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Bayesian network based FDD strategy for variable air volume terminals

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ABSTRACT

This paper presents a diagnostic Bayesian network (DBN) for fault detection and diagnosis (FDD) of variable air volume (VAV) terminals. The structure of the DBN illustrates qualitatively the casual relationships between faults and symptoms. The parameters of the DBN describe quantitatively the probabilistic dependences between faults and evidence. The inputs of the DBN are the evidences which can be obtained from measurements in building management systems (BMSs) and manual tests. The outputs are the probabilities of faults concerned. Two rules are adopted to isolate the fault on the basis of the fault probabilities to improve the robustness of the method. Compared with conventional rule-based FDD methods, the proposed method can work well with uncertain and incomplete information, because the faults are reported with probabilities rather than in the Boolean format. Evaluations are made on a dynamic simulator of a VAV air-conditioning system serving an office space using TRNSYS. The results show that it can correctly diagnose ten typical VAV terminal faults.

1. Introduction

Variable air volume (VAV) air conditioning systems are widely used in offices and commercial buildings nowadays. Building professionals usually consider that VAV systems have better performance in terms of thermal comfort and energy saving than fan coil unit systems and constant air volume systems. However, VAV terminals easily suffer from various faults which cause the performance of VAV systems to hardly meet the high expectations. Qin and Wang found that 20.9% of 1251 VAV terminals were ineffective in a site survey conducted in a commercial building in Hong Kong [1]. Preventive maintenance of VAV terminals is a difficult task since a large number of VAV terminals are installed above ceilings. Fault detection and diagnosis (FDD) tools for VAV terminals are essential for reliable indoor environment control, saving maintenance efforts, and eliminating the associated energy waste.

There was little research conducted on FDD of VAV terminals in the last decades. Yoshida proposed an automatic regressive exogenous (RARX) model and an extended Kalman filter model to detect faults in a VAV unit and an air handling unit (AHU) cooling coil system [3,4]. Seem et al. described a set of indexes to assess the performance of control loops and to detect faults in VAV terminals and AHUs [5,6]. The performance indexes were embedded in commercial VAV terminal controllers to quickly identify terminals that were not operating correctly. Schein proposed VAV box performance assessment control charts (VPACC) to assess the performance of pressure independent VAV boxes with hydronic reheat coils. VPACC introduced a small number of CUSUM charts to accumulate the error between a process output and the expected value of the output [7,8]. These FDD methods for VAV terminals focused on fault detection and seldom considered fault diagnosis. Qin and Wang proposed a hybrid approach to diagnose ten typical faults in VAV systems utilizing expert rules, performance indexes and statistical process control models [1]. Principal component analysis (PCA) was used to detect flow sensor biases. Wang et al. designed a rule-based classifier consisting of twenty expert rules and fault isolation algorithms to diagnose fifteen faults in VAV terminals [9], which was able to diagnose faults using sensor measurements and control signals which are commonly available in building management systems (BMSs).

The above FDD methods for VAV terminals can normally provide good results; however, they rarely considered the realistic situation where only uncertain and incomplete information is available for conducting FDD. Uncertainties widely exist in measurements, fault symptoms, fault–symptom relationships, expert knowledge, FDD results, etc. For instance, different faults may cause similar fault symptoms and a fault may exist with certain probability when a symptom is observed. Therefore, it is more reasonable to give the probabilities of faults at given symptoms in FDD results. However, most existing FDD methods report the FDD results in the Boolean format, i.e. *Yes*/*Faulty* and *No*/*Normal*. In addition, due to the limited number of instruments, incomplete records of system design and operation data, insufficient memory capacities of control stations and building automation systems, etc., the information available for conducting FDD is usually incomplete. Using incomplete information for FDD is also a big challenge for most existing FDD methods. On the other hand, some useful information, which is very helpful for FDD, was often overlooked. For instance, the prior probabilities of the temperature sensor fault and the damper actuator failure are 25.3% and 3.8% respectively, according to the survey [1].

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Nomenclature

Notation

F	air flow rate (L/s)
P	supply air pressure (Pa)
Q	cooling load or cooling capacity (kW)
T	temperature (°C)

Subscripts

act	actual value in practice
exh	extremely high
exl	extremely low
design	design value
m	measured value
max	maximum
min	minimum
oa	outdoor air
set	set-point
supply	supply air from AHU
t1, *t2*	temperature threshold (K)
zone	zone concerned

Greek symbols

ε	threshold
λ	VAV terminal damper opening (0–100%)
ψ	currently available evidences

When a VAV terminal is abnormal, the possibility of the temperature sensor fault is much higher than that of the damper actuator failure. Such prior experience or knowledge about faults has seldom been used by existing FDD methods.

FDD experts have already recognized that FDD of VAV terminals is quite challenging. The major reasons are listed as follows. Firstly, there are generally very few sensors installed in VAV terminals. The information is extremely insufficient which makes it difficult to diagnose the faults [1]. Secondly, faults may propagate by control loops, which lead to complex relationships between faults and symptoms. Thirdly, limitations associated with controller memory and communication capabilities further complicate the task [8]. Fourthly, the number of different types of VAV boxes and lack of standardized control sequences add extra complexities [8]. Lastly, there is almost no preventive maintenance due to the large number of VAV terminals installed above ceilings [9].

Although FDD of VAV terminals is challenging, it is interesting to see that domain experts can always find the sources of faults. Experts diagnose faults using as much useful information as possible, e.g. fault symptoms (from BMS or on-site test), configurations (e.g., control strategy, set-points), performance of peer VAV terminals in the same zone or similar zones, cooling load, as well as the experts' knowledge/experience. Fault diagnosis of VAV terminals may be more efficient and effective if the FDD methods can work in a similar way as that used by FDD experts. In this study, an intelligent method for FDD of VAV terminals is proposed to simulate the diagnostic thinking of experts based on Bayesian belief network (BBN) theory.

2. Overview of Bayesian belief network

BBN is a probabilistic graphical model that represents probabilistic dependence within a group of variables using a directed acyclic graph. It has been successfully applied in the domain of knowledge discovery and probabilistic inference [10] since it was introduced by Pearl in early 1980s [11,12]. It is powerful to represent and to diagnose complex systems with uncertain, incomplete and even conflicting information. Its applications can be found in sensor fault detection and identification [13], nuclear power systems [14], aircraft engines [15], medical diagnostic decision support systems, semiconductor manufacturing systems [10], etc. However, there are very few applications in the heating, ventilation and air conditioning (HVAC) field. Najafi et al. [17] and Wall et al. [18] introduced BBN to detect and diagnose AHU faults. Both works used BBN as a machine learning algorithm to learn the fault patterns and required a full set of fault data for the learning. However, the full set of fault data of VAV terminals is hardly available in practice. Zhao et al. [16] proposed a BBN-based method for chiller FDD, which was proven to be reliable. In this study, a diagnostic Bayesian network is developed for FDD of VAV terminals by taking full advantage of physical laws, experts' knowledge/experiences, operation and maintenance records, historical and real-time measurements, manual tests etc.

A BBN is defined by two components, i.e., structure and parameters. The structure is a graphical and qualitative illustration of the relations among the nodes using directed arcs. Nodes represent faults and fault symptoms. The arcs indicate direct probabilistic dependences among nodes. An arc points from a parent node to a child node. The node without any input arc is a root node. A node may have several states (e.g., true and false). Each state is an event. When an event occurs, it is evidence (or observed state) for diagnosing faults. A BBN represents the quantitative probabilistic relationships among the nodes using probabilities, which are parameters of the BBN. Each root node has a prior probability corresponding to its each state. A conditional probability table is usually used to specify all parameters or probabilities of a child node, considering all possible combinations of its own states and its parent nodes' states. The number of parameters needed in a conditional probability table exponentially grows with the number of its parent nodes. It is usually very difficult to obtain all conditional probabilities in the FDD applications. By assuming that the parent nodes affect their common child node independently, the child node can be simplified to be a Noisy-MAX node, whose number of parameters can be reduced from exponential to linear to the number of parents. LEAK probability is needed for a Noisy-MAX node. LEAK probability is the probability of the child node having a value 1 when all parent nodes have a value 0. More details about Noisy-MAX nodes can be found in [16,19].

Once the structure and parameters of a BBN are defined, the posterior probability can be obtained by Bayesian inference. The Bayesian theorem plays a very important role in the inference. Supposing B_1, B_2, …, B_n are a set of random variables and satisfy: (i) $P(B_i) > 0$, $i = 1, 2, …, n$; (ii) $\sum_{i=1}^{n} B_i = S$, S is the certain event; and (iii) they are mutually exclusive. Given event B ($P(B) > 0$), the conditional probability of the event A is defined by Eq. (1):

$$P(A|B) = \frac{P(AB)}{P(B)} = \frac{P(A)P(B|A)}{P(B)}, \tag{1}$$

where $P(AB)$ is the joint probability of the event A and B. For any given event A, the marginal probability can be calculated by

$$P(A) = \sum_{i=1}^{n} P(B_i)P(A|B_i). \tag{2}$$

The Bayesian theorem can be obtained based on the conditional probability and marginal probability:

$$P(B_i|A) = \frac{P(AB_i)}{P(A)} = \frac{P(B_i)P(A|B_i)}{\sum_{i=1}^{n} P(B_i)P(A|B_i)}. \tag{3}$$

Items on the right hand side of Eq. (3) are called prior probabilities, and the item on the left hand side is the posterior probability. The Bayesian theorem provides the way to calculate the posterior probability from the prior probabilities. Take fault diagnosis for instance, if the