Intelligent Model Based Fault Detection and Diagnosis for HVAC System Using Statistical Machine Learning Methods

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ABSTRACT

HVAC systems typically consume the largest portion of energy in buildings, particularly in the commercial sector. It is reported that commercial buildings account for almost 20% of the US national energy consumption, or 12% of the national contribution to annual global greenhouse gas emissions. From 15% to 30% of the energy waste in commercial buildings is due to performance degradation, improper control strategies and malfunction of HVAC systems and equipment. This paper proposes a new fault detection and diagnosis (FDD) approach by applying a statistical machine learning based FDD method with data fusion methods. The approach also includes clustering methods and an optimization technique to avoid the modeling process converging to local minimum. A number of hidden markov models (HMMs) are trained to model different catalogues of faults, and a clustering algorithm is applied to enhance the FDD accuracy. This approach has been successfully trialed on one commercial building with multiple AHUs. It can not only identify system faults that were modeled within the training process, but also can be applied for diagnosis. Preliminary experimental results are demonstrating effective performance.

INTRODUCTION

There are not many energy systems so commonly used in both an industrial, commercial and domestic setting as HVAC systems. Moreover, HVAC systems usually consume the largest portion of energy in buildings for most sectors. It is reported (EIA, 2006) commercial buildings account for almost 20% of the US national energy consumption, or 12% of the national contribution to annual global greenhouse gas emissions. From 15% to 30% of the energy waste in commercial buildings is due to the performance degradation, improper control strategy and malfunctions of HVAC systems (Wang et al., 2010).

Regular checks and maintenance is usually the key for reaching these goals. However, due to the high cost of reactionary maintenance, preventive or predictive maintenance practices play an important role. A cost effective strategy is the development of fault detection and diagnosis (FDD) based on a new classifier (Dehestani et al., 2011). During the past decades, the system maintenance strategy has experienced three development stages (Hyvärinen and Karki, 1996) and (Yoshimura and Ito, 1989): breakdown maintenance, time-based maintenance and condition-based maintenance. Presently, the condition-based intelligent preventive maintenance is gaining more and more interest for HVAC systems.

Building Management & Control Systems (BMCSs) were developed to monitor and control the HVAC systems, whilst...
Feature-based methods (Pandit and Wu, 1983) and (Du et al. 1996), model-based methods (Simani et al. 2003), and a combination of both. Although these methods have been applied in a number of industrial processes with good performance (Chen and Patton, 1999), their application in the HVAC system is still largely at the research stage in laboratories, and many of the studies focus on vapor compression based systems. For example, Kim (2005) investigated the effect of four artificial faults on the performance of a variable speed vapor compression system by using a rule-based fault classification method. Tassou and Grace (2005) also presented a fault diagnosis and refrigerant leak detection method for vapor compression refrigeration systems by using neural network and expert system. Furthermore, several studies were also presented to deal with the faults in the air handling unit (AHU) (Dexter and Pakanen, 2001), (Lee et al., 2004), (Pakanen and Sundquist, 2003) and (Yoshida et al., 1999, 2001) and sensors (Hou et al., 2006) and (Wang and Xiao, 2004), respectively. At the same time, some advanced algorithms, such as transient pattern analysis (Cho et al., 2005), general regression neural networks, and feed forward control scheme (Salsbury and Diamond, 2001), were also utilized to detect and diagnose the faults in the HVAC systems. Now it is well recognized that FDD is very important in ensuring the safety of HVAC systems, improving user comfort, energy efficiency, and reducing operating and maintenance costs (House and Kelly, 2000). However, efficient FDD methods for HVAC systems still remain a challenge and commercial FDD systems are only beginning to emerge in recent years (Hyvarinen and Karki, 1996).

Motivated by these facts, the Commonwealth Science & Industrial Research Organisation (CSIRO) is developing a novel statistical machine-learning based technique for automated fault detection & diagnosis (AFDD) in HVAC systems. Preliminary results were presented in (Wall et al., 2011) and (Guo et al. 2012), showing the performance of the statistical machine learning-based technique in detecting air-handling unit (AHU) faults based on fault data obtained from ASHRAE Project 1312-RP - Tools for Evaluating Fault Detection and Diagnostic Methods for Air-Handling Units.

This paper proposes a new approach by combining a Hidden Markov Model (HMM) based FDD method and a data fusion method. The approach also includes clustering methods and an optimization process to avoid the modeling process converging to local minimum. When used in conjunction with statistical techniques, this approach has several advantages for data analysis. On one hand, the approach uses probabilistic models that consist of variables and probabilistic links between the variables. These links can denote the physical relationship as in the model-based approaches. On the other hand, the probabilistic links are learnt from the datasets as in the data-based approaches. Since the links are pre-set as prior knowledge, the learning process is more efficient. Hence, the approach is an ideal representation for combining prior knowledge and data. It does not need very detailed understanding of the physical system as in model-based approaches. It also does not need huge data sets as in the black-box approaches. Comparing with pure model-based or data-based approaches, it can take the strengths in both areas and reduce the weaknesses by balancing the dependency on physical models and datasets.

The paper is organized as follows. Section 2 provides an overview of the methodology, including the theoretical introduction of HMMs, and clustering methods. The experimental results for discussion are available in section 3. The conclusions of this study are drawn in section 4.

**MACHINE LEARNING METHODOLOGY FOR HVAC FDD**

**Fault Detection and Diagnosis Process for HVAC Systems**

Generally speaking, HVAC systems are configured and used to control the environment of a building or room. The environmental variables controlled may, for example, include temperature, air-flow, humidity etc. The desired values/set-points of the environmental variables will depend on the intended use of the HVAC system. By way of broad example, if the HVAC system is being used in an office building, the environmental variables will be set to make the building/rooms therein comfortable to humans. A HVAC system typically services a number of zones within a building. The system
normally includes a central plant which includes a hydronic heater and hydronic chiller. A pump system, which may include dedicated heated and chilled water pumps, circulates heated and chilled water from the heater and chiller through a circuit of interconnected pipes. A valve system, which may include dedicated heated and chilled water valves, controls the flow of water into a heat exchange system (which may include dedicated heated and chilled water coils). The heated and/or chilled water circulates through the heat exchange system before being returned to the central plant where the process repeats (i.e. the water is heated or chilled and recirculated). In the heat exchange system, energy from the heated/chilled water is exchanged with air being circulated through an air distribution system.

The HVAC system also includes a sensing system which typically includes a number of sensors located throughout the system, such as temperature sensors, humidity sensors, air velocity sensors, volumetric flow sensors, pressure sensors, gas concentration sensors, position sensors, and occupancy detection sensors. The HVAC system is controlled by a control system that may be a stand alone system, or may form part of a building automation system (BAS) or building management control system (BMCS). The control system includes a computing system which is in communication with the various components of the HVAC system. The control system controls and/or receives feedback from the various components of the HVAC system in order to regulate environmental conditions for the inhabitancy or functional purpose of the building.

In a fault detection and diagnosis (FDD) process, data from the components of the HVAC system is received. This data may, for example, include sensed data from various sensors within the system and feedback data from various components of the system. Additional data from external data sources can also be received, such as the external weather data. Fault detection is processed in accordance with at least one specific fault detection models. In this paper, we implemented a machine-learning based processes, the Hidden Markov Model.

In order to develop specific fault detection models, the HMMs are trained to learn patterns of either normal or faulty operation. The theoretical introduction of HMMs and the training process details are described in following section. Once the models are trained, the correspondence with and/or deviations from the learnt patterns of operation of the system/component(s) thereof can be used to detect and/or diagnose faults. Where a model is trained on normal operation of the system/component(s), a deviation can be identified as a fault in the system or relevant component(s). Conversely, where a model is trained on faulty operation of the system/component(s), correspondence with the learnt model can indicate faulty operation of that system/component(s). Applying machine-learning based techniques to fault detection is advantageous in that such techniques do not rely on fixed rules or models to determine a fault.

The specific fault detection models may include models for detecting generally abnormal/faulty operation of the HVAC system; models for detecting generally normal operation of the HVAC system; models for detecting generally abnormal/faulty operation of a specific component or set of components of the HVAC system; models for detecting generally normal operation of a specific component/set of components of the HVAC system; or a combination thereof.

Multiple models can be generated for one HVAC system, based on different conditions. For instance, the HVAC system can operate very differently within different seasons. The way in which the system is modelled (using the general fault detection processes) and/or are trained will determine the nature of the specific fault detection models, and whether they detect faulty or normal operation in general or the existence of one or more specific faults.

Even for the same training datasets, multi models also have advantage in avoiding the overfit or the convergence in the local minimum. Hence, clustering and data-fusion algorithms are also implemented to achieve the final FDD results.

Hidden Markov Models (HMMs)

HMMs are chosen to model the HVAC system because they can infer optimal hidden states from observation sensor data while a lot of modelling technologies can only predict observations from observations. Generally speaking, a HMM is a statistical model in which the system being modelled is assumed to be a Markov process with unknown parameters. A Markov process is a mathematical model for the random evolution of a memoryless system. That is, the likelihood of a given future state at any given moment depends only on its present state and not on any past states.

The most common HMM structure is a finite set of states, each of which is associated with a (generally
multidimensional) probability distribution (Rabiner 1989). Transitions among the states are governed by a set of probabilities called transition probabilities. In a particular state an outcome or observation can be generated, according to the associated probability distribution. It is only the outcome, not the state, that is visible to an external observer and therefore states are "hidden".

To define a HMM, three basic components are needed:

1. A vector containing the prior probability of each hidden state: the initial state distribution, \( \pi = \pi_i \), where
   \[
   \pi_i = p(q_0 = i), \quad 1 \leq i \leq N. \]
   Here \( N \) is the number of states of the model, and \( q_0 \) denotes the initial state.

2. A set of state transition probabilities \( \Lambda = a_y \). Define
   \[
   a_y = p(q_{t+1} = j \mid q_t = i), \quad 1 \leq i, j \leq N, \tag{1}
   \]
   where \( q_t \) denotes the current state. Transition probabilities should satisfy the normal stochastic constraints, \( a_y \geq 0 \) for \( 1 \leq i, j \leq N \), and \( \sum_{j=1}^{N} a_y = 1 \) for \( 1 \leq i \leq N \).

3. The probability of the observation given a state, \( B = \{b_j(k)\} \). Define
   \[
   b_j(k) = p(O_k = \nu_k \mid q_t = j), \quad 1 \leq j \leq N, 1 \leq k \leq M, \tag{2}
   \]
   where \( \nu_k \) denotes the \( k \)th observation, \( M \) the number of observation, and \( O_k \) the current parameter vector.
   Following stochastic constraints must be satisfied: \( b_j \geq 0 \) for \( 1 \leq j \leq N, 1 \leq k \leq M \), and \( \sum_{k=1}^{M} b_j(k) = 1 \) for \( 1 \leq j \leq N \).

In modelling HVAC system, transitions between the same or different hidden states can be predicted using state transition matrix \( \mathcal{A} \) and state-dependent observation matrices \( B \). For fault detection, the state transition matrix \( \mathcal{A} \) and state-dependent observation matrices \( B \) are based on measurement of the system during normal operation. A HMM fault detection process for a HVAC system can be easily implemented. The only pre-defined parameters of the HMM are the number of observation states and the number of hidden states. Generally speaking, the observations states are what can be measured. The hidden states may not have real-world/physical meaning, and are generally selected based on experience and/or experimentation. Figure 1 shows an example of a HMM with five sensor readings as the observe states (above the dash line), and four hidden states (below the dash line). The arrows show the transition probabilities between hidden states.

The training process is used to find the HMM parameters that maximise the probability \( P(O \mid \pi, \mathcal{A}, B) \). This process is performed using the recursive Baum-Welch algorithm, as described in (Rabiner, L. R. 1989). In the fault detection process, new data/information (e.g. sensor measurements and other component feedback) are input and based on this the HMM calculates the likelihood of the new measurement's fitness to the learnt HMM. If the likelihood is low, a potential fault is detected. Hence, the output of the HMM fault detection process can indicate the fit between the current measurements and the learnt model.
Clustering and Data Fusion

For the same datasets, the fault detection results of the trained HMM, the likelihood, can vary from time to time, hence it is difficult to detect the fault based on the likelihood using a pre-defined threshold. Sometimes the fault detection results (the likelihood) can even converge to local minima, especially when the training datasets are not big enough. Figure 2 shows ten different testing results on ten different HMMs trained on the same training dataset, where the green, blue and brown lines are those that do not converge to the global minimum.

In order to increase reliability, the HMM training and detection processes can be repeated a number of times (N). K-Mean clustering is then applied to N detection results (N likelihood sequences) in order to identify faults. For the fault
detection in HVAC systems, one does not know whether there is any fault in the testing datasets ahead. To determine the number of clusters within the datasets (how many different faults), we defined the following distances in the K-Mean method.

Firstly assuming the cluster number is $M$, K-Mean clustering is applied to find these $M$ clusters. The distances between any two clusters $C_i$ and $C_j$ are calculated as $D(i, j)$. The radius of each cluster $R_i$ is defined as the maximum distance between a point within the cluster $C_i$ and the centre of the cluster. Three ratios are calculated as: $\gamma_1(i,j)=((D(i,j)-R2))/R1$; $\gamma_2(i,j)=((D(i,j)-R1))/R2$; and $\gamma_3(i,j)=D(i,j)/(R1+R2)$. When $\gamma_1(i,j)$, $\gamma_2(i,j)$, and $\gamma_3(i,j)$ are all less than one, clusters $C_i$ and $C_j$ merges to the same cluster, and the new centre of this cluster is calculated. The process stops when these three ratios are larger than one between any two clusters. The final cluster number minus one is the number of the faults in the testing datasets, as one cluster is for the normal situation.

![Figure 3. Online fault detection experimental results for a real HVAC system. Top: real sensor readings. Middle: log likelihood as the output of different HMMs. Bottom: the clustering results of fault detection process.](image)

**EXPERIMENTAL RESULTS**

In this section, the results of two real-world tests will be discussed: one for fault detection and one for fault diagnosis.

**Online Fault Detection Results**
In this test, real time sensor readings were received online, and the learnt HMMs need to detect the fault as real time. When the real data read in as shown in Figure 3.top, seven groups of pre-trained HMMs were used to calculate the likelihood, as shown in Figure 3.middle. The K-Mean clustering is then used to provide the class ID as shown in Figure 3.bottom. The class ID is defined as one for normal and two for fault. In this test, the chilled water valve in the HVAC system was set at 30% open from 11:00am to 11:30am on the day, and reset to normal operation after 11:30am. Hence the fault was identified successfully.

Fault Diagnosis Result

In the second test, the faults from the ASHRAE 1312-RP Summer 2007 dataset (Li and Wen, 2007) were used for fault diagnosis to analyze the proposed technique. The datasets were collected during 20th August to 24th August 2007. The description of these days’ faults is listed in Table 1. We trained a group of HMMs using the EA Damper Stuck fault data in 21st August 2007, and used it to diagnose the other datasets. As shown in Figure 4, the whole dataset in 20th August 2007 was identified as “similar” to the training dataset, which means that it is the same type of fault – EA Damper Stuck. On the other hand, the datasets on the other three days were detected “not similar” to the training dataset, hence different class ID were identified for different type of fault.

<table>
<thead>
<tr>
<th>Fault description</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>EA Damper Stuck (Fully Open)</td>
<td>8/20/2007</td>
</tr>
<tr>
<td>EA Damper Stuck (Fully Close)</td>
<td>8/21/2007</td>
</tr>
<tr>
<td>Return Fan at fixed speed (30%spd)</td>
<td>8/22/2007</td>
</tr>
<tr>
<td>Return Fan complete failure</td>
<td>8/23/2007</td>
</tr>
<tr>
<td>Cooling Coil Valve Control unstable</td>
<td>8/24/2007</td>
</tr>
<tr>
<td>(Reduce PID PB by half)</td>
<td></td>
</tr>
</tbody>
</table>

Figure 4. Fault diagnosis results for ASHRAE datasets. Class ID stands for the similarity between the testing datasets and the training datasets. The class ID is one for same type of fault, and two for different type of fault.

CONCLUSION

The paper presents a statistical machine-learning based AFDD approach, which can be seen as a good combination of model-based methods and data-based methods. The main approaches in the paper are based on Hidden Markov Model techniques, which encode probabilistic relationships among variables of interest. Two different tests were presented, one for real time fault detection and one for fault diagnosis. Preliminary test results on a commercial building in Australia have demonstrated the approach performs well for AHU FDD applications. Future research will include integration of the approach into an on-line system for real time automated fault detection and diagnosis, covering a more comprehensive set of HVAC systems and fault conditions.


Yoshida H., S. Kumar, Y. Morita, Online fault detection and diagnosis in VAV air handling unit by RARX modeling, Energy and Buildings 33: 391-401.
