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4S3F Diagnostic Bayesian Network method: discussion about application and technical design

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Abstract. In practice, automated energy performance fault diagnosis systems are seldom installed in HVAC systems. The main reason is that a specific Fault Detection and Diagnosis (FDD) setup is time-consuming and expensive because the existing methods are component-specific, not aligned with HVAC design practices, and not fully automated. 4S3F (four symptoms three faults) method, based on system engineering and Diagnostic Bayesian Networks (DBN), was proposed to decrease the gap between the design of HVAC systems for buildings and energy performance diagnosis, and proofs of concepts were tested on diverse parts of the HVAC system of one specific building. In order to test the further applicability potential of the method, it is necessary to expand these tests and to study possible problems arising in practice, like the lack of sensors installed in a specific system or practical difficulties in the construction of the 4S3F Bayesian network by HVAC or control. However, due to the small number of validations carried out on the environment, parameters, and installation process of this method still need further discussion and refinements. In this paper, we investigate how to construct the DBN for the quite generic AHU (Air Handling Unit) of a, with mechanical supply and exhaust, heating and cooling coils, and heat recovery. The paper describes the possible DBN's depending on the technical design and the measurement points. The diverse Bayesians networks are compared, and it is concluded that also, with a limited number of sensors, a diagnostic network can be set up. It is also concluded that step-by-step instructions would be needed to facilitate the work of HVAC engineers when setting up the diagnosis model.

Keywords. Bayesian network, building energy performance, building energy diagnostics
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1. Introduction

10-30% of the energy used in buildings is wasted even in the most modern ones due to malfunctioning, degradation of the installed equipment, and suboptimal setpoints. The developments in the smart meter field, sensors, building management systems, and machine learning or artificial intelligence algorithms provide an opportunity to monitor real-time building performance, occupant behaviour, energy consumption and analyze the real-time data flow for building diagnosis and control. Taking the benefit of the development of these technologies, fault detection and diagnosis (FDD) technology for buildings has taken a big leap in recent years, and various amount of FDD methods for building energy systems have been proposed and developed, such as for HVAC level energy efficiency [1-3], chillers [4-6], air handling unit [7-10], sensors [11]. Effective FDD tools for building system is estimated to save 10-40% building energy consumption [12]. However, automated energy performance diagnosis is seldom applied in practice despite many proposed methods. Many researchers have recognized the major challenges in faults diagnosing of building energy systems in the last decade [13-16]. The first reason is that the setup of FDD methods is highly customized for each building because of different types of sensors, air handling unit, chillers, hot coils and available data. This condition makes standardization and a consistent approach for a broad application difficult. Second, It is very time-consuming to design and set up a FDD model. Third, when data-driven model are used, data about the correct functioning of the equipment is needed, but very difficult to obtain Fourth, when white-box models are used, they are difficult to set up for a complex system. Fifth, it is hard to apply the current methods to novel energy systems such as smart energy grids, thermally activated building systems, and adaptive façade, it. Sixth, an integrated approach for different HVAC components, controls, indoor environments and energy performance is lacking. Sevenths, energy performance FDD is far from being automated. In most scenarios, only data monitoring from BMS is automated, and HVAC engineers or energy experts need to diagnose the faults based on their experience.

In order to fill these gaps, the 4S3F (4 symptoms and

3 faults) method was proposed and proven by Taal [16]. This method separates the detection of symptoms and the diagnosis of faults. In the symptom detection part, the complete list of possible symptoms is generated from the HVAC diagrams and all possible components and their control systems. They are then checked constantly during operation. In the fault diagnosis and isolation part, all possible faults are identified from all possible components, models, and controls in the HVAC diagram. Then, symptoms and faults are connected through Diagnostic Bayesian Network (DBN). Using DBN models, the faults are identified based on the probability of observed symptoms, and the diagnosis runs simultaneously through all system levels. However, due to the small number of installations in practice so far, the possible problems that appeared in practice during the technical design are rarely studied and discussed, such as the lack of sensors or how to choose the system level of the Bayesian network model for certain HVAC components. In this paper, the 4S3F method is set up for the AHU (Air Handling Unit) of the HHS building, a generic type with mechanical supply, exhaust, heating and cooling coils, and heat recovery. This paper describes and compares diverse possibilities for the Bayesian network and discusses how the 4S3F method could be applied under different scenarios and conditions (e.g., limited number of data points and sensors). After an introduction of the 4S3S method in section 2 and a description of the air handling unit in section 3, the setup of the Bayesian network in the current sensor environment is researched in section 4, while the setup in a sensor-rich environment is explained in section 5 and the set up in a sensor-poor environment in section 6. Current AHU's may have few sensors, and it is relevant to show which diagnostics can still be done in this case. Sensor-rich environments, on the other side, are expected to become more common and to improve the quality of the diagnostic. They are compared in section 7and conclusions are drawn in section 8.

2. Introduction of 4S3F method

2.1 4S3F method

Symptom detection methods vary in FDD methods for energy performance. The detection is made by comparing actual and simulated energy performances in quantitative model-based methods, applying "operational state of systems, components, and controls" in rule-based methods, and tracing irregularities in the possibly correct operational patterns in data-driven methods. Frequently, further information obtained from maintenance and inspection data is also collected. In order to clarify the complicated symptoms in different methods, four categories are summarized by Taal [16]: "Balance symptoms," "Energy Performance (EP) symptom," "Operational State (OS) symptoms," and "Additional systems."

1. "Balance symptoms," based on energy balance deviations, belong to the quantitative model-based approach established from system theory and the first law of thermodynamics. Only balance equations are used, but not complex white-box models.
2. "Energy Performance (EP) symptom," based on deviations in energy performance metrics, like a deviation from an expected COP, is applicable for both quantitative and qualitative model-based approaches.
3. "Operational state (OS) symptoms," based on deviations of operating state from the expected conditions, e.g., a temperature or flow is not as it should be. This symptom could be either a qualitative model-based approach or a data-driven approach, and the outliers could be estimated through the historical data.
4. "Additional symptoms," based on additional information, are gathered either from historical and maintenance data or results from specific FDD included in trade components.

DBN diagnoses provide an effective solution in the HVAC fault diagnosis area because a DBN model is based on the probability theory in which the probability of faults is calculated according to the occurrence of symptoms. Therefore, the diagnosis process of DBN is very similar to the operation methods of HVAC experts. In the 4S3F approach [17, 18], all faults are divided into three general categories:

1. Component faults: Components faults include malfunction and degradation of the components, sensors, and incorrect installation or design.
2. Control faults: Control faults include incorrect setpoints, on-off control of components, and software faults.
3. Model faults: Model faults include models that are constructed to calculate missing and derived measurements or parameters. It also includes wrong assumptions (e.g., no heat loss in ducts).

The relationship between the Four types of symptoms and three types of faults is described in ***Fig. 1***.

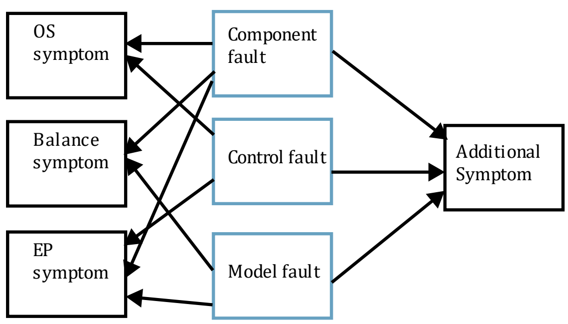

Fig. 1 – 4S3F DBN model faults and symptoms relationships from [16].

2.2 4S3F model setup

There are several steps to set up a 4S3F DBN model. Firstly, the object systems and subsystems should be selected. It is essential to choose a system or aggregated systems that have minimal necessary sensors—secondly, the presence and the absence of symptoms should be determined. There are two steps for symptom detection. At first, all possible symptoms are listed once during the setup, based on the I&PD. Secondly, and not handled in this paper, symptoms are detected in certain time spans during operation (e.g., hours, day, week, month), and the automated comparison between the recorded value and expected value is processed, see [16, 17]. Thirdly, once the list of all possible symptoms has been determined during setup, the possible faults should also be identified the same way based on the system diagrams. Fourth, as one symptom can arise from many different faults, a fault can lead to various symptoms. Hence, the combination of all observed symptoms should be analyzed and linked to possible faults. Fifth, once all possible faults and symptoms are identified, the relationships between faults and symptoms are translated to a DBN, with which the probability of a specific fault can be estimated. The structure of the DBN is very similar to the structure of the HVAC diagrams. Therefore, the construction of this DBN model is expected to be straightforward for HVAC engineers.

3. Description of the Air Handling Unit (AHU)

3.1 Scheme of the AHU in HHS building

The Air handling unit (AHU) of the HHS building is quite a standard and generic one and is used to demonstrate the different ways of setting up the Bayesian network in the 4S3F method. The HVAC diagram of the AHU system (See ***Fig. 2***) is used.

The AHU provides ventilation and partial heating, cooling to the different building zones, and consumes a significant amount of energy. The AHU in HHS has a mechanical supply and exhaust and heat recovery. For the supply part (below in the diagram), it consists of an inlet damper (ID), filter (IFI), heat wheel (WW30-01), heating coil (HC), cooling coil (CC), fan (IF) and noise reduction damper (ND1). For the exhaust part (above in the diagram), it consists of an outlet damper (OD), filter (OFI), heat wheel (WW30-01), and fan (OF). The heat wheel recovers heat from the output air to the input air. CD30-02 and CD30-1 are motors to control the opening and closing of the inlet damper (ID) and outlet damper (OD). TV30-01 and AV30-01 are motors to control the speed of the fans. The fresh air is taken from the outside. The inlet flow rate sensor FT30-03 records the intake airflow. The inlet filter (IFI) will then remove the finer particles in the intake air. After air passes through the heat wheel, the heating coil (HC) would be switched on if the heating is needed. The cooling coil (CC) will be switched on if cooling is needed. When the heated or cooled air passes through the intake fan (IF), it will be accelerated. The noise reduction damper (ND1) will reduce the noise from the system. After the air passes through the noise reduction damper, it will be pushed to the building rooms. The exhaust air will be sucked into the output duct from the building rooms. The sucked air will pass the noise reduction damper (ND2) at first. The output filter (OFI) will remove the finer particles as the intake filter. The heat wheel will recover some heat from the exhaust air to the supply air through conduction heat transfer. The output fan (OF) will accelerate the speed of air. The output flow rate sensor FT30-04 records the exhaust airflow. After passing through the output damper, the exhaust air will be pushed to the exterior of the building. The available sensors are also shown in the diagrams (***Fig. 2***). FT30-03 and FT30-04 are flow sensors. PDT30-01 and PDT30-02 are pressure difference sensors. They can record the pressure difference of the filters. TA30-01 is a temperature sensor. It records air temperature after the heating coil. TT30-05/MT30-01 and TT10-06/MT30-02 are temperature sensors and moisture sensors. PT30-01 and PT30-02 are pressure sensors. They record pressure in the duct. It can detect smoke in the duct. The output air (OA) is measured by the temperature sensor TT30-10, and the input air (IA) is measured by the temperature sensor TT30-00.

In the zoom-in diagram (***Fig. 3***), FT31-01-65-1 and 64-6 are flow sensors. TT31-01-64-7 and 64-4 and TT31-02-64-8 and 64-5 are temperature sensors. They record water temperature before and after the heat exchange process. The heating coil is connected to a heat generator (e.g., boiler or the condenser of a heat pump). The cooling coil is connected to a cold generator (e.g., the evaporator of a chiller or a reversible heat pump, or an ATES system).

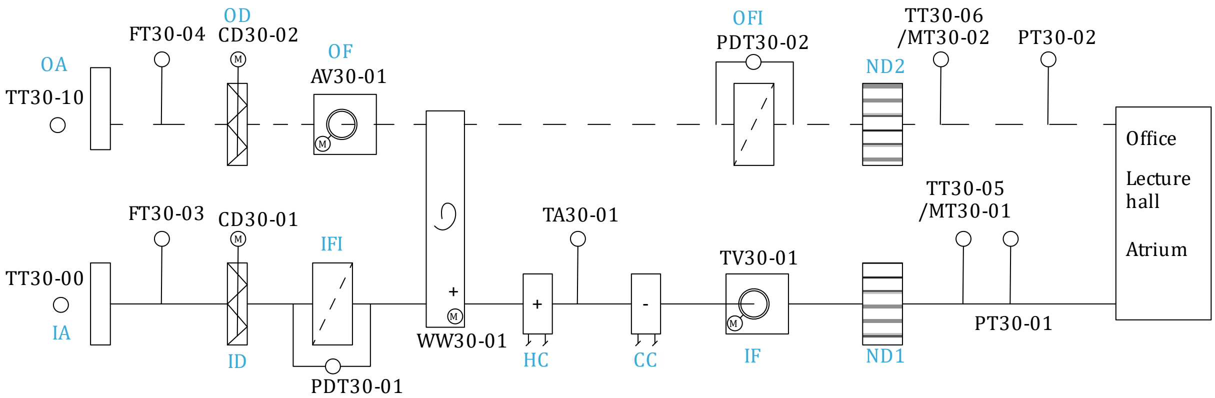

Fig. 2 – P&ID diagram of AHU in HSS

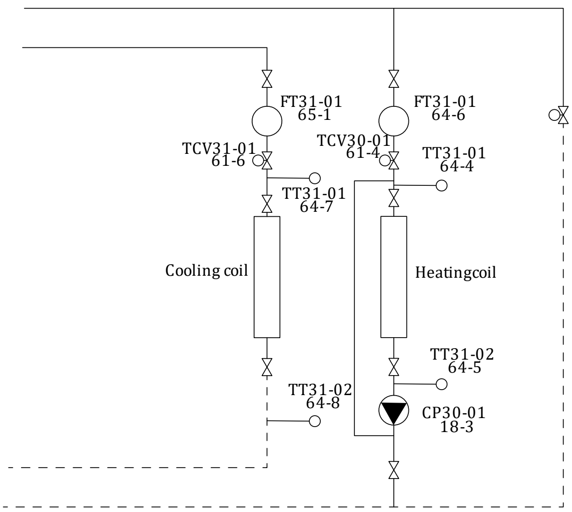

Fig. 3 – P&ID diagram of Heating and cooling coil

4. Case one: Setup in Actual environment

The AHU in the HHS building is quite generic. Once the DBN for this AHU has been constructed, it can be used in many other types of AHU systems with few modifications. In the actual setup environment, the symptoms of balance, Energy performance (EP), an operation state (OS) are considered. As described in the AHU scheme section, there are several possible balance symptoms. The heat losses in the diverse systems, components, and mechanical efficiencies are indicators for energy balance symptoms determination. These symptoms could be calculated from aggregated systems or subsystems. As shown in ***Fig. 2***, there are two levels of systems presented, which are the AHU system, including heating coil and cooling coil, and the heating coil and cooling coil as a subsystem shown in ***Fig. 3***. At the AHU system level, based on the information from the collected sensors, the following symptoms could be determined. Symptoms arise from information that can be measured and therefore relates strongly to sensors.

4.1 Energy balance symptoms

To identify energy balance symptoms, incoming energy and outcoming energy need to be calculated and measured, which means the measurement of flow rate and temperature from different components, systems, or subsystems are usually required. There are two observed energy balance symptoms. A first symptom will be if the energy balance on the heating coil is not zero. The water flow in the unit is recorded by FT30-01 (**Fig.3**). Temperature before the water goes into and after the heating coil is recorded by the temperature sensor TT30-01 and TT30-02 (**Fig.3**). By using this information, heat transfer could be calculated. The heat transferred from the heating coil to AHU can be calculated by using the total heat after the heating coil minus the heat generated before the heating coil. The total heat after the heating coil is derived from sensor TA30-01. The heat generated before the heating coil is calculated by TT30-00, FT30-03, and the recovered heat from the heat wheel. The recovered heat from the heat wheel was obtained by creating a "virtual sensor" by knowing the heat wheel efficiency, which will be introduced in 4.2. If the result of this balance is not zero, it will be considered unbalanced. Second, the energy balance on the cooling coil is not zero. Same as the heating coil, the water flow in the unit is recorded by FT30-01(**Fig.3**). Temperature before the water goes into and after the coiling coil is recorded by the temperature sensor TT30-01 and TT30-02(**Fig.3**). The heat generation of the cooling coil could be calculated through sensors information, and the total heat after the coiling coil is obtained by TT30-05. However, more symptoms may be identified if more temperature sensors were installed. This possibility will be discussed in case two.

4.2 Energy performance symptoms

The actual efficiency of the heat wheel (HW) being different from the efficiency rating listed by the heat wheel producer could be considered as a performance symptom. No other energy performance symptoms can be determined as the only specifications found from the supplier's information are the heat wheel's efficiency rating. In this AHU diagram, the intake flow rate (IFR), input air temperature (IA), Air temperature after heating coil (TAH), output air temperature in the duct(OAD), output air flowrate (OFR), and output air temperature (OA) are recorded by the various sensors. The heat generated from the heating coil (Qheat) is calculated through diagrams shown in ***Fig. 3***. Using these data, the heat recovered from the heat wheel could be estimated and compared with the efficiency rating provided by the supplier.

4.3 Operation state symptoms

The observable OS symptoms are as follows:

1. Difference between the AHU temperature setpoint and the recorded data from the temperature sensor TT30-05.
2. The cold-water supply temperature from TT31-01 is different from the specifications.
3. The hot water supply temperature from TT31-01 is different from the specifications.
4. The abnormal pressure difference of the inlet filter and outlet filter pressure sensors

These are all components being controlled. No other operational symptoms can be observed from the P&ID.

4.4 Identifiable faults

Basically, a fault is everything that can potentially ever be wrong. In the current case, all three types of possible faults can be identified as follows.
1. The control of the AHU temperature setting (TS) can be faulty.
2. The twenty-six components of the AHU can be faulty, including twenty sensors, a heating coil, cooling coil, heat wheel, fan motor, filter, and damper faults.
3. Three assumed models in 4.1 and 4.2 of heating coil heat balance, cooling coil heat balance, and the energy performance balance of heat wheel can be faulty.

connect faults and symptoms. For example, motor broken (M), damper broken (D), polluted filter (F), Pressure difference sensor broken (PD) may lead to symptoms in output pressure difference (PD2) and intake filter pressure difference (PD1). Then these faults and symptoms should be connected. Moreover, flowrate sensor broken (FT), temperature sensor broken (TT), motor broken (M), Heat wheel not working (HWW), and Heat wheel balance model incorrect (HWM) may lead to symptoms of the inefficiency of the heat wheel. So, these symptoms and faults should be connected.
The description and explanation of the probability data and how to apply a conditional probability table

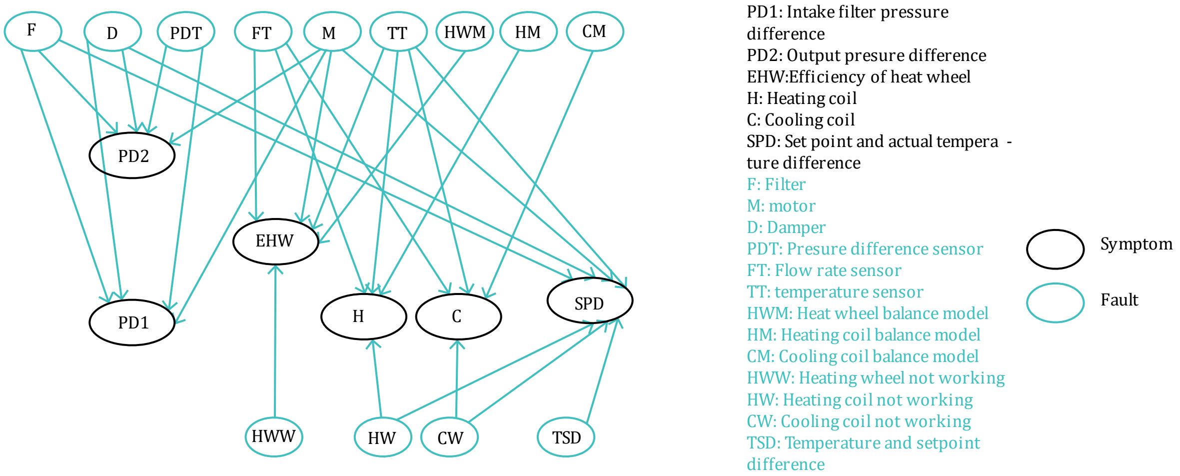

Fig. 4 – DBN model in actual scenarios

4.6 Relationship between faults and symptoms and DBN model

To decrease complexity a bit when explaining the relationships, we group together some faults and symptoms, as explained below, resulting in 6 possible symptoms and 13 fault nodes (instead of 26) To construct this DBN, six possible symptoms presented above are highlighted in black color (***Fig. 4***). Intake filter pressure difference (PD1) and output pressure difference (PD2), and setpoint and actual temperature difference (SPD) are OS symptoms. The energy efficiency of the heat wheel (EHW) is EP symptoms. Symptoms of heating and cooling coils are aggregated as heating (H) and cooling coils (C). Because faults that lead to these symptoms are almost identical, they could be isolated later. All listed faults are marked in blue color. All faults that come from the same sensor types are combined into one node for reducing the drawing complexity, such as Flow rate sensor (FT), pressure difference sensor (PDT), and Temperature sensor (TT), and they could be separated later for more accurate analysis. Three balance model fault heat wheel balance model (HWM), Heating coil balance model (HM), and cooling coil balance model (CM) are listed separately. All of these faults and symptoms are connected through the DBN (***Fig. 4***). The knowledge and experience of experts are needed to decide how to

to each node of the DBN model are not the purposes of this paper. Therefore, it will be discussed in future research. The DBN (***Fig. 4***) can be constructed and understood when compared with HVAC diagrams (***Fig. 2***, ***Fig. 3***).

5. Case two: sensor-rich environment

In this section, the case of an ideal environment will be discussed in which more sensors and information are available.

5.1 Energy balance symptoms

As described in the previous section, the heating and cooling coil's energy balance can be identified. In the ideal scenarios, if the connected or aggregated system information is available, more balance symptoms could be identified. Firstly, suppose the total amount of heat generated in the heat generator is known, as well as how this heat is distributed to separated systems, including the heating coil, via a hydronic system. In that case, the heat balance model for the efficiency of the aggregated system could be constructed. Secondly, with the measurement of heat distributed to AHU, the energy balance model of the heat generator system at the subsystem level can be made. Thirdly, the air pressure balance model could be constructed if there are air pressure sensors at the inlet air duct, output air duct, and terminal rooms.

5.2 Performance symptoms

Unlike the previous section, the performance balance symptoms could be more accurate and substantial if only a few sensors were added. Suppose the temperature sensor (TT1) is installed between the heat wheel and the heating coil. In that case, it could record the intake air temperature before it passes through the heating coil. Then several new performance balances could be identified. At first, because this sensor was absent, the heat wheel efficiency calculation was based on the total heat balance equation in the previous section. Now, with this new sensor, the heat generated from the heating coil could be isolated. The extra heat obtained from the heat wheel could be calculated by deducting the reading from TT1 and the intake air temperature sensor TT30-00. Within this sensor, the calculation of the efficiency of the heat wheel can be done more quickly and directly. Secondly, the efficiency calculation of the heating coil and cooling coil becomes possible. The efficiency of the heating and cooling coil can be calculated by comparing the heat generated or removed from these two coils and the heat obtained between sensors TT30-05 and TT1.

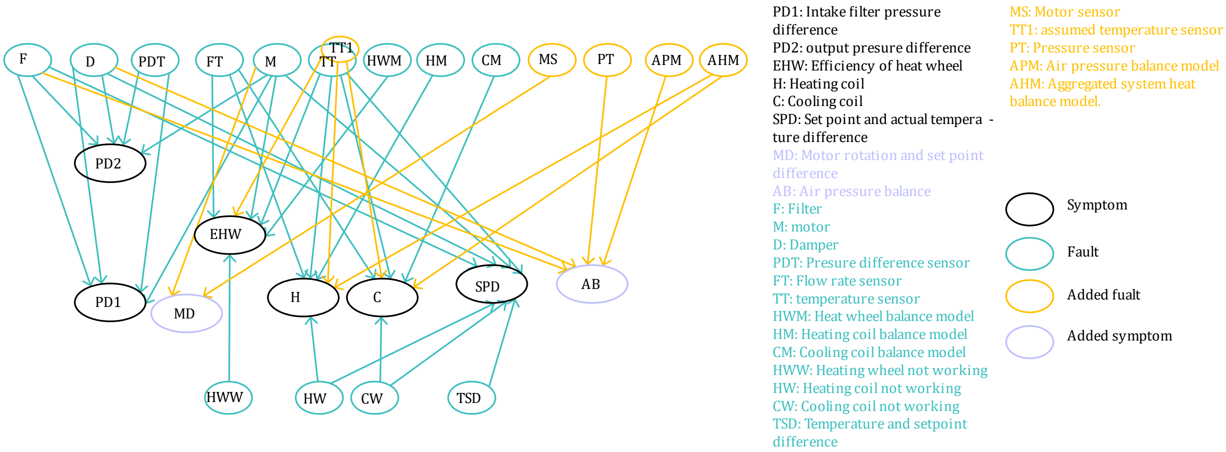

Fig. 5 – DBN model in expected scenarios

5.3 Operation state symptoms

The observable operation state symptoms will also be expanded if more information is added. At first, if the setpoint fan speed and the motor rotation data are recorded. Then the operation state symptoms of the fan will be identified by comparing this setpoint and rotation speed. Moreover, suppose the specific flow rate of the supply water in the heating and cooling coil is collected. In that case, symptoms of the cold-water supply and hot-water supply could be observed by comparing data in the flowrate sensor (FT30-01) and the specific parameter provided by the supplier.

5.4 Identifiable faults

The identified faults could also be expanded if more information is available. The new assumed sensors (e.g., TT1) will be additional potential sensor faults. Furthermore, several new model faults (e.g., the air pressure balance model) will be added as new balance symptoms are included. Additionally, the new control fault like fan speed difference between set speed and actual can be identified.

5.5 DBN model

The newly added symptoms, faults, and possibly are marked as purple and yellow ***(Fig. 5)***. The DBN model becomes more powerful and complex, with the possibility to identify more symptoms and faults at different levels. Several new energy balances and performance symptoms are added due to the information from the heat generator. It can be further analyzed if a more accurate diagnosis is needed. New added sensor fault TT1 is listed separately to compare with the previous DBN model that one added sensor could affect several components in the fault diagnosis. As presented in the DBN diagram, motor broken (M), motor speed sensor broken (MS) may lead to the symptoms of motor rotation and setpoint difference. Flowrate sensor broken (F), damper broken (D), pressure sensor broken (PT), and air pressure balance model incorrect (APM) may lead to air pressure balance difference (AB). Moreover, aggregated system heat balance model incorrect (AHM) is connected to heating coil and cooling coil symptoms. Here too, a specific DBN model could be constructed as another subsystem.

6. Case 3: sensor-poor environment

6.1 Balance symptoms

In the worst cases, necessary sensors for identifying balance symptoms may be unavailable because too few flow and temperature sensors have been placed; Therefore, no balance symptoms are detected.

6.2 Performance symptoms

It is still possible to have some basic performance information in sensor-poor environments. For example, the air is not heated or cooled, or no air comes through the AHU.

6.3 Operation state symptoms

Operation state symptoms are essential almost in all scenarios, as they are coupled to the control of the system, and there is always some kind of control. The setpoint's temperature difference and actual situation are observable in any case. The difference in water supply temperature in the heating coil and cooling coil between actual values and specifications may still be obtained.

6.4 Identified faults

The number of faults that can be identified decreases significantly in this scenario. The number of sensor faults is reduced because there are few available sensors. There are also no model faults since no balance model could be constructed. Only a few system faults and control faults are observable, such as incorrect setpoints or degradation of components.

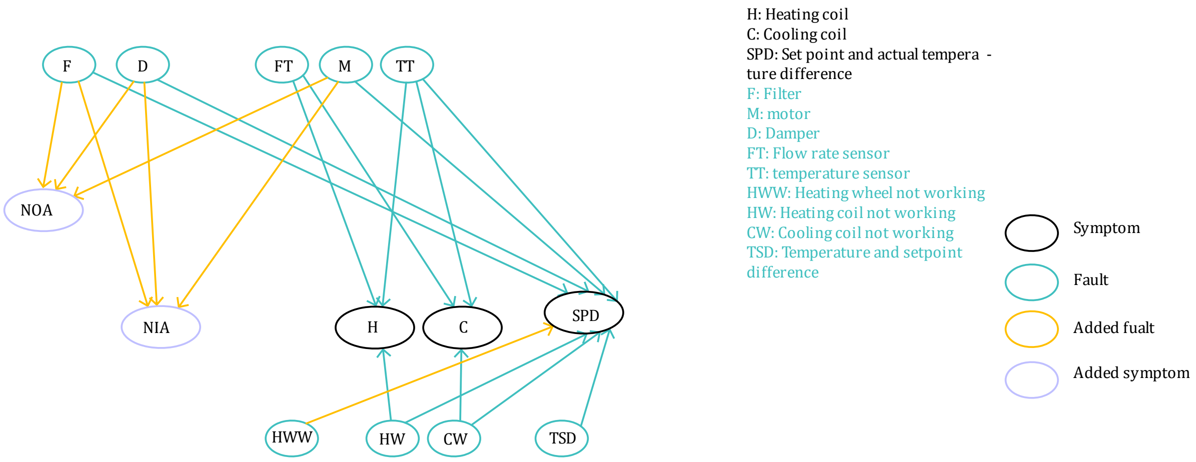

Fig. 6 – DBN model in sensor-poor scenario

6.5 DBN model

This leads to a relatively simple DBN model, constructed based on the available information (***Fig. 6)***. In the end, nine faults are identifiable. Due to the lack of sensors, almost all symptoms can lead to the set point and actual temperature difference fault (SPD). Therefore, this DBN model's fault detection and diagnosis ability have diminished a lot because of the limited data. If more sensors are placed later, more nodes can be added to this model and improve its fault detection and diagnosis ability.

7. Comparison of the three sensor environments

Three different DBN models were proposed based on different setup scenarios. It is apparent that a sensor-rich environment is an ideal condition to apply the 4S3F method. Multiple sensors will lead to more precise and effective fault diagnosis because of more identified symptoms and faults. The accuracy of the diagnosis may also increase because redundant information will lead to more precise fault probabilities. However, it also causes more complicated DBN models. It will increase the time needed for setup, computational time, and probability table requirements. Besides, it is very costly to install a large number of sensors. The 4S3F model set up in the actual environment is suitable for most practical situations where not all desired sensors cannot be placed. It can still perform specific fault-diagnosing tasks. In our example, twenty-six faults can still be identified (if happening). Many methods like virtual sensors could be applied in this situation to maximize the use of measured data. In a poor sensor environment, where many key sensors are lacking, the diagnosis ability of this method is lower due to limited information. However, the 4S3F method would still diagnose nine faults even in this situation. The accuracy of the diagnosis would be less than in the other environments. But the valuable faults and diagnosis could still be achieved. It may even be recommended for HVAC engineers to get acquainted with the 4S3F method in such a poor sensor environment, as it is easier to construct.

8. Conclusion and recommendation

This paper mainly discussed the engineering process of the proposed 4S3F method to an Air Handling Unit (AHU). Obviously, the application difficulty still exists with this recently proposed method. In general, more sensors mean a more precise model. However, it also increases the complexity of the model leading to higher computational time and time-consuming design. A solution for larger-scale complex systems needs to be explored in the future, but modular solutions will surely have a place herein. Moreover, standardization and library of module components have a great potential to accelerate the modeling setup process to avoid repetitive work.

Furthermore, we showed that by only adding one additional sensor, the accuracy and variety of the observed equations in symptoms is significantly increased, which indicates that there may be a possible economical solution for sensor installation if the places for placing sensors are well designed. In the end, step-to-step instructions would accelerate the model setup speed for HVAC engineers to avoid time-wasting of explorations of the setup method.

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Data Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.