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To cite this article: S. Miyata *et al* 2019 *IOP Conf. Ser.: Earth Environ. Sci.* **238** 012070

Model-Based Fault Detection and Diagnosis Using Convolutional Neural Networks in Heat Source System with Water Thermal Storage Tanks

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Abstract. Since a heat source system that produces and conveys the heat for air conditioning comprises various devices, and has complex controls, faults that impair performance occur. Heat source systems are customized, however, and are complicated to the extent that a 'one-fits-all' approach to fault detection and diagnosis (FDD) has not been established. Here we propose a novel method for FDD, using a fault database generated by a simulation, and using convolutional neural networks (CNNs) trained by the database. A real system, with a water thermal storage tank, was the object of this research. Firstly, system behaviors in response to faults were calculated, using a detailed simulation, and then a database was generated, using the simulation results with fault labels. There were 16 fault types in total, which included a condition without faults, four types of faults, and their combinations. The assumed four types of faults: were chiller deterioration by condenser fouling, improper sewage pump set value, heat exchanger fouling, and temperature sensor error at the supply side of the heat exchanger. Then, we preprocessed the database, and converted the data into images, with two axes of time series, and with items from one 24-hour data set as a representative image. Then, CNNs were trained by the database, and trained CNNs were tasked with the diagnosis of real data. The CNNs performed with 98.7% accuracy in training, and diagnosed the real data using probabilities. We reviewed the analysis of the real data, where the probability indicated the likely presence of a fault, and how the real data was similar to the fault severity assumed in the simulation. We concluded that this FDD method will help analyze real data, because it indicates faults emerging in the real data with probability, whereas conventional data analysis requires checking the data using expert knowledge.

1. Introduction

Faults in building heating, ventilation, and air conditioning (HVAC) systems can degrade indoor environment, and can reduce energy efficiency. Faults include equipment malfunction, which stops system operation, however, and some faults simply reduce system performance, even while the indoor environment remains properly controlled. Such faults are the object of this research. It is known that faults cause energy efficiency reductions of 5% to 30% in commercial buildings [1][2][3], making it their detection, diagnosis, and remediation important. A fault is a factor that reduces inherent performance, and fault detection and diagnosis (FDD) is to detect the presence of faults and to locate the faults [4].

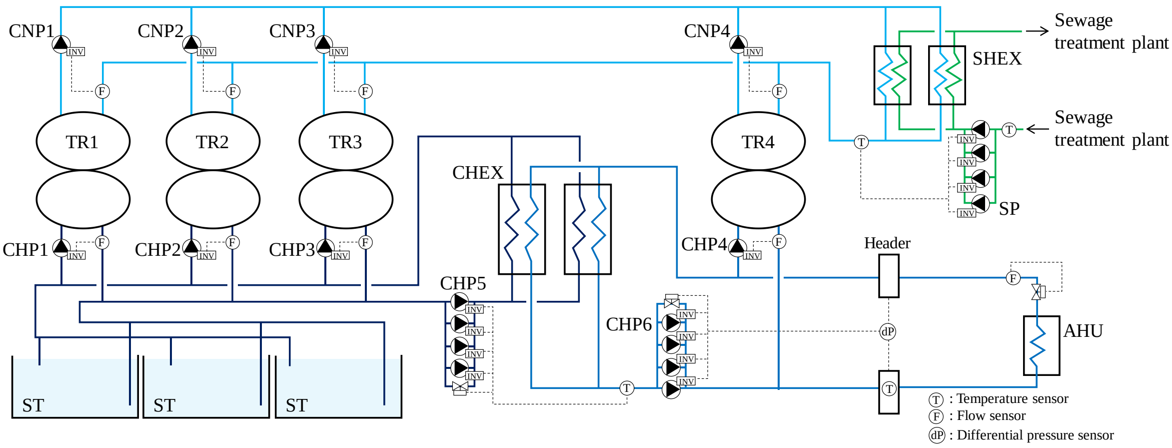
Conventional FDD methods include anomaly detection from historical data, rule-based methods, and model-based methods [5][6][7][8]. The anomaly detection method cannot detect faults which were in the system from the beginning, while the rule-based method engenders a high cost, for tuning the rules. The model-based method has difficulties in dealing with large amounts of simulation results, because compatibility between appropriate data preparation and processing has not been achieved.

On this basis, we regarded FDD as a classification problem, and diagnosed the probability of faults emerging in the system behavior data using Convolutional Neural Network (CNN). CNN requires training data, which presents fault behavior with fault labels. Real data cannot be used as training data, as it may not contain faults, although from our experience, most real data contains faults. To prepare the training data for CNN, we constructed a dynamic simulation so that complicated system behaviors, with faults, could be calculated.

2. Methodology

2.1. Target system

We targeted a real system in an office building in Tokyo, Japan. The test system was the water side of an HVAC system, known as the heat source system (Figure 1). It comprised four chillers and water thermal storage tanks, and used sewage from a treatment plant adjacent to the building for heat removal, instead of cooling towers. It charged heat from 22:00 to 08:00, and discharged heat from 8:00 to 22:00.



TR1~4: Chiller, CHP1~4: TR1~4 chilled water pump, CNP1~4: TR1~4 condenser water pump, CHEX: Heat exchanger for primary/secondary chilled water, CHP5/6: CHEX primary/secondary pump, SHEX: Heat exchanger for condenser water/sewage, SP: sewage pump, ST: Water thermal storage tank, AHU: Air Handling Unit

Figure 1. Target System

2.2. Heat source system

To prepare the CNN training data, we constructed a dynamic model of the system [9][10]. It basically followed the first principles model, so that complicated behaviors of the system, with faults, could be calculated [11]. For example, distributed water flow was calculated based on pressure and valve opening, according to the analogy of Kirchhoff's laws. In addition, temperature in the water thermal storage tank, and inlet and outlet temperature of the heat exchangers, were calculated according to heat transfer principles. The relationships between inverter frequency, water flow, and pump pressures were based on specification curves, and the control logic was based on the specification. Pumps and valves were controlled using Proportional-Integral (PI) control. The simulation calculated variables at one-minute intervals, and output 120 items, including temperature, water flow, pressure, and power, at several points.

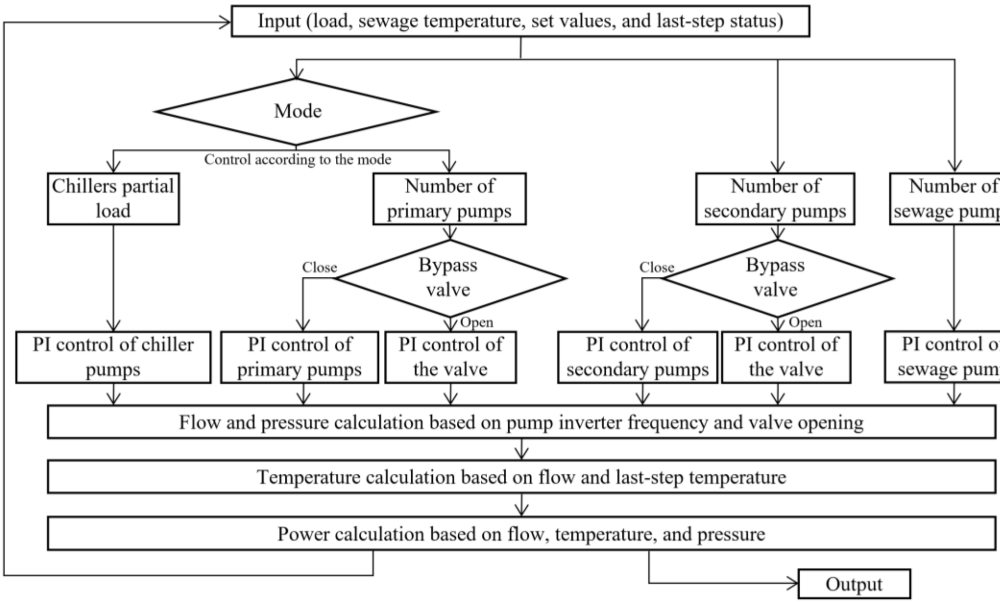


Figure 2. Simulation Flow

2.3. Fault database generation

We calculated a condition without faults, and conditions with four types of faults (Table 1). In addition to these five conditions, we calculated the combination of faults and generated a fault database for 16 conditions. We simulated for a total of 122 days over the period from July to September 2014, generating a total of 1,952 fault-days in total. The input data of the simulation was assembled from real data for the corresponding period. For the fault labelled F2, the approach temperature was the discrepancy between sewage temperature and condenser water outlet temperature, at the sewage heat exchanger (SHEX, see Figure 1). The sewage pumps (SP) were controlled according to the outlet temperature, therefore its set value affected pump power and condenser water temperature, which was a performance parameter for the chillers.

Table 1. Fault and Severities Assumed in Simulation for Database Generation

Label	Subject of fault	Fault detail and severity
F0	No faults	First principles model without faults
F1	Performance of chillers	Due to condenser fouling, the pressure loss of condenser increases by 50% and efficiency deteriorates by 10%.
F2	Sewage pump set value	The approach temperature is set 0.5 °C from 2 °C.
F3	Heat exchanger efficiency	Heat conductance area becomes half.
F4	Temperature sensor	The sensor measures lower than the true value by 1 °C.

2.4. Fault detection and diagnosis by CNN

Appropriate preprocessing of the database was necessary, to utilize the generated fault database as learning data for the CNN. In this research, we converted one set of 24-hour data into an image, as one day was the minimum cycle of the HVAC system behavior, and decision-making on fixing faults would be implemented over periods longer than one day. The real data was collected every 15 minutes, so the database was converted from units of one minute to fifteen-minute units, by averaging values. Then, each value was standardized from 0 to 1, and converted into images (Figure 3). All the images looked very similar, but we anticipated that CNN could extract information from them.

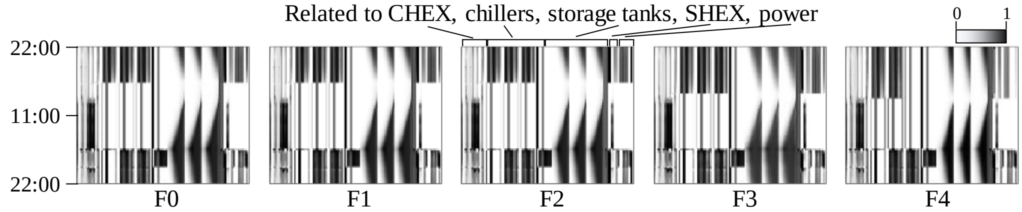


Figure 3. Imaged Data (August 1st, 2014)

CNN is an image recognition method, based on a network modeled with reference to the visual cortex of the brain [12], and the structure of our CNN was prepared referring to [13] (Figure 4). It was assumed that CNN was appropriate for extracting the features of fault behavior, because of its high accuracy. Since the 15-minute data units from one day was the data used to create the image in Figure 3, the column direction was set to 96 while the row direction was set to 120, which was the number of items outputted by the simulation.

In this research, by applying the imaged data to CNN, we made it possible to learn fault features in the column direction, for the time series feature, and in the row direction, for the relationship between items. The CNN output was the probability for each label, and expressed which fault behavior the input data was close to.

We divided the database into training data and validation data. Each fault had 122 data points, and 20 of them were randomly assigned to validation data, with the rest assigned as training data. To moderate the bias of this data assignment, the assignment was implemented 30 times, and 30 CNNs were trained. In the test phase, the trained 30 CNNs diagnosed the real data for the period corresponding to the training data, in 2015. The program was coded with TensorFlow [14].

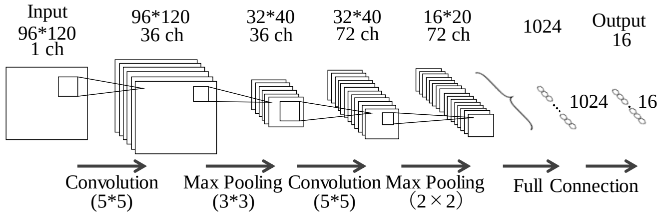


Figure 4. Structure of Convolutional Neural Network

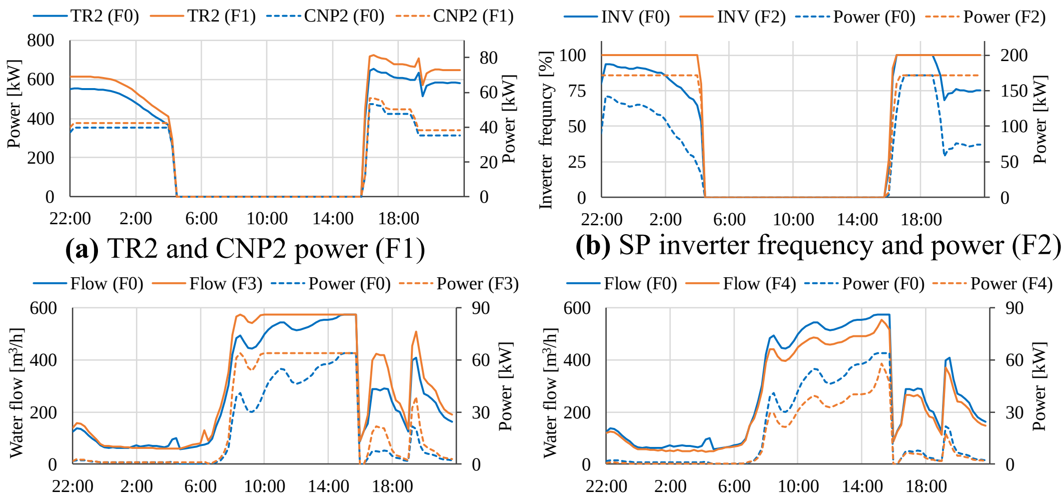
3. Results

3.1. Analysis of fault database

To examine the influence of faults on energy efficiency, a System Coefficient of Performance (SCOP), a quotient of heat supply and energy consumption, and features of the faults in a representative day, were analyzed (Table 2, Figure 5). Faults except for F4 worsened the SCOP, and the SCOP of 'F3 + F4' was almost the same as F0. In the case of F4, the supplied water temperature was higher than for other fault cases, which reduced primary pump power (Figure 5(d)). However, the high supply water temperature was at risk of cooling, at the AHU, which was not modelled in detail in this research. In the case of F3, the primary pumps worked harder to cool the supply water, due to the sensor error (Figure 5(c)). Therefore, F3 and F4 acted with opposite effect, and combined to counter each other's influence on the SCOP.

Table 2. System Coefficient of Performance of each fault

	F0	F1	F2	F3	F4	F1+F2	F1+F3	F1+F4	F2+F3	F2+F4	F3+F4	F1+F2+F3	F1+F2+F4	F1+F3+F4	F2+F3+F4	F1+F2+F3+F4
SCOP	4.92	4.46	4.67	4.82	5.02	4.27	4.37	4.55	4.53	4.76	4.92	4.14	4.35	4.46	4.67	4.26
Ratio [%]	-	-9.30	-4.98	-1.95	2.13	-13.23	-11.15	-7.41	-7.85	-3.17	0.04	-15.78	-11.62	-9.26	-5.08	-13.31



(a) TR2 and CNP2 power (F1)

(b) SP inverter frequency and power (F2)

(c) CHEX primary water flow and CHP5 power (F3)

(d) CHEX primary water flow and CHP5 power (F4)

Figure 5. Analysis of Fault Behavior in the Database (August 1st, 2014)

3.2. Training of CNN

The average validation accuracy of 30 CNNs was 98.7% (Figure 6), and based on this result, we concluded that the CNN learned the features of faults sufficiently well.

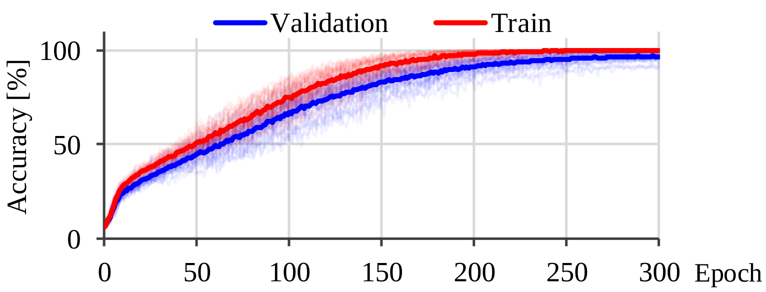


Figure 6. Learning Curves for 30 CNNs

3.3. Diagnosis of real data by the trained CNN

The trained CNN diagnosed the real data (Figure 7). The diagnosis included multiple faults, but Figure 7 shows probabilities where multiple faults were proportionally divided. The result indicated that the real system primarily presented fault F3. F1 and F4 were diagnosed as lower probability throughout the period, and F2 was diagnosed at a specific time.

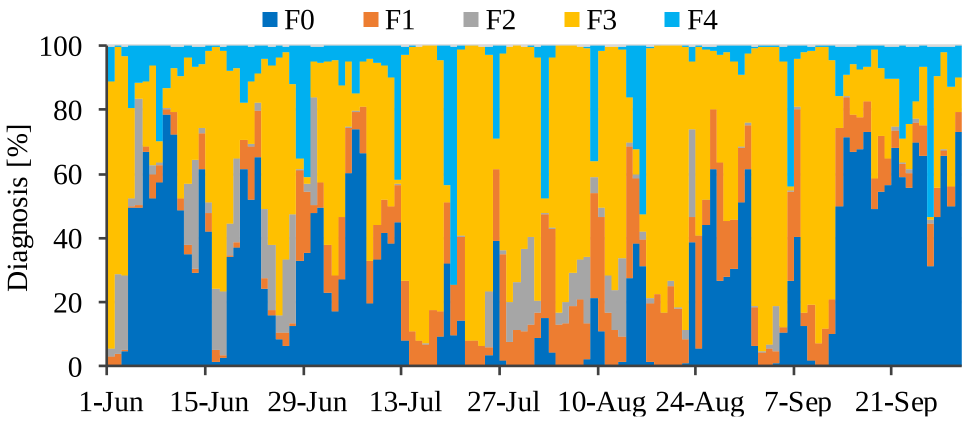
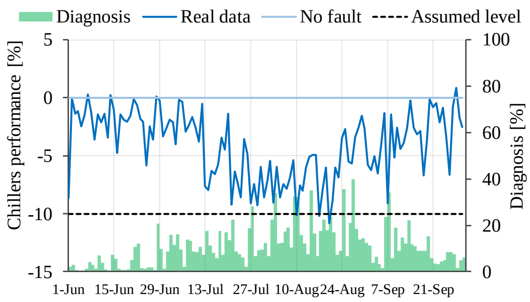


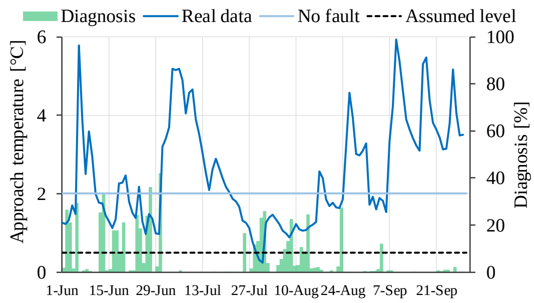
Figure 7. Fault Diagnosis of the Real Data in 2015

3.4. Analysis of the real data

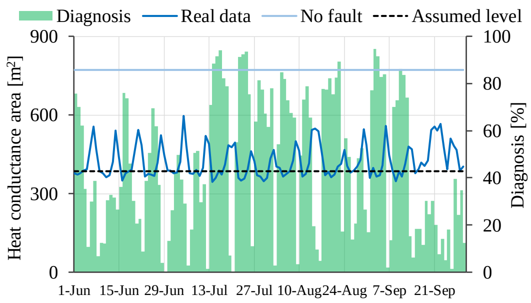
The diagnosed fault probabilities differed daily. Then, fault severities of the real data, assumed severities of the fault severity in the simulation (Table 1), and diagnosis results were compared (Figure 8). For F3, real data and the assumed severity were so close that the diagnosis probability was high. For F1, the closer the real data was to the assumed severity, the higher the diagnosis probability was. For F2, when the real data was higher than the value of no fault, the diagnosis probability was almost zero, while for F4, the real data was much lower than the assumed severity, and the diagnosis probability was also low. The temperature sensor error of the real data in F4 was calculated from temperature at the outlet of the chilled water heat exchanger (CHEX) and the temperature at the chilled water header (Figure 1).



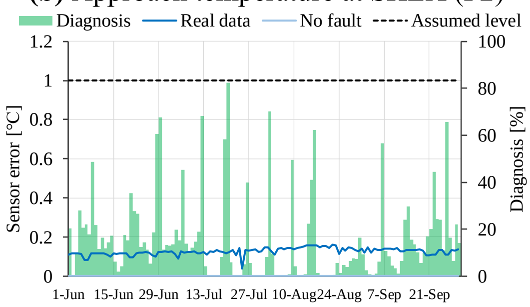
(a) Performance of chillers (F1)



(b) Approach temperature at SHEX (F2)



(c) Heat conductance are of CHEX (F3)



(d) Temperature sensor error at secondary outlet of CHEX (F4)

Figure 8. Fault Severity in the Real Data and Diagnosis Probability

4. Discussion

Considering 98.7% accuracy in training, the CNN had sufficient performance to extract features in faulty behaviors of heat source systems. The results of the real data diagnosis by the CNN basically corresponded with the real data analysis, allowing the conclusion that the proposed FDD method was effective for application to real data. It should be noted that fault severities assumed in the simulation for the database can affect the diagnosis result, because the more consistently the severity was assumed in the real data, the more the fault was diagnosed. This means that the probability indicated the presence of faults, and also how the real data was close to the fault severity assumed in the simulation. Therefore, to achieve more accurate diagnoses, it would be important for the fault severities to be assigned carefully and appropriately.

In Figure 7, F0, which is the case without faults, was diagnosed second highest, possibly because there were other faults which were not in the fault database. In addition, as we can see in Figure 5 (c) and (d), F3 and F4 could cancel out each other's effect. Therefore, the situation where the CNN indicated the status of F3 and F4 simultaneously as F0 could be a misdiagnosis. From the above, future research tasks for our project include expanding the schedule of fault types, and diagnosing multiple faults to include characteristics of faults such as mutual cancelling.

5. Conclusion and implications

Generally, an FDD methodology for building heat source systems has not been established, because the systems comprise various equipment and complex controls, which vary from building to building. We showed the process of developing an FDD through fault database generation, by a detailed simulation, CNN training by the database, and then performing FDD of real data by the trained CNN. It was elucidated that FDD of the real data using the trained CNN was possible, in addition to learning the generated database with high accuracy, as a matter of course. This methodology will help analyze real data, because it indicates faults emerging in the real data through probabilities. For example, if the result indicated that the system has a fault in the heat exchanger, we could confirm the fault by looking at data related to the heat exchanger, instead of checking all the data, or requiring expert knowledge.

Considering the calculation costs for generating the fault database and the CNN learning process, appropriate preparation of the database is very important. Developing a framework for generating fault databases is a future task.

Acknowledgements

This work was supported by Grant-in-Aid for JSPS Research Fellow Grant number JP17J08140 and JSPS KAKENHI Grant Number JP 18K13879. We would like to thank Editage (https://www.editage.jp/) for English language editing.

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