Fault Detection and Diagnosis with Modelica Language using Deep Belief Network

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Abstract

The air handling unit (AHU) is the main component of heating, ventilation and air-conditioning (HVAC) systems, and irregular faults in AHUs are major sources of energy consumption. For energy efficient operation of HVAC, this paper aims to detect and diagnose three abnormal states in the AHU with the popular deep learning model, called Deep Belief Network (DBN), where we train it using various data generated by Modelica.

Key words: Fault detection and diagnosis, Air-handling unit, Deep Belief Network, Modelica

1 Introduction

There has been a consistent significant increase in the awareness of the importance of control strategies for heating, ventilation, and air conditioning (HVAC) systems in the building energy sectors. It is available for use energy more efficient with great qualities of monitored data and well-operated control components which are essential for achievements of entire HVAC control systems. Despite its benefits, however, energy wastes are still considered the main disadvantage with HVAC systems, and therefore, the development of fault detection and diagnosis (FDD) strategies for energy saving in buildings are considered crucial. With this, there have been many studies about FDD in HVAC systems: Massieh Najafi presented modeling and measurement constraints in fault diagnostics for HVAC systems (Najafi et al, 2012); Zhimin Du developed a wavelet neural network-based fault diagnosis in an AHU. The AHU, as one of the main components of HVAC systems, is the heat exchange station between air and water (Du et al, 2008). With this, Modelica is used in the AHU for FDD to identify and prevent application faults and the difficulties they cause.

Generally, the methods of FDD are divided into three different categories which are rules-based, model-based and data-driven methods. The rules-based FDD methods are achieving with expert knowledge and experience rules without any mathematical models (House et al, 2001, Schein et al, 2006). Analysis of detection and diagnosis with checking rules of expert knowledge and experience is accomplished. Contrasting from rules-based methods, model-based FDD methods are attaining based on systematic physical and mathematical models (Salsbury et al, 2001, Yu et al 2002). This method is achieving detection and diagnosis of abnormal states with comparing real values with data gained from models. Nowadays, data-driven FDD method is adopted to apply due to a lot of data are available for gaining from building energy management system (BEMS). Data-driven FDD method is using historical data to detect and diagnose and include different analysis such as neural network (Wang et al, 2002, Lee et al, 2004), wavelet analysis (Du et al, 2008), and the statistic methods (Du et al, 2007, Xiao et al 2009) etc.

The aim of this research is to use a deep belief network (DBN) which is one of data-driven FDD methods achieving detection and diagnosis

Nomenclature

HVAC	heating, ventilation and air conditioning
AHU	air handling unit
FDD	fault detection and diagnosis
DBN	deep belief network
SAT	supply air temperature
RAT	return air temperature
EAT	exhausted air temperature
HIAT	heat exchanger input air temperature
HOAT	heat exchanger output air temperature
HIWT	heat exchanger input water temperature
HOWT	heat exchanger output water temperature
SAP	supply air fan power
RAP	return air fan power
SAE	supply air enthalpy
RAE	return air enthalpy
OAD	outdoor air damper
EAD	exhausted air damper
RAD	return air damper
OADT	outdoor air dry-bulb temperature
OAWT	outdoor air wet-bulb temperature
IT	indoor temperature
EAF	exhausted air flow rate
OAF	outdoor air flow rate
RAF	return air flow rate
SAF	supply air flow rate

abnormal states in AHU. If using data-driven FDD, it is important to use historical data appropriately. Therefore, data mining and machine learning are proper method to conduct FDD with historical data. The normal and abnormal data are gathered from model using Modelica. In this research, proper location and number of sensors are important to conduct FDD system AHU. It is difficult to apply faults in real system, through this procedure; therefore, Modelica is made use of applications of FDD in AHU like as a real system. Considering the data gained from model using Modelica, the machine learning framework uses two kinds of data: training data and test data. After machine learning, the DBN is used to detect and diagnosis specific faults, which will be mentioned in Section 2 of this paper. Figure 1 illustrates the detailed process of the entire fault detection and diagnosis procedure.

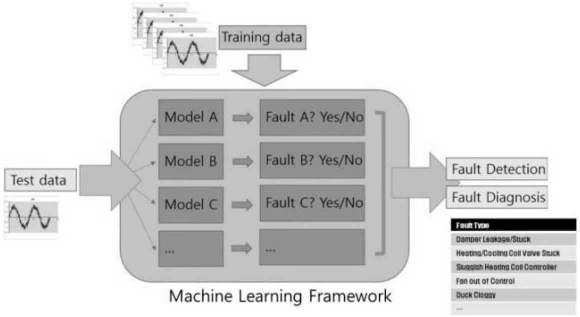

Figure 1. Process of fault detection and diagnosis using machine learning

The paper is organized in four different sections: Section 1 provides an introduction of fault detection and diagnosis with Modelica; Section 2 defines HVAC systems and discusses the faults in the system identified through Modelica; Section 3 is a method of fault detection and diagnosis using machine learning; and finally, Section 4 ends this research with a conclusion.

2 System Description

2.1 Typical system of AHU and HVAC

Figure 2 shows a typical HVAC system in a building. Here, the supply air, the mixture of the outdoor air and recycled air, exchanges heat and humidity with the chilled water in the AHU. The chilled water coming from the chillers is delivered by the pumps to the AHU. After being cooled down by the chilled water, the supply air is delivered to each air conditioning zone by the variable-speed supply fan. Moreover, the return air is divided into two streams by the variable-speed return fan: one stream is exhaust air to the outside of the building, and the other is recycled in the next air circulation (Du et al, 2014).

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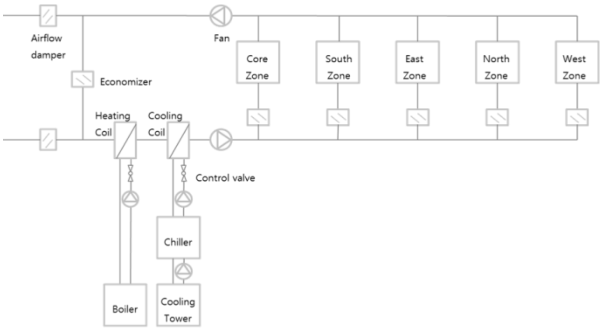

Figure 2. Typical Heating, Ventilation and Air-conditioning (HVAC) system in a building

The supply fan speed is regulated based on the duct static pressure. The return fan controller tracks the supply fan air flow rate reduced by a fixed offset. The duct static pressure is adjusted so that at least one VAV damper is 90% open. The economizer dampers are modulated to track the set point for the mixed air dry bulb temperature. Priority is given to maintain a minimum outside air volume flow rate. In each zone, the VAV damper is adjusted to meet the room temperature set point for cooling, or fully opened during heating. The room temperature set point for heating is tracked by varying the water flow rate through the reheat coil. There is also a finite state machine that transitions the mode of operation of the HVAC system among the modes: occupied, unoccupied off, unoccupied night set back, unoccupied warm-up, and unoccupied pre-cool. In the VAV model, all air flows are computed based on the duct static pressure distribution and the performance curves of the fans. Local loop control is implemented using proportional and proportional–integral controllers, while the supervisory control is implemented using a finite state machine.

To model the heat transfer through the building envelope, a model of five interconnected rooms is used. The five room model is representative of one floor of the new construction medium office building in Seoul, Korea. There are four perimeter zones and one core zone. The thermal room model computes transient heat conduction through walls, floors, and ceilings, and long-wave radiative heat exchange between surfaces. The convective heat transfer coefficient is computed based on the temperature difference between the surface and the room air. There is also a layer-by-layer short-wave radiation, long-wave radiation, convection and conduction heat transfer model for the windows.

Each thermal zone can have air flow from the HVAC system, through leakages of the building envelope (except for the core zone) and through bidirectional air exchange through open doors that connect adjacent zones. The bidirectional air exchange is modeled based on the differences in static pressure between adjacent rooms at a reference height plus the difference in static pressure across the door height as a function of the difference in air density. There is also wind pressure acting on each facade. The wind pressure is a function of the wind speed and wind direction. Therefore, infiltration is a function of the flow imbalance of the HVAC system and of the wind conditions (ASHRAE, 2006; Deru et al, 2009; Modelica Buildings Library ; TARCOG, 2006).

2.2 Modeling of HVAC System with Modelica

Most researches accomplished FDD through simple amounts of sensors or regardless of real control logic of HVAC system. However, Modelica can make the AHU and HVAC system like as a real system. Modelica `Buildings` library carried out the modeling for the HVAC system of a building as shown in Figure 2 in its illustration of specific components of the HVAC system like in Figure 3.

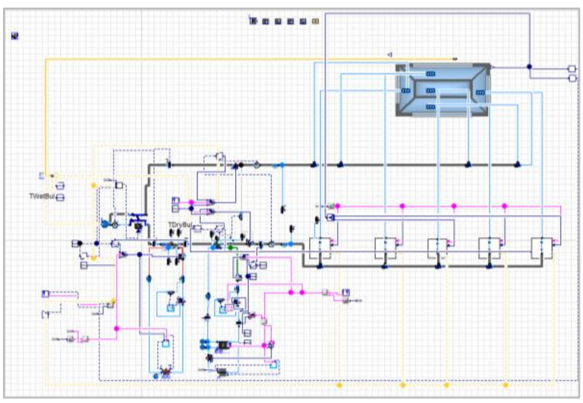

Figure 3. HVAC system accomplished by Modelica

Aside from the modeling of the entire system, the operation logic is also necessary to operate using Modelica. As described in Section 1, this research aims to apply cooling operation only. The operation logic of cooling is as follows.

▶ Cooling Logic

▪ Cooling Coil Control Valve: proportional integral (PI) control is applied to maintain the temperature of supply air at 16°C (k: 0.01, Ti: 600 sec).

▪ Chiller: set temperature of chilled water at 8°C.

▪ Chiller on/off:

- On: schedule of occupants, temperature range of cooling coil inlet at more than 12°C
- Off: temperature range of cooling coil inlet at less than 8°C

▪ Cooling Circulation Pump: PI control to remain pressure of cooling pipe (k: 0.0005, Ti: 100 sec, flow rate: 10 kg/s)

▪ Fan for Cooling mode: Unoccupied night set back, unoccupied pre-cool, safety mode

▪ Fan for Cooling on/off: VAV and PI control to maintain pressure of indoor area at 410 Pa (k: 0.5, Ti : 15sec)

▶ Terminal Box Logic

Terminal Unit Dampers: PI control of damper proportion according to the set temperature of the indoor area (k: 0.1 Ti: 120 sec)

Referenced by Buildings of Library developed by LBNL 1.5/Examples/VAVReheat/Controls/Economizer.mo

2.3 Modelica Testing

This research determined specific data of sensors compared to typical available sensors to check the accuracy of fault detection and diagnosis. Table 1 described the sensors' 21 kinds of data achieved in the research. Determined data of sensors are applied through Modelica.

Data from Sensors	SAT RAT EAT HIAT HOAT HIWT HOWT SAP RAP SAE RAE	OAD EAD RAD OADT OAWT IT EAF OAF RAF SAF

Table 1. Sensors generated by Modelica

As shown in Figure 4, various but necessary sensors in HVAC with Modelica.

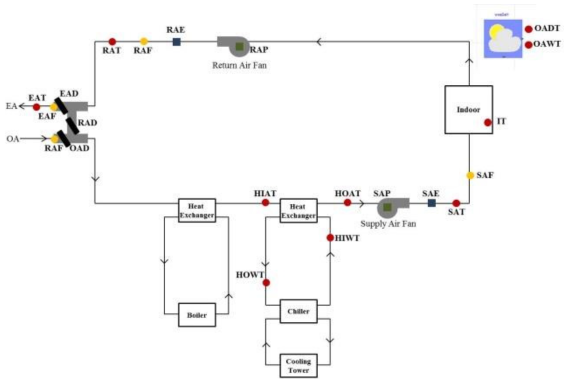

Figure 4. Location of each Sensor in Modelica

2.4 Fault Characteristics

The FDD system is applied to modern engineering fields to detect and diagnose abnormal conditions, faults, or malfunctions occurring in the routine operations of a system before these situations worsen or lead to additional damage to the entire AHU system. In the classification of faults, those with sensors and controllers are considered as one type only because feedback controllers are normally applied to modern engineering systems that mainly guarantee stability if the controller gains are suitably selected (Yuebin et al, 2014). This research focused on the three common faults of supply fans, valves, and heat exchangers. These faults are related to fans getting stuck, leakage of the cooling coil and the low efficiency of the coefficient of performance (COP) of each system. Modelica was used to change the parameters that are commonly used in normal systems.

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2.4.1 Instances of Supply Fan Getting Stuck

The instance of a fan getting stuck is one of the major problems in the use of supply fans. When a fan gets stuck, flow rates through the fan are decreased. Based on this theory, the instance of a fan getting stuck is achieved by Modelica by decreasing the flow rates at 60% compared to the normal operation of a supply fan. 60% of flow rates in the fan are assumed that flow rates are decreased when the fan getting stuck. Figure 5 described the control of the flow rates of a supply fan.

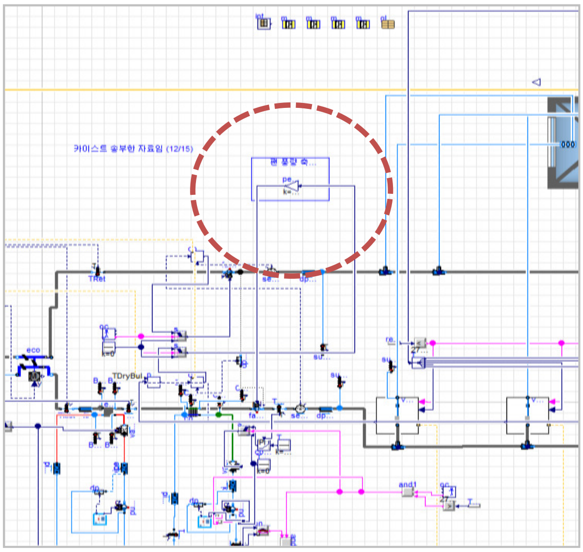

Figure 5. Implementation of supply fan getting stuck with Modelica

2.4.2 Leakage in Cooling Coil Valves

Leakage in cooling coil valves gives rise to an abnormal operation state. Modelica language can set the fault of leakage in cooling coil valves. The parameter of leakage value is represented by "L" and to accomplish the change of valve leakage from 0.0001 to 0.1 ((L=Kv(y=0)/Kv(y=1). "y=0" means fully closed state of the valve, "y=1" means fully opened state of the valve. Figure 6 describes the possible method to control the leakage in a cooling coil valve.

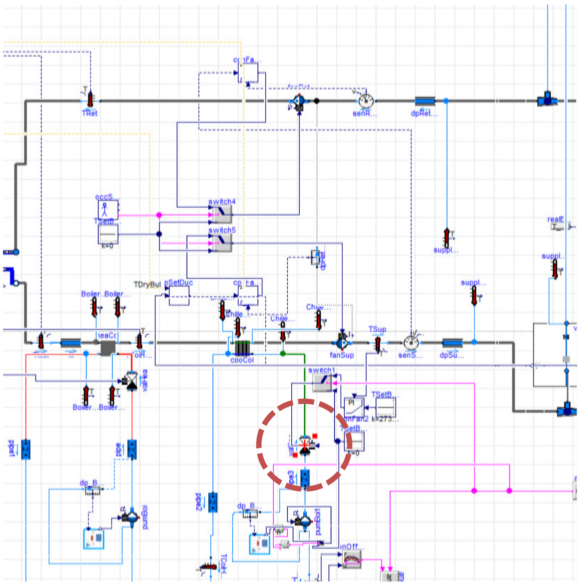

Figure 6. Implementation of leakage in cooling coil with Modelica

2.4.3 Low Efficiency of Heat Exchanger

The heat exchanger of the AHU is located between the return fan and supply fan. When the capacity of the heat exchanger is lower than that in its normal operation, the HVAC system will malfunction. Low thermal conductance means that there is low efficiency between the components of the heat exchanger. In this logic, the fault of the heat exchanger is achieved by Modelica by changing the thermal conductance from 30 kW to 15 kW. Figure 7 describes how the thermal conductance of the heat exchanger can be changed.

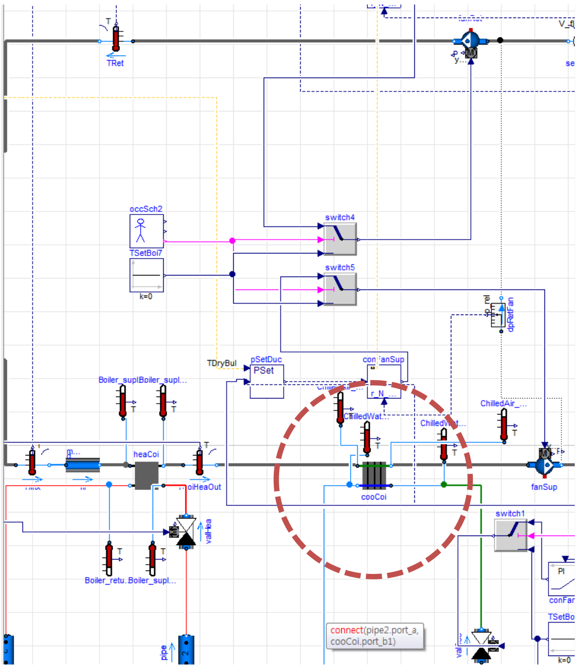

Figure 7. Implementation of low efficiency of heat exchanger with Modelica

2.5 Simulation

A total 21 kinds of data from sensors and their respective simulation with Modelica of normal state and 3 different faults states are achieved in 10 days of the summer period. Normal states of simulation are calibrated based on the logic of operation. With the results of simulation with Modelica, this research achieved various results between the normal state and the three different faults of the HVAC system. Difference between normal state and three different faults are shown from Figure 8 to Figure 10.

However, it is difficult to detect and diagnose various faults not just in the application of results of simulation in various circumstances. This means that one fault of the HVAC system has different effects on the data of sensors compared to other faults. Therefore, with machine learning, Section 3 explains the method on how to deal with wide usage involving various fault detection and diagnosis instances.

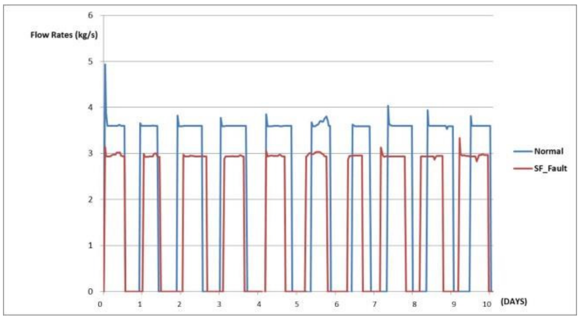

Figure 8. Comparison flow rates of return air between normal and instances of supply fan getting stuck with Modelica simulation

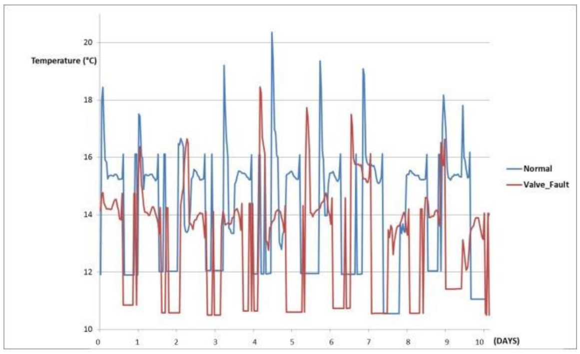

Figure 9. Comparison water temperature of heat exchanger outlet between normal and leakage of valve with Modelica simulation

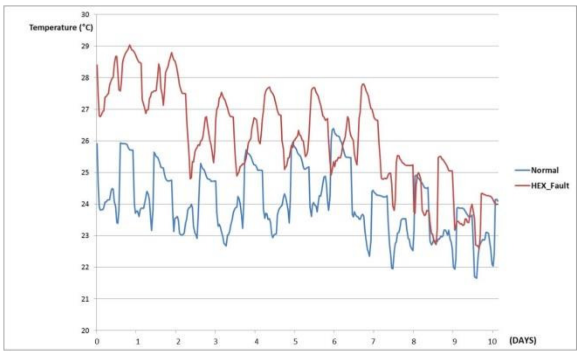

Figure 10. Comparison room temperature between normal and heat exchanger with Modelica simulation

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3 Fault Detection and Diagnosis

After the application of results with Modelica as the normal and abnormal data, the fault detection and diagnosis process using machine learning is achieved as shown below. Data are filtered through the pre-process procedure, machine learning with a classifier procedure, and fault detection and diagnosis accomplished by the post-process procedure.

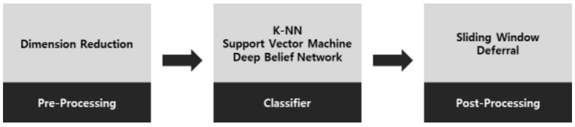

Figure 11. Process of FDD

3.1 Pre-processing

"Pre-processing" is a necessary procedure to minimize several irregular a number of results from sensors of AHU in Modelica due to status of building and environments. First, normalization process is essential process for the analysis of data gained by Modelica to standardize irregular data which are regardless of times and seasons into regular data. Mean and standard deviation values are attained in normalization process, and these values are normalized to distinguish normal from abnormal states. Second, there is a need to binarize all data because of the structure of a DBN. DBN only uses to binarized data. The binarized data have great effects of accuracy to establish the performance before classification (Masmoudi et al, 2013). After normalization, most data are shown near the value of zero, assuming low frequency when the values are far from zero. In this process, the data are quantized and assigned with their respective bits—to be compressed into either 8 bits or 10 bits. The error rates of 8 bits and 10 bits are as follows. The research assumed that 8 bits and 10 bits are enough to conduct the performance appropriately.

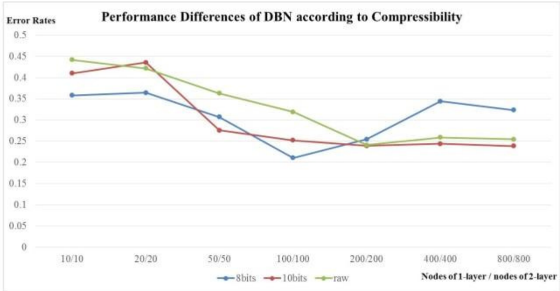

Figure 12. Performance differences of DBN according to compressibility

As a result, 10 bits of compressibility have better performance compared to others. Therefore, this research applied 10 bits of compressibility of data into fault detection and diagnosis.

3.2 Classifier: Deep Belief Network

"Classification" is the process of fault detection and diagnosis when the data of the sensors with Modelica are attained. Among the various classification methods such as support vector machines (SVM), k-nearest neighbors (K-NN) and so on based on other researches, this research used the "deep learning method," which is one of the most popular machine learning methods available. Because there is no information on normal or abnormal data of sensors with Modelica using a classifier, this research made use of a deep belief network (DBN) as a classifier, which uses various data to assess whether the data are normal or abnormal. Before using the DBN classifier, durations (number of iterations) and structures are needed to be determined. Tests are repeatedly carried out to attain the appropriate the number of iterations and structures of the DBN. The results of such tests are as follows.

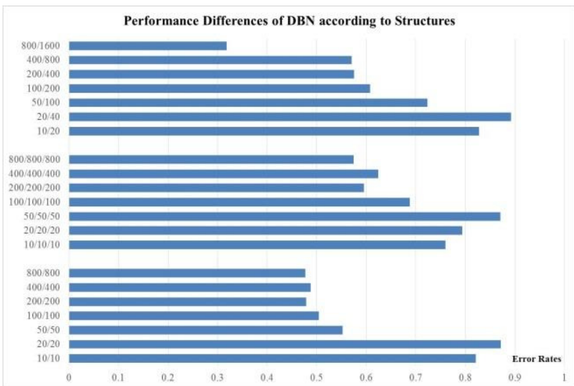

Figure 13. Performance differences of DBN according to structure

The structures of DBN are attained from 2-layer models to change the number of nodes of layers. As in the first row of Figure 11, 800/1,600 means that the test conducted 800 nodes of the first layer and 1,600 nodes of the second layer.

Also, this research conducted the number of iterations that is suitable to achieve optimal values. The results of 300 and 1000 as the number of iterations are as follows.

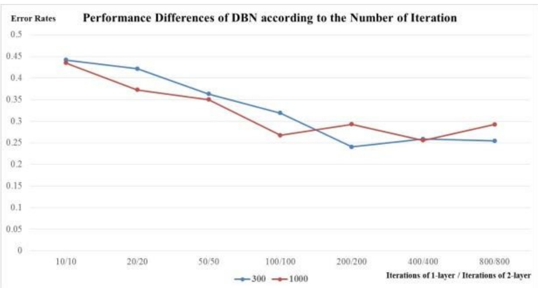

Figure 14. Performance differences of DBN according to the number of iteration

As the results, 800–1,600 of 2-layers and 300 as the number of iterations are appropriate to the application of the DBN. In this research, 2-layers are enough to accomplish the performance due to short-time calculations.

In Section 2, three faults are appointed and the results of fault detection and diagnosis are shown in Table 2.

Faults	Detection and Diagnosis (%)
Supply Fan	81%
Valve	85%
Heat Exchanger	99.16%

Table 2. Results of FDD

3.3 Post-processing

"Post-processing" is the process that increases the rates of detection and diagnosis, and this is where the deferral rate is set. "Deferral rate" means the instance in which no decision is made as the judgment does not ensure whether which is normal or abnormal. If there is a deferral rate of 11%, 89% of the data are used to determine the test. The results of the detection and diagnosis rates that take the deferral rates into consideration are shown in the Table 3.

Faults	Detection and Diagnosis (%)	Deferral Rate (%)
Supply Fan	95%	11%
Valve	95%	31%
Heat Exchanger	99.16%	0%

Table 3. Results of FDD considering deferral rates

4 Conclusion

Various researches on fault detection and diagnosis in HVAC systems have been published; however, these studies lack inclusion of data on real sensors and disposal of noises. In addition, actual application of data measurement of simple correlation is difficult despite the use of complicated models and methods. To overcome such limitation, this research used the machine learning method, and verified fault detection and diagnosis using specific data with Modelica like as a real AHU of HVAC system. The accuracy of the results of this study's fault detection and diagnosis was given an approximate score of above 95%. With this, it is necessary to verify actual data from real buildings for future studies.

Acknowledgments

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