Finding the Simple Rule for Diagnosing the Operation Fault of Freezer

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***Abstract*—This study aims to find a simple rule to see if a freezer door is left open, or if refrigerant is insufficiently charged. We devised a comparative experiment to find an opportunity where the simple rule is able to replace the machine learning approach. In contrast to the previous study performed with the machine learning approach, this paper has derived more explanatory variables and rules for diagnosing the operation faults of a freezer. i) Freezer wall temperature is found to be the most sensitive variable for diagnosing the door opening. When the open door rule based on the freezer wall temperature is applied to the actual state, however, only 62.4% of windows are assessed as "True". In other words, there is 37.6% chance of a false alarm. ii) We also assume that refrigerant mass is proportional to the ratio of accumulated power to power factor. However, only 51.5% of windows turn out "True" when the insufficient refrigerant rule is applied to the actual state. When refrigerant is actually insufficient, there is a 33% chance that critical false alarms still occur, which can harm the credibility of the insufficient refrigerant rule. iii) To diagnose if the door is left open by means of using machine learning, all three variables (Active Power, Laboratory indoor temperature, Refrigerator wall temperature) may not be necessary. Only the refrigerator wall temperature framed within a 3 minute window appears sufficiently credible, rather than the refrigerator wall temperature at each time step. iv) To diagnose if the refrigerant is insufficiently charged, instead of using the three variables, only power related variables including active power and power factor would be sufficient for simpler monitoring and more accurate assessment.**

***Index Terms*— FDD, fault detection, rule, diagnosis, machine learning**

I. Introduction

Freezer malfunctions most frequently occur when refrigerant leaks and/or when the door is left open by mistake. The most frequent freezer malfunctions are caused when refrigerant leaks and/or the door is left open by mistake. The first of these factors can occur with secondhand freezers which are not under proper maintenance or attention. The latter can occur with almost all freezers. While the first factor causes refrigeration to be delayed, the latter causes a sudden temperature rise. Both cases can eventually cause unexpected Faults and a subsequent deterioration of the content. If the freezer contains temperature-sensitive foods and ice, this can result in serious financial loss.

In the previous study, we developed a freezer monitoring system called the Freezer Keeper, as shown in Fig. 1. The Freezer Keeper monitors the freezer temperature, power consumption and power-related variables; such that when it appears to work abnormally, alarms are sent to the client before any damage occurs. One of the research issues was how to diagnose the operation fault as quickly as possible. To address this issue, we adopted machine learning algorithms. Since the previous work is still under publication [1], a brief description of the process and selected machine learning algorithms and summary of the results can be found in Section 2.

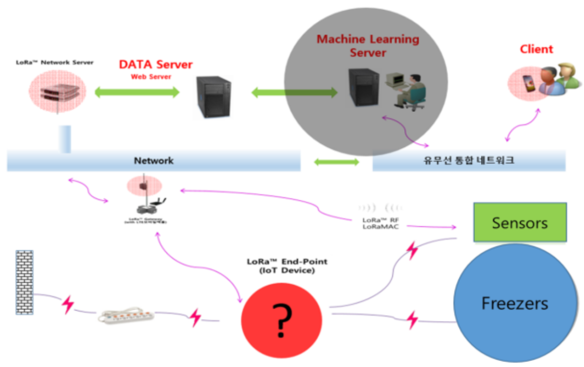

Figure 1. System architecture of the freezer keeper [1].

The machine learning algorithms showed an outstanding performance in predicting and detecting the operation fault [1]. However, only the well-trained machine learning model with accurately "labelled" data can assure its rated accuracy when the model is actually applied in this field. This raises a question concerning what would happen if a freezer expert needed long term monitored data to make a state judgement for training the machine learning model, but it was not actually available in this field. Additionally, to ensure a certain degree of accuracy when machine learning algorithms are used for diagnostics and prediction, a sufficient amount of field data must be firstly collected.

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TABLE I. STATES OF THE FREEZER [1]

States	Description	Door State	Refrigerant Mass	Freezer Temperature
Door_open	Regardless of refrigerant mass, the door leaves open	Open door	Ignored	Ignored
Lack_rfg	Insufficient refrigerant, and the door is closed	Closed door	30g, 40g 50g, 60g	Tries to reach at -20℃
Normal	Sufficient refrigerant with the door closed	Closed door	70g, 80g, 90g	Tries to reach at -20℃
Steady state	Sufficient refrigerant with the door closed	Closed door	70g, 80g, 90g	Already reached at -20℃
Steady_lack_rfg	Less refrigerant, and the door is closed	Closed door	30g, 40g 50g, 60g	Already reached at -20℃

This study, therefore, aims to find a simple rule to tell if a freezer door is left open, and/or if the refrigerant is insufficiently charged. To achieve this, we divided an experiment to see whether the simple rule is able to replace the machine learning approach.

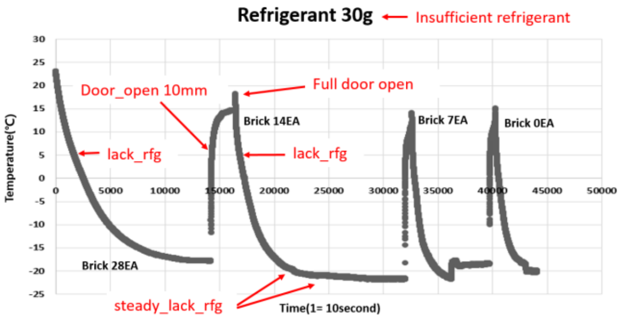

Figure 2. Schematic definition of states [1].

II. SUMMARY OF THE PREVIOUS STUDY

A. *Demonstration of Freezer Operation and Data Collection*

We analyzed frequent operation faults of freezers and then identified five freezer states, as described in Table I. Each state is also depicted in Figure 2. To demonstrate the five states, refrigerant mass was varied from 30g to 90g increasing by 10g for each refrigerant condition (7 conditions in total); The number of bricks varied from 0 to 28 by 7 bricks for each food content condition (4 conditions in total); the door was left open for 1-2 hours and was closed again (total 2 conditions). A total of 56 combinations were made in the lab.

Then, we started with 13 monitoring variables including A (Current), P (Active Power), Q (Reactive Power), S (Apparent Power), PF (Power factor), T1 (Central temperature in the refrigerator), T2 (Laboratory indoor temperature), T3 (Refrigerant temperature entering the evaporator), T4 (Refrigerant temperature leaving the evaporator), T5 (Refrigerator wall temperature), RFG (Refrigerant mass), M (Number of bricks), and D (Door open/closure).

For each combination, raw data were collected every 10 seconds. Eventually about 190,000 sets of the 13 monitoring variables were collected.

```
lm(formula = D ~ ., data = DataSET3)

Residuals:
     Min       1Q   Median       3Q      Max
-0.68014 -0.05814  0.00000  0.04259  1.01575

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.647e-02  9.460e-03  -3.855 0.000116 ***
RFG          2.607e-03  3.544e-05  73.563  < 2e-16 ***
P            2.758e-04  1.214e-05  22.712  < 2e-16 ***
PF           6.536e-04  1.040e-03   0.629 0.529624
T2           8.462e-03  2.895e-04  29.226  < 2e-16 ***
T3          -9.940e-04  6.772e-05 -14.679  < 2e-16 ***
T5           1.789e-02  5.269e-05 339.480  < 2e-16 ***
M           -3.385e-03  3.478e-05 -97.345  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.179 on 196301 degrees of freedom
Multiple R-squared:  0.436,     Adjusted R-squared:  0.436
F-statistic: 2.168e+04 on 7 and 196301 DF,  p-value: < 2.2e-16
```

Figure 3. Regression analysis when door opening (D) is used as the control variable [1].

B. *Machine Learning and Accuracy*

The five machine learning algorithms [2] were applied for experiments, KNN (K-Nearest Neighbors) [3], SVM (Support Vector Machine) [3], Decision Tree [3], ANN (Artificial Neural Network) [3], and Naïve Bayes Classification [3].

Since the 13 variables may not all be significant, and it takes quite a long time to train the machine learning model with the full dataset, purging variables was a necessary pre-processing step.

Firstly, we started with a correlation analysis to select 8 out of the 13 variables. Then we chose the final 6 variables (P, T2, T5, RFG, M, D) via regression analysis (Fig. 3). While RFG (Refrigerant mass), M (Number of bricks), and D (Door open/closure) are control variables, the rest of the variables represent the freezer response [4].

75% of the collected data was used for training the model, and the rest of the collected data was used for testing the model [5].

Because predicted states by machine learning algorithms may or may not match actual states, the accuracy of each model needs to be calculated to estimate how accurately each model predicts. Thus, the accuracy was defined as the amount of correctly predicted data out of the entire test data. Their accuracy is listed in Table Ⅱ.

Kernel-based algorithms such as KNN and SVM have higher accuracy than others. Naïve Bayes algorithm, however, has the lowest accuracy because it does not consider independence between data, i.e., Naïve Bayes algorithm assumes all data are related, although some variables apparently behave independently from others. Decision Tree was not able to suggest clear criteria when data values are discrete.

TABLE II. ACCURACY OF MACHINE LEARNING ALGORITHMS

ML Algorithms	Accuracy
KNN	99.24%
SVM	96.21%
ANN	92.79%
DT	85.54%
Na ïve Bayes Classification	75.43%

III. EXTRACTING THE RULE TO DIAGNOSE THE OPERATION FAULT

In the previous study, we selected P (Active Power), T2 (Laboratory indoor temperature), and T5 (Refrigerator wall temperature) as the indicators of freezer states; they were chosen by inductive reasoning, rather than an analytical deductive approach.

We, thus, restart the deductive analysis with 13 variables to figure out simple rules and explanatory variables of the rules.

A. Simple Problem Solving

Most engineering problems are compound in that wherever there are choices of materials, subsystems or methods that emphasize one or another property, the problem is compound [6]. Since they are only partly deductive, deductive problem solving can only be triable with some part of the entire problem.

Even complex real world problems, however, can be simplified, if their scope, constraints and criteria are well defined. In this study, we focus more on the explicit causality to simplify the problem and also to try deductive analyses if the freezer door is left open, freezer temperature would go up, and if the refrigerant is fully charged, freezer compressor would consume more electricity to get the refrigerant circulated.

B. Open Door State

When the door is left open, indoor air enters the freezer, causing the freezer temperatures, such as T1 and T5, to start to increase. Regardless of refrigerant mass, it is observed that temperature rises show some patterns as depicted in Fig. 4. Specifically, T5 increases as time goes on while maintaining a certain pattern. By setting the monitoring window at each 3 minutes, we derive the equation (1).

$$T5 = a \times \ln Time + c \tag{1}$$

Since equation (1) is closer to a linear regression equation, the R^2 at each ‘a’ value is calculated and listed in Table III. After several tests, we found that as long as the slope ‘a’ is a positive value, it can be determined that the door is left open. When refrigerant mass is over 80g, T5 appears to not increase following (1), because a fully charged refrigerant is able to keep the current freezer temperature for the time being even if the door is left open.

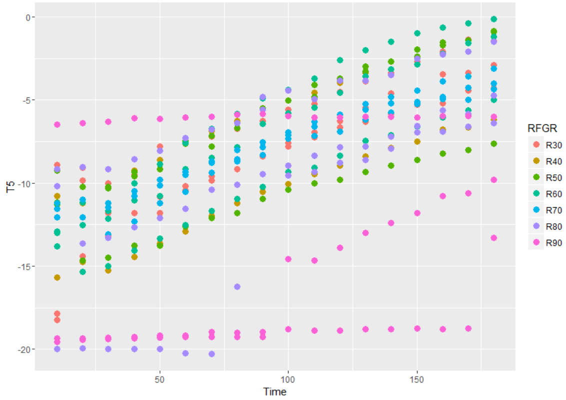

Figure 4. T5 per refrigerant mass varying from 30g to 90g.

TABLE III. SLOPE ‘A’ OF (1) WHEN THE DOOR LEAVES OPEN

Refrigerant mass [g]	Slope ‘a’ of Equation (1)					
	Number of bricks [M]					
	M=14	R^2	M=7	R^2	M=0	R^2
30	3.867	83%	5.304	96%	3.181	77%
40	3.719	87%	3.934	89%	(NA)	(NA)
50	2.196	57%	4.060	89%	3.664	79%
60	3.659	75%	4.833	90%	5.060	92%
70	3.990	82%	3.178	88%	2.678	85%
80	2.422	63%	6.699	66%	3.034	83%
90	0.183	72%	3.742	61%	0.694	12%

B. Insufficient Refrigerant State

Although T5 is a good indicator to diagnose the door opening, T5 can vary not only per refrigerant mass, but also per other disturbance factors. We, therefore, considered another indicator to see if the refrigerant was still insufficient.

TABLE IV. DEFINITION OF POWER VARIABLES

Signals	Description
S	Apparent Electric Power
P	Active Power
Q	Reactive Power
PF	Power Factor

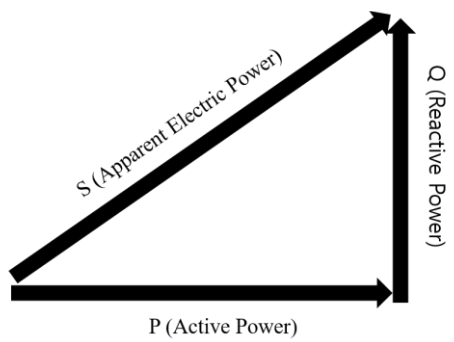

Figure 5. The power factor.

If refrigerant is fully charged and also sufficiently subcooled, the refrigerant does not need to circulate between the evaporator and compressor as frequently as it should do when the refrigerant is less charged. This eventually results in a lower power factor, because there is a lower cooling load even at the same apparent power (Table Ⅳ and Fig. 5) [7][8]. Therefore, it can be derived that refrigerant mass is inversely proportional to the power factor.

Additionally, if refrigerant is fully charged, the compressor needs to work harder to "squeeze" more refrigerant [9]. Thus, the freezer consumes more power compared to when the refrigerant is less charged. When the power consumption accumulates over some time, the accumulated power becomes more obvious in distinguishing between a fully charged refrigerant and a lower charged refrigerant. Therefore, it can be derived that refrigerant mass is proportional to the accumulated power (WP).

Finally, we arrive at the assumption that refrigerant mass is proportional to WP/PF as described in the equation (2).

$$\frac{WP}{PF} = a \times Time + b \tag{2}$$

We calculated slope "a" of (2) while monitoring WP and PF for each 30 minutes. As depicted in Fig. 6, WP/PF shows specific patterns per refrigerant mass. Additionally, for each combination of refrigerant mass and the number of bricks, slope "a" of (2) was calculated as listed in Table Ⅴ.

Eventually we classified slope "a" into three groups:

- If a $< 4.0 \times 10^{-2}$, then the refrigerant is insufficiently charged (yellow cells in Table Ⅴ).
- If $4.0 \times 10^{-2} <$ a $< 4.2 \times 10^{-2}$, then although refrigerant is insufficiently charged, T1 can still arrive at the steady state (blue cells in Table Ⅴ)
- If a $> 4.2 \times 10^{-2}$ then refrigerant is fully charged (white cells in Table Ⅴ)

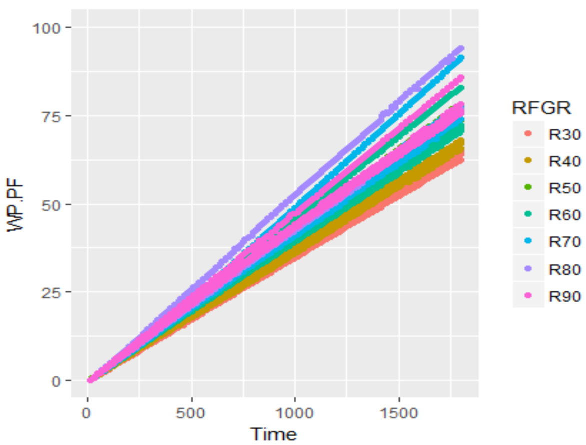

Figure 6. WP/PF varying per refrigerant mass.

TABLE I. SLOPE 'A' OF (2) AT EACH COMBINATION OF REFRIGERANT MASS AND NUMBER OF BRICKS

Refrigerant mass [g]	Slope 'a' of the (2) ($\times 10^{-2}$)			
	Number of bricks [M]			
	M=28	M=14	M=7	M=0
30	3.597	3.627	3.591	3.494
40	3.659	3.799	3.745	(NA)
50	4.357	4.031	4.121	(NA)
60	4.623	3.926	4.009	4.051
70	5.174	4.35	4.226	4.118
80	5.297	4.257	4.276	4.293
90	4.781	4.363	4.234	4.236

IV. VERIFICATION OF THE RULES

A. The Open Door Rule to See if the Door Is Left Open or Closed

To verify the accuracy of the open door rule, we divided up the full data into 3 minute windows, because it is composed with a series of data acquired for each 3 minutes. As shown in Table Ⅵ, total 10,904 windows were obtained. If someone opens the door at the beginning of a 3 min window, and then the door is left open until the end of the 3-minute window, the open door rule would determine the door is open. Unfortunately, if the door is kept closed and someone starts to open it during the last time step of a 3-minute window, the door open rule will determine the door is closed. In the next 3-minute window, however, it is likely the open door rule would determine that the door is left open.

When the open door rule is applied to the actual state, only 6,783 windows out of 10,904 windows (62.4%) are assessed as true, as listed in Table VI. In other words, there is a 37.6% chance of a false alarm; even when the door is actually left open, the rule makes a judgement that the door is "closed" for 92 windows.

TABLE II. ACTUAL STATE VS. ASSESSED STATE BY THE OPEN DOOR RULE

Assessed by the open door rule	Actual State	
	Door closed	Door open
Door closed	6,250 (True)	92
Door open	4,029	533 (True)

B. The Insufficient Refrigerant Rule to See if Refrigerant is Still Insufficiently Charged

To verify the accuracy of the insufficient refrigerant rule, we divided up the full data with 30 minute windows. Although a total of 1,090 windows were obtained, the cases when PF is almost zero (i.e., it arrives at the steady state) were excluded, because it made WP/PF in (2) exceptionally high. Consequently, the insufficient refrigerant rule was applied to only 378 windows.

As described in Table VII, only 195 (=138+48+9) windows out of 378 windows (51.5%) turned out "True" when the insufficient refrigerant rule is applied.

Additionally, when refrigerant is actually insufficiently charged, the rule makes a judgement that 62 and 6 windows are fully and intermediately charged, respectively. This means there is a 33% (68/206) chance that critical false alarms may harm the credibility of the insufficient refrigerant rule.

TABLE VII. ACTUAL STATE VS. ASSESSED STATE BY THE INSUFFICIENT REFRIGERANT RULE

Assessed by the insufficient refrigerant rule	Actual State		
	Insufficient Refrigerant	Full Refrigerant	Intermediate
Insufficient Refrigerant (R30, R40)	138 (True)	6	53
Full Refrigerant	62	48 (True)	51
Intermediate	6	5	9 (True)

V. CONCLUSION

To supplement the previous study, this paper has derived more explanatory variables and rules for diagnosing the operation faults of a freezer. The resulting open door rule and the insufficient refrigerant rule are simple, and they enable a quicker assessment than the machine learning approach. However, these rules have a higher chance of false alarms than the machine learning approach. The detailed prediction performances of the two rules are summarized as follows:

- Freezer wall temperature is found to be the most sensitive variable for diagnosing an open door. When the open door rule based on the freezer wall temperature is applied to the actual state, however, only 62.4% of windows are assessed as “True”. In other words, there is a 37.6% chance of false alarm.
- We also assume that refrigerant mass is proportional to the ratio of accumulated power to the power factor. However, only 51.5% of windows turn out “True” when the insufficient refrigerant rule is applied to the actual state. When refrigerant is actually insufficient, there is a 33% chance that critical false alarms still occur, which can harm the credibility of the insufficient refrigerant rule.

Simply speaking of the prediction performance, machine learning algorithms outperform the simple rules. This underperformance is attributed to their overly simple structure and relationship between variables; thus the rules need to be more sharply defined.

Despite the low performance, the lessons following were learned from this experiment of developing simple rules for diagnosing the operation faults of a freezer:

- To diagnose if the door is left open by means of using machine learning, all three variables (active power, laboratory indoor temperature, refrigerator wall temperature) may not be necessary. Only the freezer wall temperature framed within 3 minute windows appears sufficiently credible, rather than the freezer wall temperature at each time step.
- To diagnose if refrigerant is insufficiently charged, only power related variables including active power and power factor would be sufficient for simpler monitoring, instead of using the three variables (active power, laboratory indoor temperature, freezer wall temperature).

As long as a sufficient amount of baseline data is available, machine learnings may be an easier method than a rule-based method for fault detection, since a certain degree of accuracy is ensured, and the effort to understand the system dynamics and first principle may not be necessary - i.e., they are black box methods. However, we have at least learnt that the variables selected through the typical pruning method of the machine learning process – correlation analysis and regression - could be even more selective when a domain expert understands system dynamics. For future work, we will test the machine algorithms again with the three variables chosen for the simple rules, by which the monitoring cost of the Freezer Keeper (sensors, loggers and etc.) would be downsized if the resulting accuracy is satisfactory.

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