AUTOMATIC COMMISSIONING OF MULTIPLE VAV TERMINALS

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Summary: A site survey on a modern operating commercial building screened 261 ineffective VAV (Variable Air Volume) boxes (20.9% of the total boxes in the building) and summarized ten typical faults for VAV air-conditioning system(s) resulting in energy waste, performance degradation or totally out of control. A strategy is developed to automatically check the health condition of VAV terminals and diagnose the faults. Hybrid approach is employed to establish a commissioning and re-commissioning tool of VAV air-conditioning system. Performance indices with expert rules based on system physical characteristics are adopted to detect and diagnose the nine of the ten faults. PCA (Principal Component Analysis) method is developed to detect and diagnose the VAV box flow sensor bias (Fault 10) and to reconstruct the faulty sensors. A multiple VAV fault FDD strategy for a VAV entire system is developed, which is validated in simulation and filed tests.

Keywords: Variable Air Volume, fault detection, fault diagnosis, commissioning tool, Principal Component Analysis

INTRODUCTION

VAV (variable air volume) air-conditioning system, which is deemed more economical than other alternative systems, has been widely adopted in the building engineering to maintain the cooling and heating demands. However, in complex VAV systems, faults at system level, sub-system level, component level, control and sensor level would not only reduce the economic benefits of the system but also lead to occupant discomfort. Though the benefits for fault detection and system improvement are difficult to quantify, the potential waste out of faulty and non-optimal operation of HVAC system alone in commercial buildings were estimated to be 20-30% [1].

Faults typically found in VAV systems are due to improper design, application, or operation of the systems [2]. Previous studies mainly focused on the major equipment/processes of the system, such as air handling units, fans, local water circulation pumps and coil heat exchange processes [3,4,5,6,7]. Researchers extended their efforts to sub-systems in the recent years. Katipamula et al. [8,9] noticed that a failure of the economizer may go completely unnoticed and developed a strategy for the monitoring and fault diagnosis of the sub-system. Dodier [10] particularly studied the fan-power mixing box for taking into account both damper failure and power failure. Wang [11] paid particular attention to the air flow sensor failure of sensor-based demand control ventilation systems. A fault-tolerant control strategy was developed in case of failure in outdoor ventilation air flow sensor by means of neural network.

As overall system reliable control relies on proper operation of every component, researchers began to particularly throw light on VAV terminals and valves. Seem [12] looked into VAV terminal on-line control recently. Two indices were calculated from BMS driven data for VAV box on-line monitoring and fault detection. Yoshida [13,14,15] intensively worked on VAV damper failure and tested his approach on both sudden and consecutive faults. By making artificial faults in the tested system, it was verified that the ARX method is robust and can even detected different faults including damper getting stuck at half open position.

On the whole, the most significant technical problem perceived in VAV systems is interaction among VAV units equipped with a control loop, where information exchange takes place between several control strategies [15]. This interaction must be carefully analyzed and measured for achieving optimal control and therefore, in development of any FDD (fault detection and diagnosis) techniques. The previous researches focused on sub-systems. There is no applicable FDD tools for real entire VAV system application while concerning the interaction. This paper summarizes ten typical faults of VAV systems and studies hybrid approach to establish a FDD strategy for multiple VAV faults as an online commissioning and re-commissioning tool. Performance indices together with expert rules are adopted to develop the strategy. PCA (Principal Component Analysis) method is used for VAV box flow sensor fault detection and reconstruction.

SITE SURVEY ON FAULTS OF VAV TERMINALS

All VAV terminals of a 39-storey office building in Hong Kong, which was completed in 1995, were re-commissioned in 2002. The building enjoys a fully automated building management system (BMS) which ensures required comfort in a controlled environment. The air-handling units and the VAV systems controlled by DDC stations provide ventilation, cooling or heating, as appropriate, throughout the year. The VAV terminals are pressure independent VAV boxes under cascade control. Four groups of data are used to control each pressure independent VAV terminal: i). Space temperature, ii). Space temperature set-point, iii). Demanded air flow, iv). Measured airflow rate. Due to the limitation of BMS hardware, the four groups of data for the VAV boxes of 3 floors could be logged at 5-minute intervals for 3 days simultaneously. Therefore, re-commissioning of each VAV terminal was based on the trend data of 3 days.

By checking on the logged data, it was found that very often the measured flow could not approach the demanded flow and the space temperature could not approach the set-point. General screening got 261 "suspected" VAV boxes out of 1251 ones, which was 20.9% of the total boxes in the building. Twelve faulty symptoms were recorded after investigation. Yoshida's survey [13] revealed that zone air temperature deviation and DDC error were common, which tallies with our investigation results. Based on the investigated faulty symptoms, 10 typical faults are summarized in this study: *Fault 1* - space temperature sensor reading frozen, *Fault 2* - VAV box under/over capacity, *Fault 3* - VAV box damper stuck, *Fault 4* - VAV box flow sensor reading frozen, *Fault 5* - VAV box flow sensor reading deviation to minimum/maximum, *Fault 6* - oscillation of static pressure, *Fault 7* - poor tuning of temperature/air flow controller; *Fault 8* - VAV box damper sticking, *Fault 9* - VAV box damper hysteresis, *Fault 10* - VAV box flow sensor soft error. Space temperature sensor soft fault would not be detected by the system characteristics and could be offset by adjusting the zone temperature setting. Thus this fault is not included in this study.

VAV systems are widely used for commercial buildings nowadays. Each building may have thousands of VAV boxes and a rough check revealed that significant number of VAV boxes may be out of order. As manual checking on each terminal unit is impracticable, automatic commissioning and re-commissioning tool for VAV system is essential.

FDD STRATEGY FOR MULTIPLE VAV FAULTS

Performance indices [12,16,17] were widely used to represent the faulty performance characteristics when developing the FDD tools for quick assessment and little memory requested. However, simple performance index are not sufficient to build a FDD strategy for the whole complex system. In this study, performance indices are used for fault detection. Fault diagnosis is achieved by analyzing the pattern of abnormal performance indices using expert rules developed based on performance characteristics concerning the system interaction. Eight performance indices, which are based on the system physical characteristics directly, and eight relevant thresholds are used for the detection of the above first nine faults (Fault 1-9). Where, fault 2 and 3 cannot be differentiated by the strategy automatically and it does not cause much inconvenience in application as the fault is rather focused. For flow sensor soft fault (Fault 10), PCA method is applied. The strategy consists of seven steps (Figure 1) arranged in an order that the FDD ability of the schemes at the preceding steps would not be affected by the faults to be dealt at the later steps. The FDD strategy of multiple faults (Figure 2) is developed as an automatic commissioning and re-commissioning tool. VAV box damper openness is the key element for analyzing the faults. However, in normal pressure independent VAV systems, the signal of damper openness are not available. For position algorithm controller, the control signal to damper (u) typically represents the position of an actuator and therefore the openness of the VAV damper [18]. Therefore u is used to represent the damper openness in the strategy.

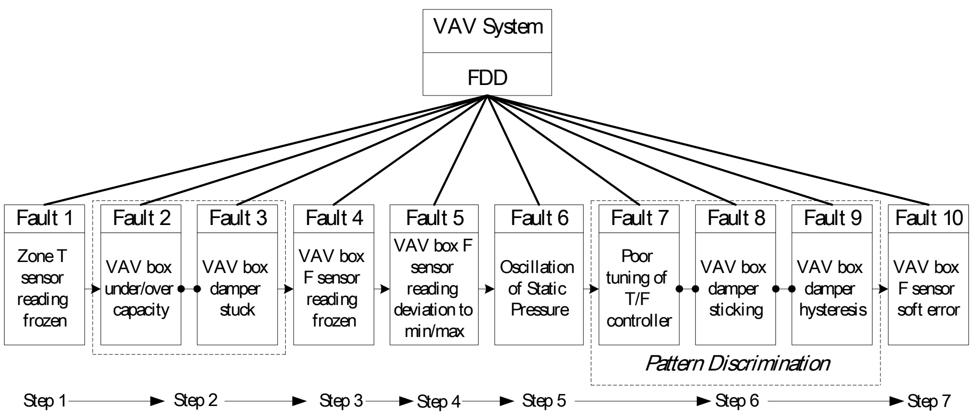


Figure 1. VAV system FDD overall workflow

To minimize the false alarms and to ensure the accuracy of the data used by the strategy, the controlled variables and the errors (difference between the set-points and actual measurements) have to go through a filter based on the exponential weighted moving average techniques for performance indices calculation. In Step 1, the Fault 1 is detected if the demanded flow is fixed for a certain time limit (a threshold of 5 hours was used in this study). In Step 2, the performance indices and their thresholds concern the deficiency of temperature control

($\overline{T}_k - T_{set} \geq 1.5$ or $\overline{T}_k - T_{set} \leq -1.5$) and deficiency of VAV airflow control ($\mu = \mu_{max}$ or $\mu = \mu_{min}$) as well as no variation of measured flow rate ($\overline{F}_{\max} - \overline{F}_{\min} \leq 0.05 \times F_{design}$). Fault 2 and 3 are detected if the existence of deficiency in temperature control *or* flow control exists over certain period (i.e. 0.5 hour) *and* the measured flow has no change over the same period. In Step 3, when the measured flow is frozen, the number of zone temperature oscillations and demanded flow oscillations are also deemed as performance indices. Fault is detected when a few (i.e. five) such oscillations are counted. In Step 4, Fault 5 is detected if the measured flow rate is fixed at the minimum *or* maximum value ($F_{measured}$=F_{min} or $F_{measured}$=F_{max}) when deficiency of temperature control exists ($\overline{T} - T_{set} < 1.5$ or $\overline{T} - T_{set} > 1.5$) over certain period (i.e. 0.5 hour) with the control signal is fixed at the maximum *or* minimum value (u= u_{max} or u= u_{min}) *and* the demanded flow is fixed at the minimum *or* maximum value (F_{demand}= F_{min} or F_{demand}= F_{max}). At Step 5, fault 6 is detected if a large number of static pressure oscillations have been counted, which was proposed by Seem [12]. At Step 6, controller hardware failure (unresponsive control process) sluggish response and oscillatory behavior can be detected using the rules illustrated in Figure 3. The controlled process is said to be unresponsive when the controlled variable does not change in response to changes in the set-point. If the set point is subjected to a step change and the time taken for the controlled variable to approach the new steady-state value is significant longer than an open loop response, the behavior is usually said to be sluggish. Oscillatory behavior occurs when the controlled variable alternately overshoots and undershoots its steady-state value.

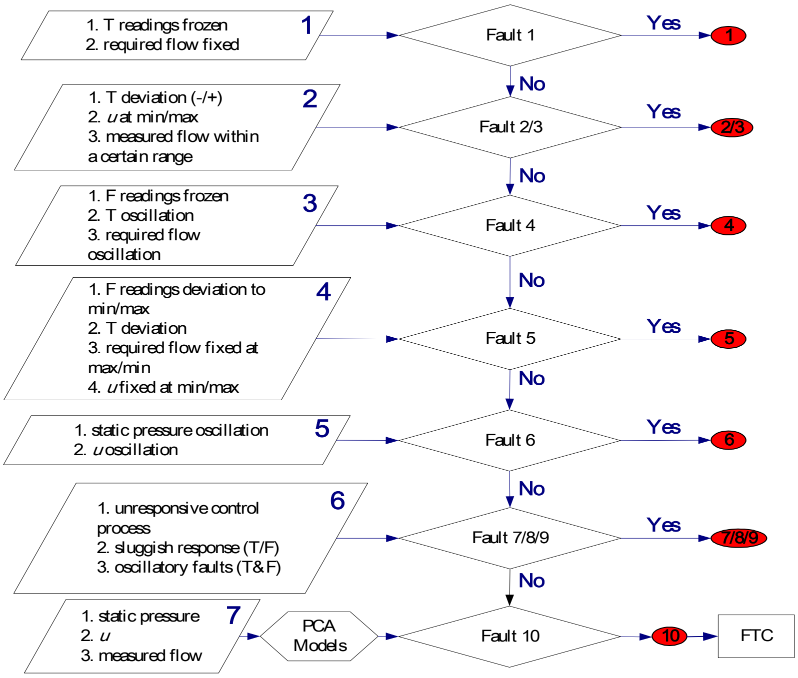


Figure 2. Multiple VAV FDD strategy

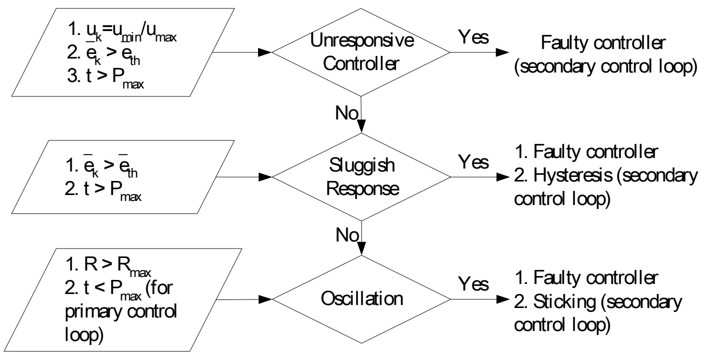


Figure 3. FDD scheme for controller failure, damper sticking and hysteresis

Air flow sensor bias (Fault 10) in a typical VAV terminal might not affect the normal control process if the reading is within certain range as it can be compensated by resetting the air flow set point. However, when sensor drift, bias or precision degradation is developed beyond a certain level, the reading will reach minimum or maximum of the VAV box design flow and ruins the control process. Furthermore, advanced supervisory control strategies need the accurate air flow measurement rates of VAV terminals and soft sensor faults make the control systems fail in optimization. Therefore, Step 7 of sensor FDD and sensor recovery of VAV terminals are important to the reliability and robustness of air-conditioning system control.

Principal Component Analysis (PCA) produces a lower dimensional representation in a way that preserves the correlation structure between the process variables, and is optimal in terms of capturing the variability in the data [19]. PCA method has been studied in the sensor FDD of a few engineering fields and attention has been paid on using PCA method for sensor FDD in air-conditioning system recently by the authors [20,21].

The normalized training matrix (X_{nxm}) is obtained by scaling the process variables to zero mean and unit variance. An eigenvalue decomposition of the sample covariance matrix (equation 1) of the training set is deduced as equation (2).

$$R = X^T X \big/ (n-1) \tag{1}$$

$$R = V \Lambda V^T \tag{2}$$

where the weights on each variable are given by the loading matrix V_{mxm}. In order to optimally capture the variations of the data while minimizing the effect of random noise corrupting the PCA representation, only those eigenvectors in V_{mxm} corresponding to the a largest eigenvalues (P_{mxa}) are retained in PCA models. Experiences show that variance of reconstruction error (VRE) can be used as the index to determine the number of principal components (a) in a PCA model for best reconstruction [22].

In FDD applications, the new observations x_{new} are projected to the principal component (PC) subspace to get their PCA estimation (equation 3). Both T^2 statistic (equation 4) and Q statistic (equation 5), which is called SPE (Square Prediction Error) as well, are used for fault detection. Generally speaking, T^2 relates to process upset and SPE relates to sensor faults [23]. When faults exist, one or both thresholds would be exceeded. Contribution plot is used for multiple fault isolation. After flow sensor fault detection and isolation, sensor reconstruction is conducted to get the recovered data. The iterative approach [24] is employed in this study.

$$\hat{X}_{new} = X_{new} P P^T \tag{3}$$

$$T^2 = X_{new}^T P \Lambda_a^{-1} P^T X_{new} \leq T_\alpha^2 \tag{4}$$

$$Q = SPE = \left\| X_{new} - \hat{X}_{NEW} \right\|^2 \leq SPE_\alpha \tag{5}$$

For VAV terminal flow sensor fault detection and diagnosis, PCA models at two levels are developed and used in serial. They are system level and terminal level (Figure 4). As all VAV terminals are involved in the system level model, the reliability and sensitivity of fault detection and isolation may be affected by the process stability and multiple faults in the system. Therefore, a terminal level PCA model is designed to further monitor on the suspicious terminal box(es), which are isolated by the system level FDD. The FDD strategy (Figure 5) is strengthened by the recovered data and the process terminates until no further fault could be detected.

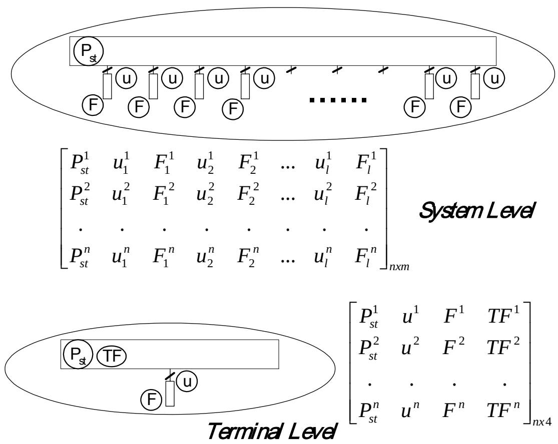


Figure 4. PCA models of system level and terminal level

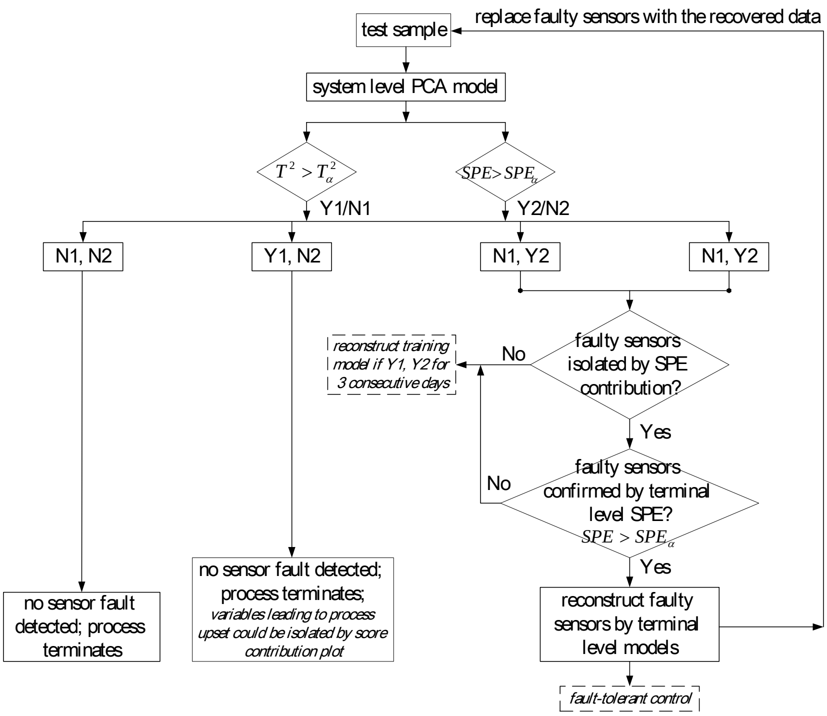


Figure 5. PCA-based flow sensor FDD strategy

VALIDATION USING SIMULATION RESULTS AND IN-SITU MEASUREMENTS

Simulation Tests

To test the FDD strategy for VAV systems, both simulation and site data were used. In simulation test, an AHU/VAV system covering a floor area of 1166 m^2 is simulated. The floor area is divided into eight zones. Two variable blade angle fans are equipped as VAV supply fan and return fan, respectively. The pitch angle of the VAV supply (axial) fan is moderated to control the supply static pressure. TRNSYS is used as the platform for the above mentioned VAV system dynamic simulation. Wang's [25] models are used in this study except the system pressure-flow balance model. The "Fluid flow rate and pressure calculation" model developed by Yingxin Zhu [26] is modified for the simulation tests. The schematic of system pressure-flow balance model is illustrated in Figure 6.

The VAV terminals are pressure independent VAV boxes under cascade control. The design air flow rate of the VAV system is 6 m^3/s and the design VAV supply fan pressure at the location of the pressure sensor is 650 Pa. The parameters of VAV models to be used for simulation are determined according to the in-situ monitoring data. Multiple faults are introduced into this simulation deck to get the system faulty performance characteristics in the following sections.

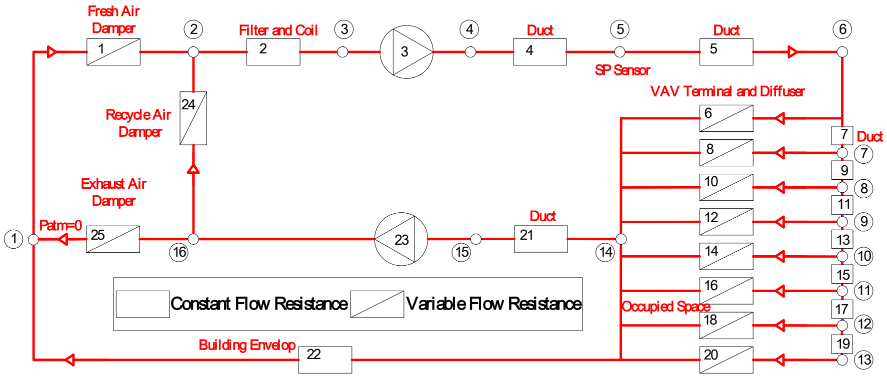


Figure 6. Schematic of system pressure-flow balance model

The simulation results in Figure. 7-10 testified the ability to detect Fault 1-5 (Step 1-4). Figure 11 shows test results of Step 6 of the strategy when controller failure exists. However, tests show that similar responses of the processes can be observed when damper sticking or hysteresis exists.

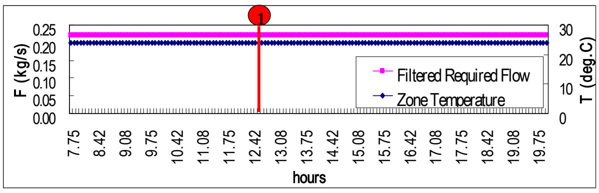


Figure 7. Step1 for Fault 1

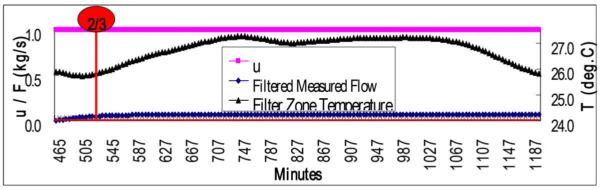


Figure 8. Step 2 for Fault 2/3

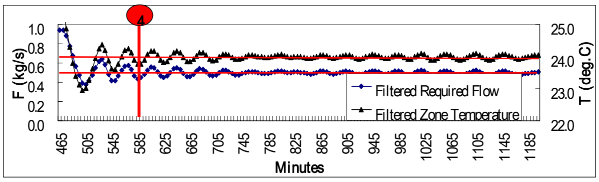


Figure 9. Step 3 for Fault 4

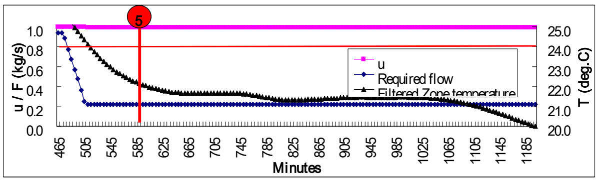


Figure 10. Step 4 for Fault 5

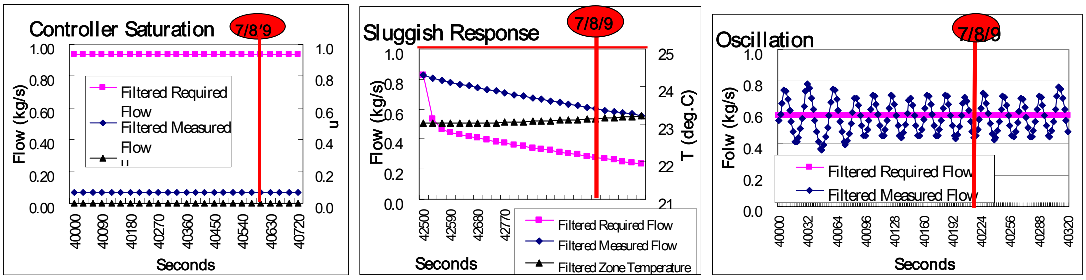


Figure 11. Step 6 for Fault 7/8/9

To distinguish the mechanical faults from the improper flow controller setting at Step 6, the pattern discrimination models (PDM) are established. The PDM for sluggish response can be established using the measured flow rate. After set-point adjustment or disturbance occurrence, the measured flow keeps unchanged ($\bar{F}_k - \bar{F}_{k-1} = 0$) if hysteresis exists. The index of ($\bar{F}_k - \bar{F}_{k-1}$) shown in Figure 12 indicates the PDM for root cause isolation. Similarly, the PDM for oscillation can be established using the measured flow as well. The discrimination index of ($\bar{F}_k - \bar{F}_{k-1}$) is employed to track the change of the measured flow. As shown in Figure 13, the fault of sticking is detected by dominated zeroes.

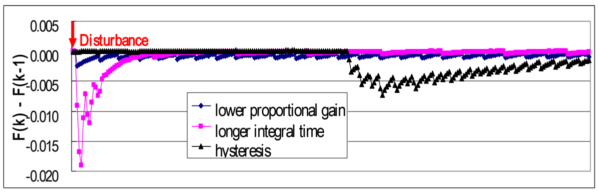


Figure 12. PDM for sluggish response

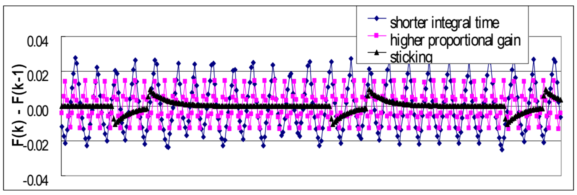
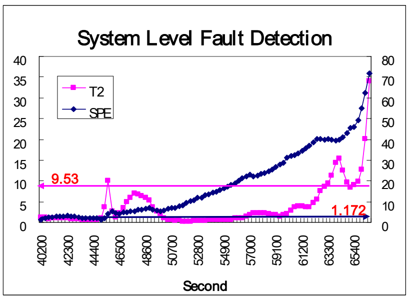
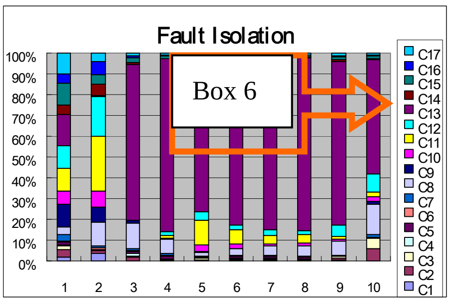
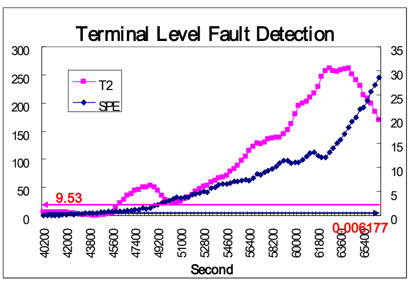


Figure 13. PDM for oscillation







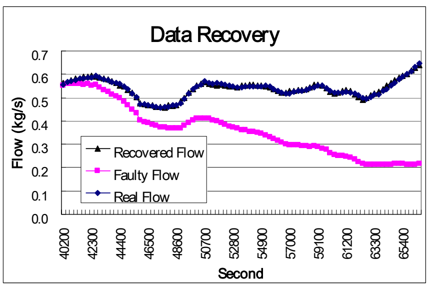


Figure 14. PCA-based FDD for Box 6 flow sensor fault and data recovery

To get the training data for Step 7 validation test, simulation of one operating day was carried out with fault free sensors. In the strategy validation test, developing sensor fault was introduced into Box 6 at 11:06:40 a.m. (i.e. 40000s). Both system level training matrix (*33x17*) and terminal level training matrix (*4x17*) are constructed from the simulation results under normal operation. Three PCs are retained in both models based on the minimum VRE. The FDD results of both levels and the data recovery results are shown in Figure 14. It can be concluded that the serial use of two PCA models enhances the robustness of the FDD strategy. Besides, the recovered data could be further used for fault-tolerant control.

In-situ Tests

The PCA-based VAV terminal flow sensor FDD strategy was also tested using measurements from a pressure dependent VAV system of a real high-rise commercial building. The air-conditioning system under study is a pressure dependent VAV system serving half floor open office. The system operates 12 hours (8:00~20:00) per working day. The control and performance monitoring are handled using the BMS. Data trend at 30-minute intervals of a week (5 working days) were recorded by the BMS system. After an initial checking on the data of VAV boxes, Box 34, 35, 37, 42 and 44 were left out of the training matrix as the damper openness and the flow measured observed to be abnormal. The data of the first three working days are used to construct the training model. Applying a filter based on T^2 statistic, outliers in the measurements were eliminated before applying the PCA-based scheme. Three tests were conducted using the measurements of fourth and fifth days. In the first test, the measured flow of Box 38 was added with fixed bias ($F38_{e1}$ = F38 + 100, Error I). In the second test, it was added with a developing bias ($F38_{e2}$ = F38 + 2 + 2t/0.5, Error II). In the third test, it was added with another fixed bias ($F38_{e3}$ = F38 + 50, Error III).

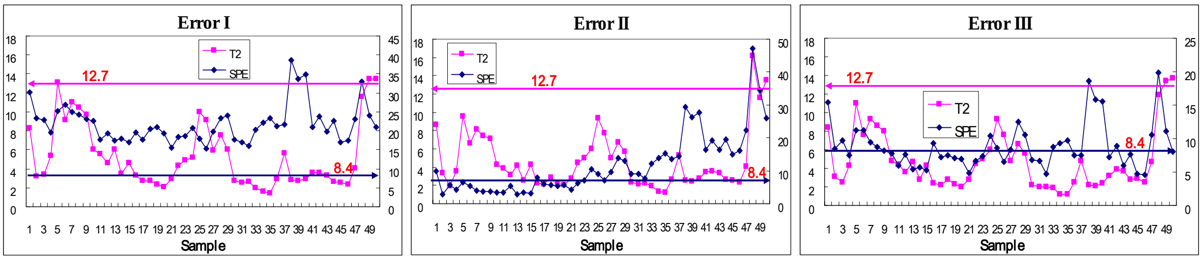


Figure 15. T^2 statistic and SPE plot of the tests in the real building (4th and 5th days)

Figure 15 presents the T^2 Statistic and SPE plot of the tests with Error I, Error II and Error III respectively. The process is under control since T^2 Statistic plot is obviously below the threshold lines. The flow sensor bias was detected by SPE when it was 100 l/s (Error I). However, the developing bias (Error II) could be detected only when the reading deviation was significant (above 50l/s). It was also demonstrated by the right graph that the bias of +50l/s (Error III) was marginally detectable. In the tests, the airflow rate of the concerned VAV box was around 200l/s. The tests indicate that the sensor biases could only be detected when those exceed a certain level in practical applications. As a little sensor reading deviation would not affect the normal control process, the sensitivity of the FDD strategy is acceptable. SPE contribution plot approach is used to isolate the faulty sensor. In Figure 16, for the fixed error test (Error I&III), the average SPE contribution of each variable is compared (the left graph and the right graph). For the developing bias test (Error II), the SPE contribution of each variable was compared at 3-hour intervals (the middle graph). The flow rate of Box 38 in the test data matrix was isolated as it had a major SPE contribution. Investigating Box 38 with terminal level PCA model revealed that flow sensor of Box 38 was faulty.

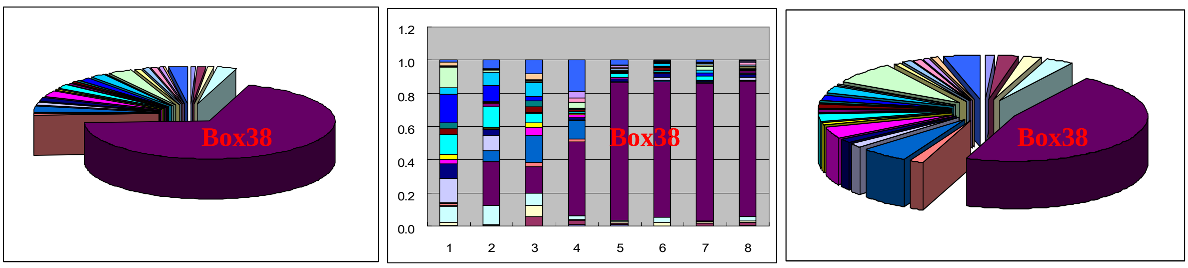


Figure 16. SPE contribution plot of the test in the real building (4th and 5th days)

CONCLUSION

Ten typical faults for system faults are summarized in this study. The multiple fault detection strategy developed using performance indices can detect and diagnose typical faults in VAV terminals for on-line commissioning and re-commissioning. Most of the faults can be isolated by analyzing the fault pattern of the system characteristics, which are presented by performance indices and expert rules. PCA based method using models at both system level and component level can be an effective tool for VAV box flow sensor FDD and sensor recovery.

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