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Fault evaluation process in HVAC system for decision making of how to respond to system faults

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Abstract. One of the effective methods for energy conservation in buildings is to operate the building system with high efficiency and to reduce the waste of power consumption. However, buildings are often considered to contain faults, and a fault is one of the causes of hindering high-efficiency operation. Therefore, in a maintenance plan for building systems, it is necessary process that to detect and diagnose faults. In addition, an operation and maintenance process of building systems using fault detection and diagnosis (FDD) essentially requires evaluating the impacts of faults in order to decide how to respond to faults. However, many studies on FDD have not considered a fault evaluating process. Here we focused on faults in a real heat source system and evaluate the impact of faults and determine the priority to repair faults in order to develop an appropriate maintenance plan of the system. We developed a detailed simulation model of the system combining automatic control system based on the specifications. Using this simulation, we calculated the system behavior without faults and behaviors with thirty-five faults. We evaluated the yearly impact of the faults using the system coefficient of performance (SCOP) and the peak power as indicators. In addition, using the actual FDD results in previous studies, we also evaluated faults in consideration of the actual daily impacts of them. We found that there were differences in the priority depending on the indicators. we expected that this fault evaluation method helps an operation and maintenance of the system.

1. Introduction

One of the effective methods for energy conservation in buildings is to operate the building system with high efficiency and to reduce the waste of power consumption. However, buildings are often considered to contain faults, and a fault is one of the causes of hindering high-efficiency operation. In commercial buildings which of systems are not properly managed and optimally controlled, an estimated 5% to 30% of the energy is wasted [1] [2]. Therefore, in a maintenance plan for building systems, it is necessary process that to detect and diagnose faults and to decide how to respond to them appropriately. Many studies on fault detection and diagnosis (FDD) in a building's operation have been carried out. On the other hand, many studies on FDD have not considered a process of deciding response to faults appropriately. In order to decide appropriate response to faults, an operation and maintenance plan of building systems using FDD essentially requires evaluating the impact of faults [1]. Here we evaluate the impact of faults and determine the priority of faults to repair in order to develop an appropriate maintenance plan of the system.

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In previous studies on the impact evaluating of faults, the yearly impact of each fault on a country unit was calculated using actual measurement data of target buildings [3] [4]. However, the method cannot be used for examination of daily impacts in specific systems. Therefore, in this study, we focused on a specific heat source system and evaluated the yearly and daily impact of faults in the system.
First, we developed detailed simulation model of a real heat source system. Based on it, we calculated faulty system behaviours. Using these results, we evaluated the yearly impact of the faults using the system coefficient of performance (SCOP) and the peak power as indicators. In addition, using the actual FDD results in previous studies [5], we also evaluated faults in consideration of the actual daily impacts of them.

2. Methods

2.1. Target system

In this study, we focused on a heat source system of a real building. The building is a factory completed in 2003. Specifications of equipment in the target system and a conceptual diagram of the system are shown in table 1 and figure 1. This system consists of centrifugal Liquid chiller, primary chilled water pump, secondary chilled water pump, condenser water pump, direct-contact cooling tower. In this system, a control of the number of chillers and secondary chilled water pumps, variable flow rate control on primary chilled water pumps, secondary chilled water pumps and condenser water pumps, condenser water bypass valve control and variable air volume control on cooling towers is performed. Actual operation data were collected by the building energy management system (BEMS) at 15-minute intervals and in this study the data of 2013 and 2014 was used.

Table 1. Equipment specification

Equipment	Name	Specification
Centrifugal Liquid chiller	TR-1 TR-2	Refrigerating capacity: 1,758 kW (500 USRT) Water flow of chiller: 3,145 L/min (15 ℃ → 7 ℃) Water flow of condense: 5,925 L/min (32 ℃ →37 ℃) Output: 298 kW
Primary chilled water pump	CP-1 CP-2	Water flow: 3,145 L/min (15 ℃ → 7 ℃) Pump head: 200 kPa Output: 18.5 kW Calibre: 150 φ × 125 φ
Secondary chilled water pump	CP-3 CP-4 CP-5	Water flow: 3,145 L/min (15 ℃ → 7 ℃) Pump head: 400 kPa Output: 37 kW Calibre: 150 φ × 125 φ
Condenser water pump	CWP-1 CWP-2	Water flow: 5,295 L/min (Min: 12 ℃) Pump head: 250 kPa Output: 45 kW Calibre: 200 φ × 150 φ
Cooling tower	CT-1 CT-2	Water flow: 5,295 L/min (37 ℃ → 32 ℃) Outside air wet-bulb temperature: 27 ℃ Output: 7.5 × 2 kW

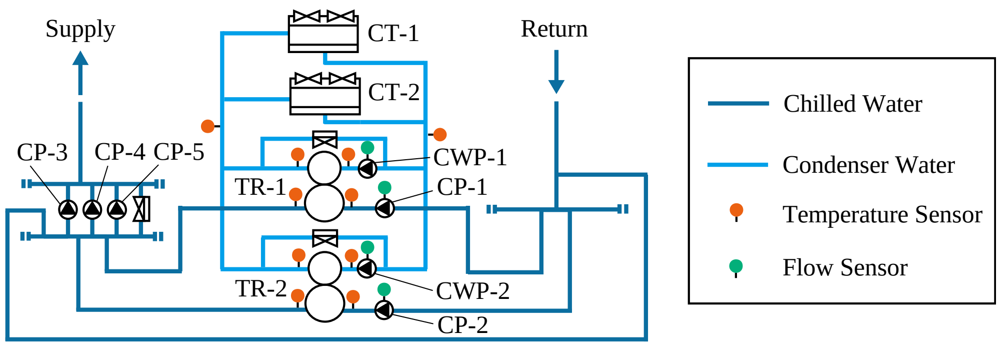

Figure 1. Target system

2.2. Simulation model

In order to quantify the impact of faults in the target system, we developed a simulation model that can calculate the behaviour of the system. Using this model, we can calculate the system behaviour as designed based on the specifications of equipment and control of the target system.

This simulation model was developed by combining automatic control logics based on the specifications and control with the physical models of the equipment. The calculation flow of the model is shown in figure 2. It is performed in the order of automatic control, calculation of flow, calculation of heat, and calculation of power consumption. Five input values are used from the BEMS data: set value of supply chilled water flow rate, a load heat quantity, a set point of supply water temperature, an outside air dry-bulb temperature, an outside air relative humidity. Finally, this model outputs 50 items such as a flow and temperature of chilled water and condenser water, a power of equipment, and so on. In this model, the calculation period is one year, and the calculation interval is one minute by performing linear interpolation on input values. In this study, we calculated by using the BEMS data of 2013 and 2014 as input values.

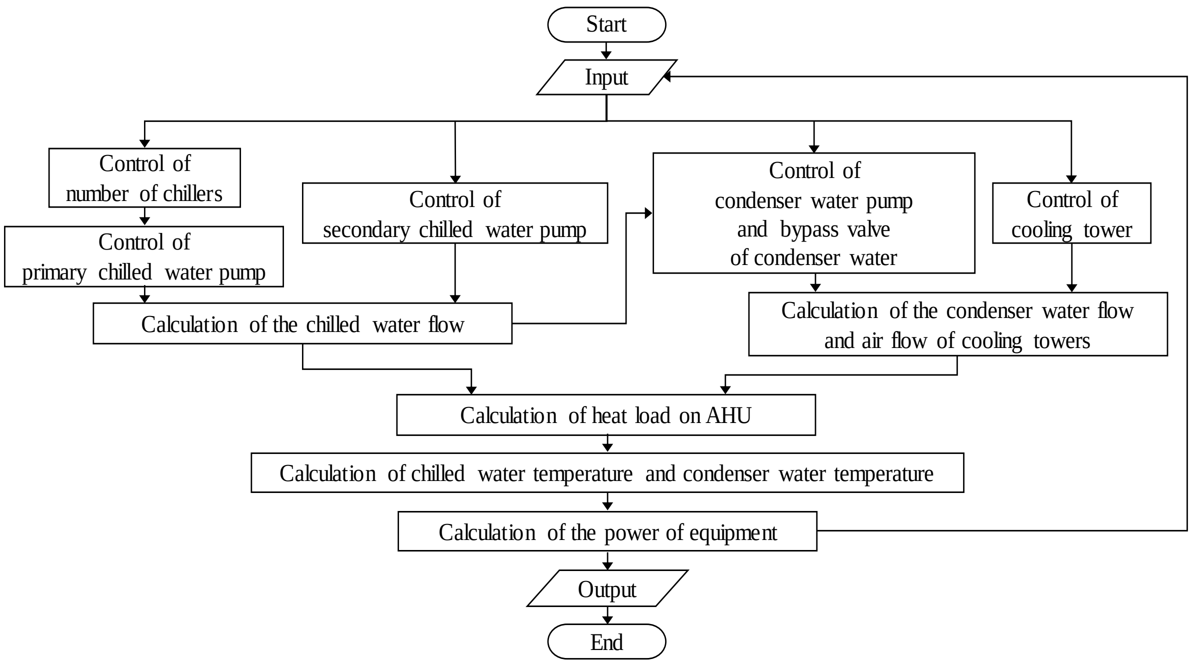

Figure 2. The calculation flow of the simulation model

2.3. Data generation of faulty system behaviour

By using this simulation model, we calculated the system behaviours without faults and with each fault. These behaviours are calculated by incorporating a fault into the simulation model which can calculate the system behaviour without faults. We assumed 35 types of faults shown in table 2 in order to cover a wide range of faults occurring in the system. For each fault, we calculated the system behaviours for two years in 2013 and 2014. In the following fault impact evaluations, we used these calculation results.

3. Results

We evaluated the impact of faults using the calculation results in 2.3. In this study, in order to evaluate the impact of faults, two indicators were used: the SCOP and the peak power. The peak power is a criterion for determining the contract power and the electricity charge. Therefore, the peak power is also an important indicator in the impact evaluation of faults.

For each indicator, we quantified the impact of each fault on the system and compared them. Considering cases where the interval of maintenance is long or short, we calculated the yearly and daily impact of faults in the system.

3.1. Evaluation of yearly impact of faults

Using the calculation result of 2014, we calculated the yearly impact of faults on each indicator. In the case of using the SCOP as an indicator, from the annual SCOP of system behaviour without faults (F0) and with each fault (F1 to F35), the change rate of annual SCOP was calculated as equation (1).

$$RC_{SCOP,Fn} = \{(SCOP_{year,Fn} - SCOP_{year,F0})/SCOP_{year,F0}\} \times 100 \tag{1}$$

where Fn is a fault label, $RC_{SCOP,Fn}$ is a rate of change of annual SCOP due to Fn [%], $SCOP_{year,Fn}$ is the annual SCOP of Fn.

From these results, we ranked the faults in descending order of the annual SCOP decreasing rate. The results are shown in table 3(a). The change rate of annual SCOP was large in F5 and F1. Analysing these faults, it was found that both had the impact of increasing the power consumption of the chiller. In addition, the impact of annual SCOP due to a fault related to condenser water was significant.

In the case of using the peak power as an indicator, from the annual peak power of system behavior without faults (F0) and with each fault (F1 to F35), we calculated the change rate of annual peak power as equation (2).

$$RC_{PP,Fn} = \{(PP_{year,Fn} - PP_{year,F0})/PP_{year,F0}\} \times 100 \tag{2}$$

where Fn is a fault label, $RC_{PP,Fn}$ is a rate of change of annual peak power due to Fn [%], $PP_{year,Fn}$ is the annual peak power of Fn.

From these results, we ranked the faults in descending order of the increasing rate of annual peak power. The results are shown in table 3(b). In the case of using the peak power as an indicator, the impacts of F16 and F26 were significant, and it was different from the impact of the annual SCOP. In addition, the impact of annual peak power due to a fault related to chilled water was significant.

3.2. Evaluation of daily impact of faults

In the analysis on daily impacts of faults, a calculation of fault impacts was taking into consideration the occurrence probability of each fault.

In this study, we used the diagnosis probability obtained from FDD result of this system [5]. The figure 3 shows the calculation result of diagnosis probability in 2014. In a method of calculating the probability of diagnosis, all 35 types of fault data shown in the table 2 were used as training data and test data.

Table 2. Assumed Fault list

Label	Subject of fault	Fault location	Detail of degree of fault
F1	Performance of chillers	TR-1, TR-2	Due to stains inside condensers, the pressure loss of condenser water increases by 15% and the performance of chillers deteriorates by 10%.
F2	Performance of cooling towers	CT-1, CT-2	The heat exchanger effectiveness decreases by 10%.
F3	Performance of secondary chilled water pumps	CP-3, CP-4, CP-5	The pressure loss of chilled water increases by 20%.
F4	Control of the number of chillers	TR-1, TR-2	Only one of the chillers always drives.
F5			Two of the chillers always drive.
F6	Lower limit of chilled water flow	CP-1	The lower limit of chilled water flow rises from 50% of rated value to 70%.
F7		CP-2	
F8		CP-1	The lower limit of chilled water flow drops from 50% of rated value to 30%.
F9		CP-2	
F10	Lower limit of condenser water flow	CWP-1	The lower limit of condenser water flow rises from 45% of rated value to 70%.
F11		CWP-2	
F12		CWP-1	The lower limit of condenser water flow drops from 45% of rated value to 30%.
F13		CWP-2	
F14	Set point of chilled water flow	CP-1	The set point of chilled water flow rises by approximately 10% of the rated value (0.3 m3/min).
F15		CP-2	
F16		CP-1	The set point of chilled water flow drops by approximately 10% of the rated value (0.3 m3/min).
F17		CP-2	
F18	Set point of condenser water flow	CWP-1	The set point of condenser water flow rises by approximately 10% of the rated value (0.6 m3/min).
F19		CWP-2	
F20		CWP-1	The set point of condenser water flow drops by approximately 10% of the rated value (0.6 m3/min).
F21		CWP-2	
F22	Set point of chilled water outlet temperature of chiller	TR-1	The set point of chilled water outlet temperature of chiller rises by 2 degree.
F23		TR-2	
F24	Set point of condenser water outlet temperature of cooling tower	CT-1, CT-2	The set point of condenser water outlet temperature of cooling towers rises by 10% of the rated value (0.5 degree).
F25			The set point of condenser water outlet temperature of cooling towers drops by 10% of the rated value (0.5 degree).
F26	Sensor of chilled water flow	CP-1	The sensor of chilled water flow measures higher by 0.3 m^3/min.
F27		CP-2	
F28		CP-1	The sensor of chilled water flow measures lower by 0.3 m^3/min.
F29		CP-2	
F30	Sensor of condenser water flow	CWP-1	The sensor of condenser water flow measures higher by 0.6 m^3/min.
F31		CWP-2	
F32		CWP-1	The sensor of condenser water flow measures lower by 0.6 m^3/min.
F33		CWP-2	
F34	Sensor of condenser water outlet temperature of cooling tower	CT-1, CT-2	The sensor of condenser water temperature measures higher by 0.5 degree.
F35			The sensor of condenser water temperature measures lower by 0.5 degree.

Table 3. *Yearly impact of faults*

(a) Change rate of annual SCOP

Label	$RC_{SCOP,Fn}$ [%]
F5	-14.46
F1	-7.86
F18	-5.15
F32	-5.15
F10	-4.08
F26	-1.72
F19	-1.64
F33	-1.64
F14	-1.62
F25	-1.49
F34	-1.43
F6	-1.20
F28	-0.71
F2	-0.52
F16	-0.47
F15	-0.45
F3	-0.30
F11	-0.27
F27	-0.26
F7	-0.14
F29	-0.05
F13	-0.02
F24	-0.01
F9	0.00
F8	0.00
F12	0.00
F35	0.07
F17	0.25
F23	1.07
F21	1.13
F31	1.13
F30	2.48
F20	2.48
F22	4.15
F4	4.66

(b) Change rate of annual peak power

Label	$RC_{PP,Fn}$ [%]
F16	32.37
F26	31.73
F1	8.82
F18	2.96
F19	2.96
F32	2.96
F33	2.96
F25	2.17
F34	2.17
F2	0.88
F3	0.35
F14	0.25
F15	0.24
F27	0.20
F6	0.01
F8	0.01
F9	0.01
F5	0.00
F10	0.00
F11	0.00
F12	0.00
F13	0.00
F7	0.00
F29	-0.57
F28	-0.58
F17	-0.74
F24	-0.79
F35	-0.79
F22	-1.80
F23	-1.80
F20	-2.10
F21	-2.10
F30	-2.10
F31	-2.10
F4	-4.09

Next, the convolutional neural network (CNN) conducted FDD for BEMS data of 2014. In order to properly carry out learning by CNN, it is necessary to process missing data which is abnormal data. In this study, we deleted the data for 5 days in 2014 which have missing value.
The diagnosis probability was calculated for other 360 days. The diagnosis probability is result of FDD in a daily basis and is expressing the severity of the diagnosed fault as a relative weighting factor. For

example, on January 1st, F10, F18, F35 were occurring and the severity of them is relatively 45%, 50%,5%. In this study, we used the diagnosis probability as the relative severity of the fault. We assumed that the rate of change of SCOP and the rate of change of peak power change linearly with the severity of faults.

In the case of using the daily average SCOP as an indicator, we calculated the decrease amount of the daily average SCOP due to each fault considering the relative severity equation (3). The calculation result is shown in figure 4

$$DA_{SCOP,Fn} = \left(SCOP_{day,Fn} - SCOP_{day,F0}\right) \times RS_{day,Fn} \tag{3}$$

where Fn is a fault label, $E_{SCOP,Fn}$ is decrease amount of the daily average SCOP due to Fn [%], $SCOP_{day,Fn}$ is the daily average SCOP of Fn in day, $RS_{day,Fn}$ is the relative severity of Fn in day.

In the case of using the daily peak power as an indicator, we calculated the increase amount of daily peak power due to each fault considering the relative severity equation (4). The calculation result is shown in figure 5

$$IA_{PP,Fn} = \left(PP_{day,Fn} - PP_{day,F0}\right) \times RS_{day,Fn} \tag{4}$$

where Fn is a fault label, $E_{SCOP,Fn}$ is increase amount of daily peak power due to Fn [%], $PP_{day,Fn}$ is the daily peak power of Fn in day, $RS_{day,Fn}$ is the relative severity of Fn in day.

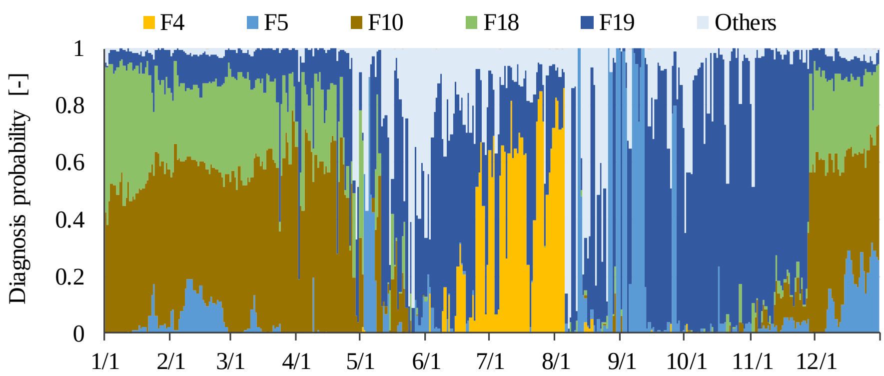

Figure 3. The diagnosis probability in 2014

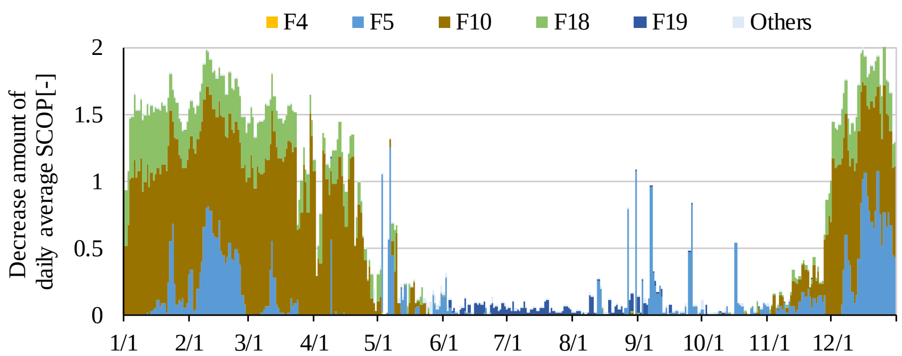

Figure 4. the decrease amount of the daily average SCOP

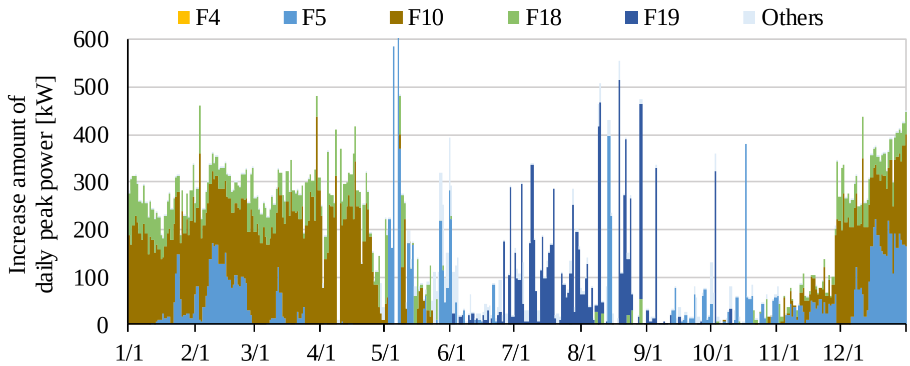

Figure 5. the increase amount of daily peak power

In both cases, the impacts of F5, F10, F18, and F19 were significant. However, there were some differences in the order of them. In addition, although F19 was detected throughout the year, the impact appeared during summer season from June to October in both cases. This is because F19 is a fault of CWP-2 which is a condenser water pump on the side of the chiller TR-2, and the chiller TR-2 are operated mainly in summer.

4. Discussion and Conclusions

We considered that faults with a large impact had a high priority to repair for any indicators. In these results, there was a difference in the priority depending on the indicators. Therefore, when the system manager applies the priority to the maintenance plan of the actual heat source system, the planning policy changes depending on what indicator is emphasized in the maintenance plan by the system manager. In addition, in the cases of using the diagnosis probability of FDD, the high priority faults were narrowed down to several types for both indicators.

We consider that the priorities to repair faults in this study can be applied to another heat source system that has the same heat source equipment configuration (chiller, cooling tower, various pumps) and operates in the same operation method as the target system in this study. In addition, we expected that this fault evaluation method helps an operation and maintenance of a system which have a different heat source configuration. As future work, we considered that it is necessary to investigate more diversely by increasing fault types and indicators. It is also a future work to evaluate faults in a different heat source system.

References

[1] Katipamula S and Brambley M R 2005 Methods for fault detection, diagnostics, and prognostics for building systems—a review, part I *HVACR Res.* **11(1)** 3–25.

[2] Roth K W, Westphalen D, Feng M Y, Llana P and Quartararo L 2005 *Energy impact of commercial building controls and performance diagnostics: market characterization, energy impact of building faults and energy savings potential* (Massachusetts: TAIX LLC) pp 2-1–2-15

[3] Kim J, Cai J, Braun E J 2017 *Common Faults and Their Prioritization in Small Commercial Buildings* (West Lafayette: NREL) pp 14–27

[4] Roth K W, Westphalen D, Llana P, Feng M 2004 *The energy impact of faults in us commercial buildings* (West Lafayette: Purdue University)

[5] Miyata S, Akashi Y, Lim J 2018 Fault Detection and Diagnosis in Building Heat Source Systems Using Machine Learning(Part 2)Preprocessing of Fault Data for Improvement in Diagnosis Performance and Application to BEMS Data *Transactions SHASE. Jpn.* **261** 1–9