charge amount, and the right plots show the data of an equipment with gradual refrigerant leak during operation. And the thick gray line shows the measured *RLI* and *DSH* values calculated directly from the operating data, the thin black line shows the *RLI* and *DSH* values predicted by the normal prediction model, and the plots at the bottom show the difference between them, *ΔRLI* and *ΔDSH*.

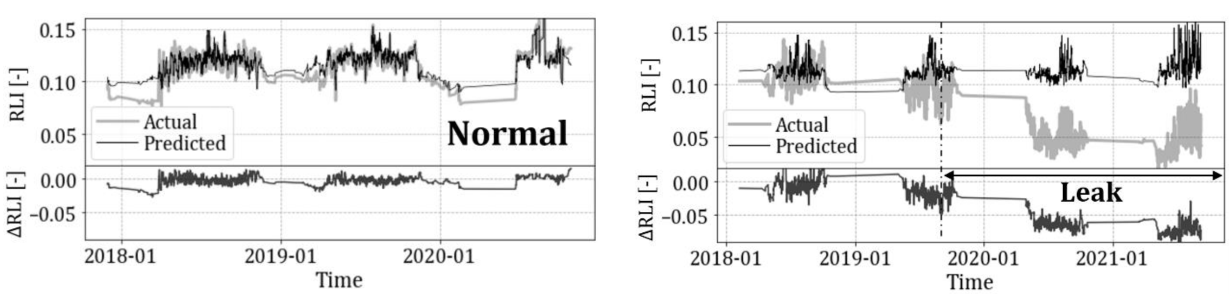

Figure 6: *RLI* and *ΔRLI* responses to normal and leak data during cooling operation

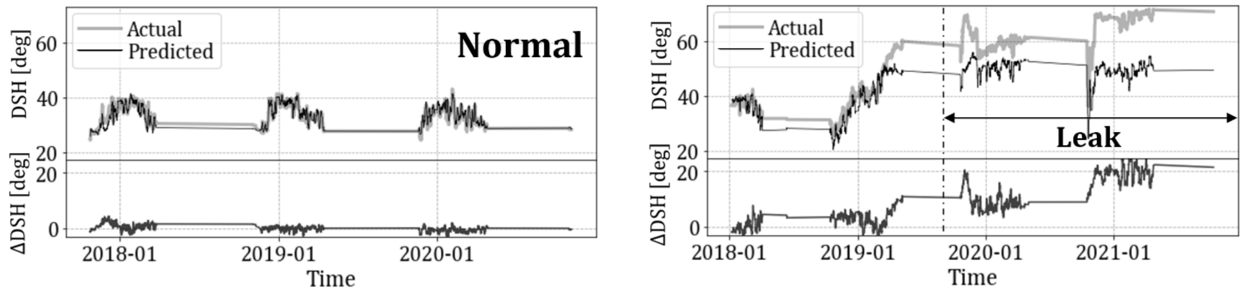

Figure 7: *DSH* and *ΔDSH* responses to normal and leak data during heating operation

The leaking equipment is estimated to have started leaking at the end of the heating operation in 2018 and to have leaked significantly during the cooling operation in 2019. In both figures, the area indicated by the arrow "Leak" is the period during which the detection logic judged a leak. In the normal equipment, the actual values for both cooling and heating are close to the predicted values, and the differences *ΔRLI* and *ΔDSH* are almost 0. On the other hand, during the period when the refrigerant charge amount decreases in the leaking equipment, the actual values for both cooling and heating differ significantly from the predicted values. Thus, the *ΔRLI* and *ΔDSH* values are sufficient for the automatic detection logic to detect the leak correctly.

Next, the leakage detection was carried out for several test data obtained from the stored data and the detection accuracy was evaluated from the confusion matrix of the detection results. The confusion matrix is a combination of the correct and incorrect judgment results for the actual equipment state (normal or leaking), and its definition is given in Table 1. The judgment performance was evaluated by two indices, accuracy (*ACC*) and false discovery rate (*FDR*), as shown in Equations (2) and (3) below.

Table 1: Definition of confusion matrix

		Predicted	
		Normal	Leak
Actual	Normal	TN (True Negative)	FP (False Positive)
	Leak	FN (False Negative)	TP (True Positive)

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$FDR = \frac{FP}{TP + FP} \tag{3}$$

The *ACC* is the ratio of correct predictions among the total number of test cases. The *FDR* is the ratio of normal equipment misclassified as leaks among the equipment classified as leaks. In actual operation of the refrigerant leakage detection system, it is important to keep the *FDR* as low as possible. This is because misjudgment of normal equipment as leaking equipment not only increases operating costs due to the unnecessary dispatch of service personnel, but also leads to a loss of user confidence in the detection system.

Table 2: Confusion matrix of leakage detection evaluation results during cooling

Cooling		**Predicted**	
		Normal	Leak
Actual	Normal	97.4% (149)	2.6% (6)
	Leak	18.7% (4)	81.3% (26)

Table 3: Confusion matrix of leakage detection evaluation results during heating

Heating		**Predicted**	
		Normal	Leak
Actual	Normal	95.7% (45)	4.3% (2)
	Leak	13.3% (2)	86.7% (13)

Considering these factors, the target *ACC* and *FDR* of the current fault diagnosis by remote monitoring is set to be 80% or higher and 10% or lower, respectively. The detection sensitivities of the automatic leakage detection logic were adjusted to meet the above indices.
Table 2 and Table 3 show the confusion matrices for cooling and heating, respectively, that were calculated after adjusting the detection sensitivities. Each element of the confusion matrix in the table shows the incidence rate of normal and leakage detection against the actual number of normal and leak equipment. The number in () is the number of detections.
Equations (2) and (3) were used to obtain the *ACC* and the *FDR* from the confusion matrices for cooling and heating, respectively. The target values for *ACC* of 80% or higher and the *FDR* of 10% or lower were achieved in both cooling and heating. The incidence rates in the tables were used for the calculations. The reason is that if there is a large difference between the number of normal equipment and the number of leaking equipment, the judgment result is affected. By using the incidence rates, this effect can be eliminated.

Table 4: *ACC* and *FDR* in cooling and heating operation

Operation mode	Cooling	Heating
ACC	89.3%	91.2%
FDR	3.1%	5.7%

Finally, the leakage detection sensitivities were evaluated by obtaining the estimated leakage amount at the time of the first detection by the automatic detection logic for the true positive (TP) equipment. The definition of refrigerant leak rate is the ratio of leaked refrigerant amount to the initial charge amount, as commonly used in refrigerant regulations. To estimate the leakage amount at the time of the detection, the conversion coefficient of the changed refrigerant charge amount (% of total refrigerant amount) and the *RLI* and *DSH* were determined first. To do this, the data of equipment for which the leakage amount could be identified from repair records and equipment with intentionally adjusted refrigerant charge amount were used. The leakage amount at the time of the leak detection was calculated by multiplying the change in the *RLI* and *DSH* by the conversion coefficient. The relative frequency distribution of the estimated leakage amounts obtained for all the true positive (TP) equipment is shown in Figure 8. The distribution can be approximated by a normal distribution, and assuming that the mean value of the distribution is defined as the mean detection sensitivity, it was 14.8% for cooling and 14.2% for heating. Assuming a normal distribution as shown by the dotted line in Figure 8, the worst detection sensitivity is defined as the value of $\mu+3\sigma$, which is determined from the mean value μ and variance σ and is estimated to be 20.2% for cooling and 19.3% for heating. Since the current detection logic for VRF has a detection sensitivity of more than 50%, this method improves the detection sensitivity by 30% over the conventional method.

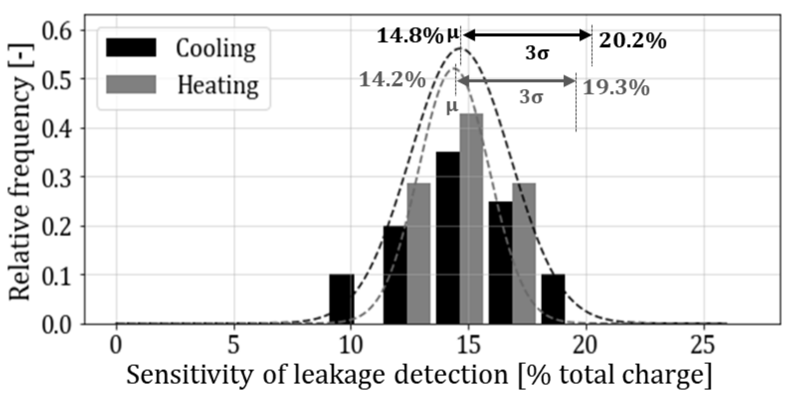

Figure 8: Sensitivity of leak detection in cooling and heating operation

3.2 Chiller data validation results

The method of creating an RLI prediction model and calculating ΔRLI using experimental data, and the evaluation results of ΔRLI for the normal and leakage data were described in our previous paper [7] and will be skipped here. This section describes the issues in the detection logic that were discovered in one equipment where a leak was detected in the actual operating system.
It was found that the detection logic would judge the equipment with initial undercharge as leaking. It was detected as leaking by the detection logic, but no leakage points were found during the on-site inspection. From the analysis

of its operating data, ΔRLI was found to be always negative from the beginning, rather than gradually decreasing as in the case of leakage. Therefore, it may had undercharged initially.
No detection logic for initial refrigerant undercharge was included in the detection system for chillers. As chillers, unlike VRFs, are not additionally charged with refrigerant at the time of installation, the variation in initial refrigerant charge amount was considered to be small. However, in the future, the detection logic for the initial undercharge will be added if necessary. As a detection method, a logic to detect initial undercharge is being considered when the initial ΔRLI value is smaller than the predetermined negative threshold value.

3.3 Investigations to Improve Performance of Leak Detection

Assuming that the allowable leakage in the refrigerant regulations will be tightened in the future, further measures to improve the detection sensitivities, *ACC* and *FDR* are being considered. The following methods for improving performance are currently under consideration and will be developed and put into practical use in the future.
(1) Efficiency enhancement of detection model improvement by automating the search for leaking equipment from historical data
Until now, experts familiar with the behavior of air conditioners were searching for leaking equipment by analyzing the data, so there was a limit to the number of data that could be analyzed. Consequently, the number of equipment labeled with potential leakage was sometimes insufficient to verify the accuracy of the detection model. Therefore, the expert's know-how will be converted into software to automatically search for equipment with potential leakage. The search will be accelerated by first using the software to extract candidate equipment that might be leaking, and then the expert will analyze the candidates in more detail.
(2) Automation of explanatory variable selection for machine learning models
Conventionally, explanatory variables were selected based on physical considerations of the refrigeration cycle. However, our analysis revealed that such a selection method may not always improve detection performance. Therefore, new software will be developed to automatically search for an explanatory variable that increases the deviation of the leakage index from normal as much as possible during leakage. This will enable automatic selection of the optimal explanatory variables.
(3) Automatic hyper-parameter tuning in creating machine learning models for the automatic leak detection section
When creating the ML model for the automatic leak detection logic described in sub-section 2.6, the hyper-parameter settings are automated so that the *ACC* and *FDR* satisfy the target values because the *ACC* and *FDR* fluctuate with small changes in the hyper-parameter values and are difficult to tune manually.
(4) Improved detection performance for new products using ML models of existing products
For existing products, there is sufficient operating data available at the data center, which can be used for training to achieve high performance. However, it takes about one year to collect sufficient data for new products that are just launched to the market. Therefore, higher detection performance for new products can be achieved by transfer learning using ML models of existing products and a small amount of data from the new products.

3.4 Application of Refrigerant Leak Detection Technology

Applications of the refrigerant leak detection technology are being considered, such as performance degradation detection and compressor life extension. For the former, it not only reduces the amount of refrigerant leakage but also improves performance during operation and contributes to the reduction of CO2 emissions.
When refrigerant leakage occurs, the condenser SC and the evaporator SH change, air conditioning operation deviates from the optimal state, and thus the COP declines. Therefore, the COP can be recovered by detecting leakage using the detection system, repairing the leak, and restoring the correct amount of refrigerant. For the latter, since refrigerant leaks cause compressors to operate under harsh conditions, detecting leaks at an early stage, repairing, and returning to proper operating conditions will extend the service life of compressors. Currently, a large amount of refrigerant is released into the atmosphere during repairs, so this system can also contribute to reducing such emissions. It is planned to put these technologies to practical use as soon as possible.

4. CONCLUSIONS

An indirect refrigerant leakage detection system based on machine learning technics was developed and its performance was validated on VRFs and chillers. The relationship between the detection sensitivities and the number of leaking equipment followed a normal distribution for all VRFs (heat pump equipment, heat recovery equipment) and chillers. For VRF heat recovery equipment, our system was able to detect leaks of 15% of the initial refrigerant charge amount on average and of 20% at worst. The *ACC* and *FDR* were 89.3-91.2% and 3.1-5.7%, respectively.

There is potential for further improvement in the detection sensitivities, *ACC*, and *FDR*, through the method shown in 3.3 etc. The next target is improvement of the detection sensitivities to detect 10% of leaks while maintaining the *ACC* and *FDR* in the future.

NOMENCLATURE

The nomenclature should be located at the end of the text using the following format:

ACC	accuracy	(–)
ANS	anomaly score	(–)
DSH	superheat at compressor discharge	(deg-C)
FDR	false discovery rate	(–)
HP	heat pump	
HR	heat recovery	
RLI	refrigerant leak index	(–)
S	entropy	(J/kgK)
T	temperature	(degC)

Subscript

a	air
c	condensing
d	discharge
e	evaporating
hx	heat exchanger
sc	subcooling heat exchanger

REFERENCES

[1] Sata H., Ochiai Y., Saito M., Suzuki K., Ikeda T. (2018). R410A condensing unit with functions to detect refrigerant shortage, and to assist refrigerant charging. Proc. 2018 JSRAE Annual Conference, D134. JSRAE. (in Japanese)

[2] Hosseini Gourabpasi A, Nik-Bakht M. (2021). Knowledge Discovery by Analyzing the State of the Art of Data-Driven Fault Detection and Diagnostics of Building HVAC. CivilEng. 2021;2(4):986-1008.

[3] Wakui T., Yokoyama R. (2018). Performance Monitoring and Diagnostics of Multi-Split Type Air-Conditioning System by Support Vector Machine Diagnostics of Performance Degradation Under Steady Operating Condition. Proc. 2018 JSRAE Annual Conference, C222. JSRAE. (in Japanese)

[4] Yoshimi M., Hikawa T., Kasahara S. (2019). Research and Development of Remote Refrigerant Leak Monitoring System for VRF Systems The 1st Report Outline of the Leak Monitoring System and the Monitoring Test Result. Proc. 2019 JSRAE Annual Conference, C342. JSRAE. (in Japanese)

[5] Yamada S., Yoshimi M., Hikawa T., Kasahara, S. (2020). Research and Development of Remote Refrigerant Leak Monitoring System for VRF Systems The 2nd Report Development of Automatic Refrigerant Leak Detection Method Using Machine Learning. Proc. 2020 JSRAE Annual Conference, C323. JSRAE. (in Japanese)

[6] Yamada S., Kojiyama K., Yoshimi M., Kasahara S. (2021). Research and Development of Remote Refrigerant Leak Monitoring System for VRF Systems The 3rd Report Application Development for Applied Air Conditioning Systems. Proc. 2021 JSRAE Annual Conference, C312. JSRAE. (in Japanese)

[7] Kimura S., Moriwaki M., Yoshimi M., Yamada S., Hikawa T., Kasahara S. (2022). Development of a remote refrigerant leakage detection system for chillers and VRFs. Proc. 2022 CLIMA REHVA 14th HVAC World Congress, ID1603. REHVA. (in press)

[8] https://lightgbm.readthedocs.io/en/latest/