Commissioning and Diagnosis of VAV Air-Conditioning Systems

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Abstract: This paper presents a fault detection and diagnosis (FDD) strategy based on system knowledge, qualitative states and object-oriented statistical process control (SPC) models for typical pressure-independent variable air volume (VAV) air-conditioning systems. Eight FDD schemes are built to detect the eleven pre-defined VAV faults using the qualitative and quantitative FDD approaches within the strategy at two steps. The ten hard faults, which would affect the system operation, are analyzed at Step 1. The soft fault, which would not affect the basic system operation but would impact the supervisory controls, is analyzed at Step 2. The strategy is tested and validated on typical VAV systems involving multiple faults, both in simulation and in-situ tests. A software package is developed as a BMS-assisted automatic commissioning tool based on the FDD strategy. Off-line tests were conducted in both the simulated building and the real building.

Keywords: fault detection and diagnosis, variable air volume, statistical process control, qualitative and quantitative reasoning

1. INTRODUCTION

VAV (variable air volume) air-conditioning systems and their control strategies become more and more complex to achieve better energy performance. 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. Fault detection and diagnosis (FDD) has been approved to be an essential and efficient supporting tool in commissioning by fixing faults timely and reducing the impacts of them in building HVAC applications.

In VAV air distribution systems, as terminals serve the end-users, their performance have significant effects on the environmental quality provided by HVAC system and the energy efficiency of buildings. Literature survey [1] shows that study on the faults of VAV terminals is far from sufficient, particularly concerning the system integrating a large number of VAV terminals. 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 [2]. This interaction must be carefully analyzed and measured for achieving optimal control and therefore, in development of any FDD techniques.

When system interaction is of concern, the conventional FDD method based on quantitative models suffers from the lack of ability to handle qualitative knowledge especially under complex circumstances [3] like VAV air distribution systems. Qualitative reasoning is developed based on qualitative descriptions to provide a theoretical framework for expertise reasoning about the physical system using incomplete knowledge [4]. The basic idea of qualitative reasoning is to obtain system structure, i.e., components and connections among them for physical system, describing it either by qualitative equations or by causal constraints, then to solve these equations or analyze these constraints. Integrating quantitative models with qualitative knowledge helps to solve decision making problems more effectively and efficiently.

In this study, an overall architecture of qualitative/quantitative reasoning for FDD is presented. The VAV FDD strategy is developed within the architecture to deal with multiple VAV faults in VAV air distribution systems. Eight FDD schemes are set up to deal with 11 pre-defined root faults. The strategy is validated in both simulation and in-situ tests. A software package is developed as a BMS-assisted automatic commissioning tool and the off-line tests of the tool application are conducted.

2. OVERALL ARCHITECTURE OF QAULI-TATIVE/QUANTITATIVE REASONING FOR FDD

An overall architecture integrating system structure, qualitative reasoning and quantitative models [3] are modified for VAV FDD as shown in Fig. 1. Compared with conventional quantitative FDD methods, this method takes advantage of both qualitative knowledge and quantitative models. The framework consists of two levels of frames. The first level presents the physical knowledge about the system structure. On the second level, the qualitative/quantitative reasoning is conducted.

Knowledge representation on the first level (the upper part of Fig. 1) is the base. It presents faults and the related domain knowledge consisting of three parts: frames, parameters and rules. A conceptual model describes the physical processes that are part of an environment, how they relate to each other and which processes dominate the system. It defines the general physical framework within which the process details can be worked out and associated numerical relations can be developed. Based on the conceptual model, the faults are grouped and the FDD structure is set up.

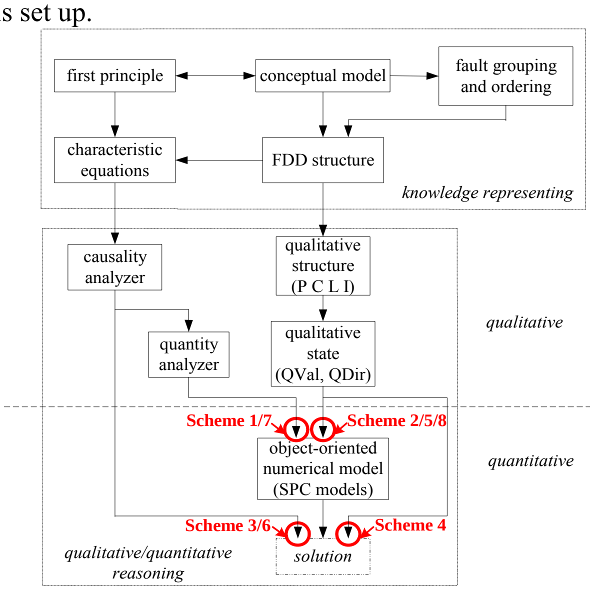

Fig. 1 Overall architecture of qualitative/quantitative reasoning

Qualitative structure is defined as a tuple (*P, C, L, I*) [3], where $P = \{f_i : i = 1,\dots,n\}$ is the set of n parameters, $C = \{C_i(f_1,\dots,f_n, df_1,\dots,df_n) : i = 1,\dots,k\}$ is the constraints on *P*, $df_1,\dots df_n$ are the differentials of $f_1,\dots,f_n$ respectively, $L = \{l_j : j = 1,\dots,m\}$ is the set of landmark points, and $I = \{IQ(f_i) : i = 1,\dots,n\}$ is the set of incremental qualitative values. Qualitative state (*QS*) is defined as Equation 1.

$$QS(f_i, t) = (QVal, QDir) \tag{1}$$

where qualitative value

$$QVal = \begin{cases} l_j, f_i(t) = l_j \\ (l_j, l_{j+1}), l_j < f_i(t) < l_{j+1} \end{cases} \tag{2}$$

qualitative direction

$$QDir = \begin{cases} inc, \dfrac{df_i(t)}{dt} > \delta \\ std, \left|\dfrac{df_i(t)}{dt}\right| \le \delta \\ dec, \dfrac{df_i(t)}{dt} < -\delta \end{cases} \tag{3}$$

In Equation 3, the moving slope estimation is employed, which estimates the slope of the linearly regressed line of the parameter and a sufficiently large slope indicates the presence of *inc* (increasing) or *dec* (decreasing).

On the second level, qualitative reasoning uses physical information such as relative magnitudes, and the directions of change in variable values, as opposed to precise values to understand the initial problems qualitatively. However, there is an inherent limitation of the qualitative reasoning since only qualitative terms are employed. The object-oriented statistical process control (SPC) sub-models are integrated into the framework to solve quantitative sub-problems after recognizing the limitation of qualitative reasoning.

3. FDD STRATEGY FOR VAV FAULTS

3.1 Root Faults in VAV Systems

Site investigation on all 1251 VAV terminals in a commercial building summarized 10 root faults for the pressure-independent VAV terminal systems [5]. When the whole air distribution system is of concern, the control of static pressure serves as the key issue to the system. Therefore 11 root faults are summarized for the pressure-independent VAV air distribution systems as listed below (The same serial numbers of faults are used in the late part of the paper), which are concerned by the strategy developed: *Fault 1 – Poor tuning of static pressure control loop; Fault 2 – Zone temperature sensor reading frozen; Fault 3 – VAV controller hard failure; Fault 4 – VAV terminal under/over capacity; Fault 5 – VAV damper stuck; Fault 6 – VAV flow sensor reading frozen; Fault 7 – VAV flow sensor reading deviation to minimum/maximum; Fault 8 – Poor tuning of VAV controllers; Fault 9 – VAV damper sticking; Fault 10 – VAV damper hysterics; Fault 11 – VAV flow sensor bias.*

3.2 FDD Strategy

The FDD strategy for multiple VAV faults forms within the above-mentioned FDD architecture. The conceptual model about the physical process relationships in VAV system is developed from Wang's models and system interaction [6]. When the faults of VAV air distribution system are of concern, the temperature and flow control process, the static pressure control process and the network pressure-flow balance process dominate the system. The root faults of air distribution systems are within these processes.

Fig. 2 illustrates VAV fault grouping and logic structure, which plays an important role in describing the FDD strategy. Eleven faults are classified into eight groups which are dealt with by eight relevant FDD schemes. Fault 1-10 are treated in parallel by Scheme 1-7 at Step 1. Fault 11 is treated by Scheme 8 at Step 2. As some faults could not be easily differentiated from each other, both Fault 4 and 5 are analyzed under Scheme 4. Similarly, Fault 8, 9 and 10 are analyzed together under Scheme 7. VAV terminal flow sensor bias, Fault 11, would not affect

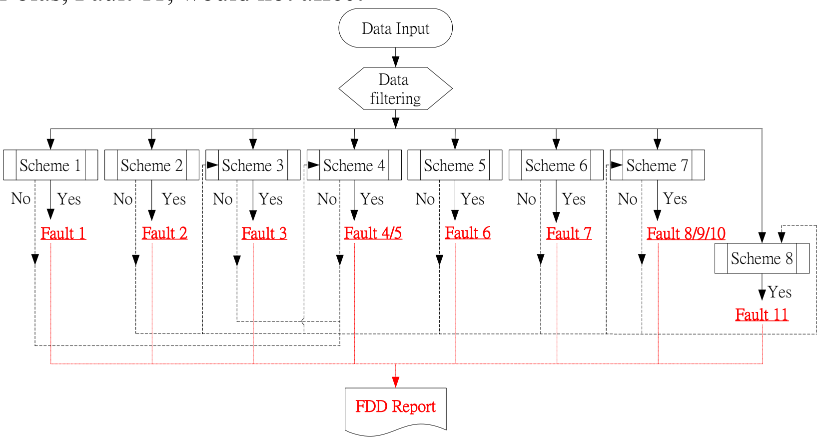

Fig. 2 VAV fault grouping and ordering

the normal control process if the readings are within the normal range as it can be compensated by resetting the air flow set-point. This fault is analyzed at Step 2 when it is confirmed that the system is faultfree at Step 1. Considering the interaction amongst the faults, the results of respective FDD schemes at Step1 should be studied simultaneously. When the faults are dealt with in parallel, the ability of the FDD schemes designed for the specific faults could be interfered by the other faults. Therefore, the fault(s) could only be detected by the relevant schemes while the associated schemes give the indication of fault free as illustrated in Fig. 2. The automatic commissioning tool is developed on the basis of the FDD strategy.

3.3 FDD Schemes

The VAV terminal damper openness is an important parameter to build up the qualitative/quantitative models in the FDD schemes. However, in normal pressure independent VAV systems, the signal of damper openness is not available. Position algorithm controllers are commonly used for VAV damper control. The control signal to damper (μ) typically represents the position of an actuator and therefore the openness of the VAV damper [7]. Therefore, μ is used to represent the damper openness in the FDD strategy developed in this study. Other data for qualitative/quantitative modeling are normally available in modern BMS including the static pressure and its set-point, zone temperature and its set-point, VAV flow rate and its set-point. The intervals of the data collection are 1 minute in most FDD schemes. To eliminate the effects of system dynamics and ensure the reliability of the measurements used, some of the measurements have to go through a filter constructed on the basis of exponential weighted moving average before they are used.

The illustration of reversal counting is shown in a univariate statistical control chart in Fig. 3, where σ is the standard deviation. The reversal counting starts when the process variable exceeds the Shewhart control limit from the in-control range ($R=1$) and one more reversal is counted ($R=R+1$) once the variable exceeds the threshold at the opposite direction. In most circumstances, the maximum tolerable number of reversals is set to be four [8]. In addition, the sensor reading frozen could be completely frozen at a fixed figure (Case 1) or floating within a certain range (Case 2) as shown in Fig. 4. The reading frozen of Case 2 is further confirmed by the cumulative sum (CUSUM) control method besides the readings are within Shewhart control limits.

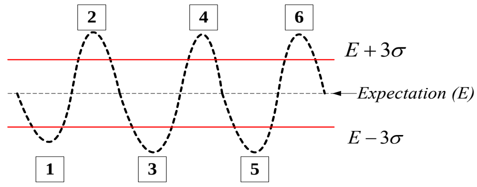

Fig. 3 Illustration of reversal counts

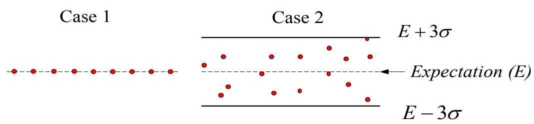

Fig. 4 Illustration of sensor reading frozen

The eight FDD schemes are built up within the overall FDD architecture (Fig. 1) with some of them using the above-mentioned statistical techniques. As shown in Fig. 1, Scheme 3 for Fault 3 and Scheme 6 for Fault 7 are developed from causality analyzer. Scheme 1 for Fault 1 and Scheme 7 for Fault 8/9/10 need quantity analyzer supported by SPC models to fulfill the schemes. Scheme 4 for Fault 4/5 is developed purely using qualitative states. Scheme 2 for Fault 2, Scheme 5 for Fault 6 and Scheme 8 for Fault 11 are accomplished using SPC models after the qualitative states classify the faults at the qualitative level. The algorithms of the schemes are listed in Table 1.

Scheme 8 is for Fault 11, air flow sensor bias analysis. This soft fault in a typical VAV terminal might not affect the normal control process if the readings are 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

Tab. 1 Algorithms of FDD schemes

FDD Scheme	Fault	Algorithm	Remarks
Scheme 1	Fault 1	$R_{P,st} \geq 20 \mid \Delta time < t_{delt}$ (4)	Fault is detected by excessive consecutive reversals.
Scheme 2	Fault 2	$\left.\begin{array}{l}(T_E - 3\sigma_T < T < T_E + 3\sigma_T) \\ AND(C_T^+ < 5\sigma_T) \\ AND(C_T^- < 5\sigma_T) \\ AND(F_{set,E} - 3\sigma_F < F_{set} < F_{set,E} + 3\sigma_F) \\ AND(C_{F,set}^+ < 5\sigma_F) \\ AND(C_{F,set}^- < 5\sigma_F)\end{array}\right\rvert \Delta time > t_{delt}$ (5)	Fault is detected if both temperature and flow set-point are within their CUSUM control.
Scheme 3	Fault 3	Simple characteristic equations	
Scheme 4	Fault 4/5	$QVal_1 = \begin{cases}(-\infty, -T_{th}), \overline{T} - T_{set} \\ \mu_{\min}, \mu \\ (0, 0.05), \Delta\overline{F} / F_{\max}\end{cases}$ (6) $QVal_2 = \begin{cases}(T_{th}, \infty), \overline{T} - T_{set} \\ \mu_{\max}, \mu \\ (0, 0.05), \Delta\overline{F} / F_{\max}\end{cases}$ (7)	Fault is detected by the deficiency of the temperature control loop and flow control loop as well as no variation of the measured flow rate over a preset period.
Scheme 5	Fault 6	$\left.\begin{array}{l}(R_{\overline{F},set} \geq 5) \\ AND(F_E - 3\sigma_F < F < F_E + 3\sigma_F) \\ AND(C_F^+ < 5\sigma_F) \\ AND(C_F^- < 5\sigma_F)\end{array}\right\rvert \Delta time < t_{delt}$ (8)	Fault is detected by excessive flow set-point consecutive reversals while the flow reading is detected frozen.
Scheme 6	Fault 7	$\left.\begin{array}{l}(\overline{T} - T_{set} < -T_{th}) \\ AND(\mu = \mu_{\max}) \\ AND(F \leq F_{\min}) \\ AND(F_{set} = F_{\min})\end{array}\right\rvert \Delta time > t_{delt}$ (9) $\left.\begin{array}{l}(\overline{T} - T_{set} > T_{th}) \\ AND(\mu = \mu_{\min}) \\ AND(F \geq F_{\max}) \\ AND(F_{set} = F_{\max})\end{array}\right\rvert \Delta time > t_{delt}$ (10)	
Scheme 7	Fault 8/9/10	Flow controller sluggish response: $\left\lvert \overline{F} - F_{set} \right\rvert > F_{th} \mid \Delta time > t_{delt}$ (11) Temperature controller oscillation: $R_{F,set} \geq 15 \mid \Delta time < t_{delt}$ (12) Flow controller oscillation: $R_F \geq 20 \mid \Delta time < t_{delt}$ (13) Temperature controller sluggish response: $\left\lvert \overline{T} - T_{set} \right\rvert > T_{th} \mid \Delta time > t_{delt}$ (14)	To sort out the faults, the air flow control loop is analyzed first. The faulty pattern of sluggish response and oscillation is defined by 4 equations step by step. The root cause(s) of faulty pattern is identified by pattern recognition indices.
Scheme 8	Fault 11	Principal Component Analysis (PCA)	The details of PCA models for flow sensor bias detection and sensor reconstruction are presented in the context.

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, Scheme 8 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 [9]. Thus PCA method is chosen as the suitable method to build up the SPC models in this scheme.

The operating data under normal conditions are used to train the PCA model and obtain the eigenvalues (Λ) and eigenvectors (V) to present the correlation structure amongst variables. Only those eigenvectors (P_{mxa}) optimally capture the variations of the data while minimizing the effect of random noise 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 [10].

In FDD applications, the new observations X_{new} are projected to the principal component (PC) subspace to get their PCA estimation (Equation 15). Both T^2 statistic (Equation 16) and Q statistic (Equation 17), which is called SPE (Square Prediction Error) as well, are used for fault detection. Generally speaking, T^2 relates to process upsets and SPE relates to sensor faults [11]. 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 [12] is employed in this study.

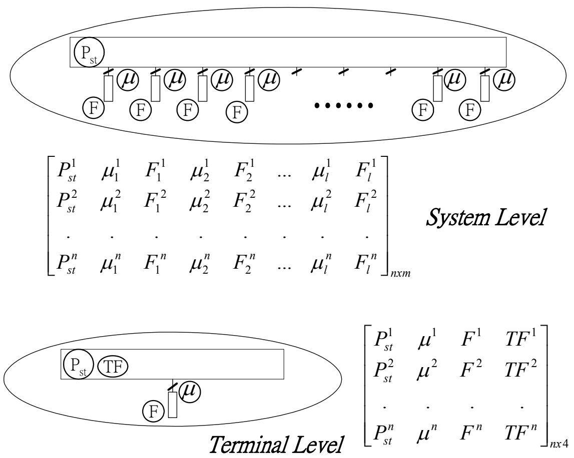

Fig. 5 PCA models at system level and terminal level

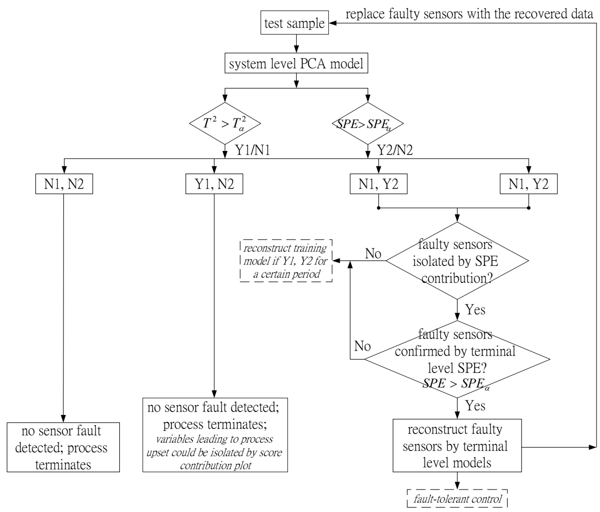

Fig. 6 PCA-based flow sensor FDD

$$\hat{X}_{new} = X_{new} P P^T \tag{15}$$

$$T^2 = X_{new}^T P \Lambda_a^{-1} P^T X_{new} \le T_\alpha^2 \tag{16}$$

$$Q = SPE = \left\| X_{new} - \hat{X}_{new} \right\|^2 \le SPE_\alpha \tag{17}$$

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 (Fig. 5). The system level model indicates that, in a network, the hydraulic characteristics are related to the static pressure ($\boldsymbol{P_{st}}$), the damper position (μ) and flow rate (F) of all VAV terminals. 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 is isolated by the system level FDD. The PCA-based sensor FDD (Fig. 6) is strengthened by the recovered data and iteration of the FDD process. The process terminates until no further fault could be detected.

4. VALIDATION OF FDD STRATEGY

4.1. Simulation Tests

An office building was simulated as the test facility for scheme validation [6]. Dynamic simulation of the system with different combinations of faults provides a convenient and low cost tool in testing and evaluating the FDD strategy. Single hard fault (Fault 1-10) was introduced into the simulation deck individually to generate ten groups of testing data. The FDD ability of Scheme 1-7 for single fault detection was verified. Figure 7 gives an example of the scheme performance. Frozen sensor reading (Fault 6) at 0.5 kg/s was detected by Scheme 5 after the SPC model counting five reversals of the flow set-point.

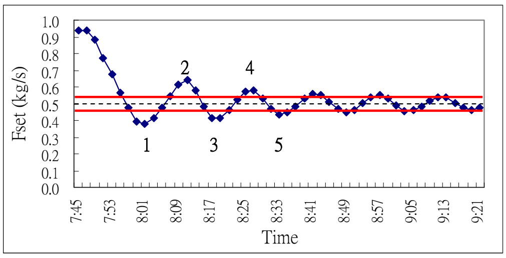

Fig. 7 VAV Flow Sensor Reading Frozen at 0.5 kg/s

As the existence of multiple faults will affect the fault detection results of some FDD schemes, the interaction amongst the faults were carefully studied when developing the strategy and the problem was solved by considering the seven schemes simultaneously with the essential exchange of the FDD output as shown in Fig. 2.

Scheme 1, 2, 5 and 6 are independent as their fault detection results would not be affected by the existence of multiple faults. Therefore, different combinations of multiple faults were introduced into the same simulation deck to generate the test data for evaluation. The independence of those schemes was verified. Under Scheme 3 and Scheme 4, zone temperature is a key parameter for fault detection. The existence of Fault 2 would give the counterfeit fault detection results of both Scheme 3 and Scheme 4. However, the existence of other faults would not affect these two schemes. The simulation tests of multiple hard faults except Fault 2 validated the both schemes. The above validation tests with different groups of simulation data verified the FDD ability at Step 1 of the developed FDD strategy.

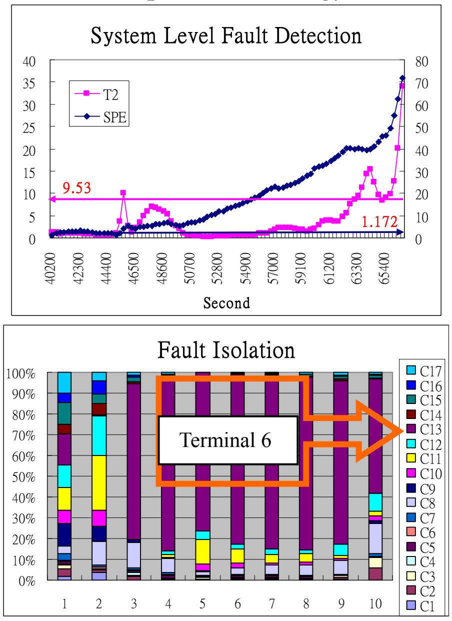

Fig. 8 System level fault detection and isolation

To evaluate Scheme 8 at Step 2, simulation of one fault –free operating day was carried out to get the training data for PCA models. In the validation test, developing sensor fault was introduced into Box 6 at 11:06AM. Both system level training matrix (*33x17*) and terminal level training matrix (*4x17*) were constructed from the simulation results under normal operation. Three PCs are retained in both models based on the minimum VRE. The scheme examined the system by deducing both T^2 statistic and *SPE*. The system level T^2 statistic and *SPE* plot is presented in Fig. 8. It is found that most of the points were within the limit of T^2 but quickly out of control on *SPE* as the flow sensor error developed. The results strongly indicate the existence of sensor bias. *SPE* contribution isolated the fault. Further looking into the terminal level model confirmed the fault.

4.2. In-Situ Tests

The in-situ validation of the schemes was conducted in a commercial building located in Hong Kong, which is a 39-storey building completed in 1995. The site survey for re-commissioning carried out in 2002 recorded the performance of all VAV boxes in the building. The validation was based on some VAV faulty performance recorded and the particular FDD tests at the same building. The validation is summarized below.

According to the performance pattern of the VAV 35 at the 31st floor, the zone temperature sensor frozen (Fault 2) was confirmed by the SPC models, which verified the FDD ability of Scheme 2. According to the site survey, Fault 4 and Fault 5 were common. They were detected by further logging the control signal to the damper (μ) by a portable digital voltage meter. The manual measurement on the control signal also helped identify Fault 7.

For VAV flow sensor reading frozen (Fault 6), another in-situ test was carried out by replacing the flow sensor signal of VAV Box 30 at 18th floor with an emulated control signal of 4V DC, which represented 200l/s of the reading. Under the temperature set-point of 21.5°C, the trend data of the flow set-point were recorded at 1-minute intervals for an hour afterwards. Scheme 5 detected the fault after counting five consecutive reversals of the flow set-point.

5. AUTOMATIC COMMISSIONING TOOL AND ITS OFF-LINE TESTS

The automatic commissioning tool is developed from the FDD strategy. Based on the BMS measurement points, the database could be set up which includes all the trend data required by the tool. A basic managing platform is developed to provide the human machine interface, arranges the data files, run the commissioning software and to generate the FDD reports. The structure of the commissioning software package is presented in Fig. 9. It includes a FDD main program, eight functional modules (subroutines) for the eight schemes, VAV flow sensor fault isolation module (subroutine) and some mathematical modules (subroutines).

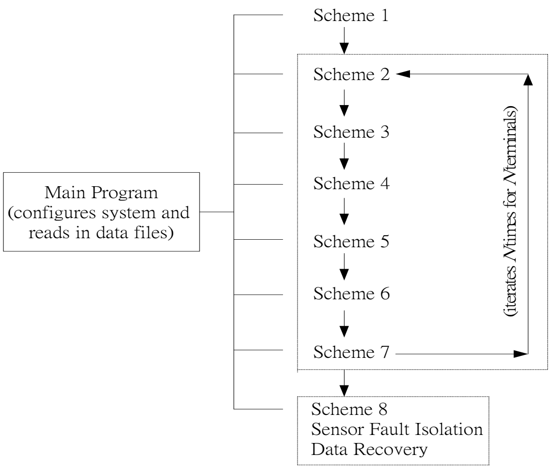

Fig. 9 Structure of the commissioning software package

The FDD main program defines the system configuration by inputting the number of VAV terminals (*N*) and reads in data files. It calls the functional modules (Scheme 1-8) and other subroutines to work together to detect faults and gives the output of FDD results as well as the recovered measurement data if any. The FDD results are reported by giving the output of the fault detection indices (FF1-8) associated with the relevant FDD schemes (Scheme 1-8), where '0' indicates fault free and '1' indicates the relevant fault(s) detected under the scheme.

Exercises of the software application were conducted using the simulated data generated from the same simulator. Several groups of the simulated data were prepared in text files. Different faults were introduced in each group of the simulated data, which was detected by the software as the FDD report showed '1' of the relevant fault detection indices. Table 2 demonstrates an example of main FDD report, where Fault 2 of Terminal 6 is reported.

Tab. 2 An example of main FDD report

Main FDD Report								
Index (FF1-8)	1	2	3	4	5	6	7	8
Terminal 1	0	0	0	0	0	0	0	0
Terminal 2		0	0	0	0	0	0	
Terminal 3		0	0	0	0	0	0	
Terminal 4		0	0	0	0	0	0	
Terminal 5		0	0	0	0	0	0	
Terminal 6		1	0	0	0	0	0	
Terminal 7		0	0	0	0	0	0	
Terminal 8		0	0	0	0	0	0	

Off-line application in a real building was also carried out. A full set of BMS data of a recently upgraded pressure-independent VAV system was recorded at 1-minute intervals. The data were prepared in text files to be read in by the software package.

The commissioning analysis started when the main program read in the total number of VAV boxes (N=28). The software configured the system with 28 VAV terminals and began to read in the required groups of data and implement FDD schemes in an iterating way. Scheme 8 for flow sensor bias analysis was not activated as hard faults were detected and specified. The commissioning tool located all the faults in the system correctly.

6. CONCLUSION

Malfunction of VAV components and sensors occur easily. However, it is difficult to identify the root cause(s) of fault(s) manually as so many variables are involved and the accesses to most terminals are limited. Integrating of qualitative reasoning and quantitative computation helps analyze the pre-defined eleven faults automatically based on the available BMS measurements. FDD strategy developed based on qualitative/quantitative reasoning was verified by both the simulation tests and in-situ tests as an effective approach for VAV FDD. The BMS-assisted automatic commissioning tool based on the FDD strategy provides an applicable tool for VAV system on-going commissioning. Effort is needed to develop further the tool for on-line application.

ACKNOWLEDGEMENT

The research work presented in this paper was financially supported by a grant from the Research Grants Council (RGC) of the Hong Kong SAR.

NOMENCLATURE

ΔF:	air flow variation
$\Delta time$:	time counted
Λ:	matrix of eigenvalues
DP:	differential pressure
F:	air flow rate
P:	principal loading matrix
$\mathbf{P}$:	pressure
R:	reversal
SPE_α:	threshold of SPE
t:	time
T:	temperature
T^2_α:	threshold of T^2 statistic
TF:	total flow
X:	variable matrix

Greek symbols

δ:	threshold of the slope
μ:	control signal to terminal damper
σ:	standard deviation

Subscripts and superscripts

$\bar{}$:	estimated output on EWMA
^:	estimated output on the score space
a:	number of PCs
$delt$:	preset period
E:	variable expectation

F: air flow rate
max: maximum
min: minimum
new: new observations
set: set-point
st: static
T: temperature
th: threshold

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