RARX ALGORITHM BASED MODEL DEVELOPMENT AND APPLICATION TO REAL TIME DATA FOR ON-LINE FAULT DETECTION IN VAV AHU UNITS

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ABSTRACT

Assimilation of cost-effective Fault Detection and Diagnosis (FDD) technique in building management system can save enormous amount of energy and material. In this paper, Recursive Autoregressive Exogenous Algorithm is used to develop dynamic FDD model for variable air volume air handling units. A methodology, based upon frequency response of the model is evolved for automatic fault detection and diagnosis. Results are validated with data obtained from a real building after introducing artificial faults. It is concluded that the method is quite robust and can detect and diagnose several types of faults

INTRODUCTION

The performance of Heating, Ventilation and Air Conditioning (HVAC) systems often do not achieve the same level attained at commissioning stage. During long time operation, sensors and actuators degrade and fail, valves and dampers leak and stick, coils become fouled, and any number of other problems may arise. These faults often leads to occupant discomfort, higher health and safety risks, increased energy use, and shorter equipment life. The potential savings out of improved energy management and faulty and non-optimal operation of HVAC systems alone in commercial buildings is estimated to be 20 - 30 % [1]. Fault Detection and Diagnosis (FDD) technique aims to detect, locate and, if possible, predict the presence of the defects causing faulty operation well in time, thereby, reducing energy consumption, new materials and inoperative time.

Energy management practices and its optimization process in buildings being employed by the current supervisory strategies cannot respond efficiently to the occurrence of faults since the processes and systems in buildings have become more an electronics black box. When the process enters a failure state, the supervising computer program or methods currently available do not adequately assist in finding the underlying cause of the fault. This task is generally left to the operator judgment as in general there is hardly any automatic FDD tool in the building management system. Though, FDD techniques have been devised and used for decades in sensitive areas of operation like process industries and nuclear power plants, the technique employed is dominated by extensive use of sensors (sometimes more than one sensor at one position), and highly reliable as well as costly monitoring instruments. According to the results of a survey, occupants wait for 30 to 60 minutes without much complain about the undesirable thermal environment due to malfunctioning of HVAC system [2]. Therefore, providing an cost-effective system for prompt detection and repair of faults are more important than operational reliability.

MODEL BASED REASONING

The kernel of model-based FDD is the model, which simulates the functionality of the concerned system. The difference between the system measurement and its model output corresponding to a healthy system is called residual. A large variation in residuals may indicate fault in the system. A straightforward "Physical Model" can be obtained if the characteristics of each component in the system are described by equations derived from the basic laws of physics. In practice though, it is almost impossible to make a model on the basis of strict physical knowledge of the system that exactly simulates the real behavior of a particular system since reliable values of model parameters are often not available as either the design data or the manufacturer's data are often not provided by the manufacturer and even if provided, they are quite general to describe the actual operation.

Since prediction of individual process behavior in a system is not the ultimate goal in fault detection, a simple "Black Box Model" can well be used in most cases for a subsystem. In black box modeling, the whole system is represented by a set of parameters obtained by system identification process. These parameters usually do not have any physical meaning. Black box models are easier to set up and require much less detail information about the system to be modeled. Another advantage of the black box Model Based Diagnosis (MBD) is that even with a new system, for which no repair experience exists, it can be used. A vague model is always obtainable from a relatively small training data sets and can be further refined as data accumulates in the process. Since system variables change without direct outside influence (their values depending upon earlier applied signals), the dynamic response of the system may also be represented by a set of nearly constant parameters in dynamic modeling. Any change in the state of the system due to faults is likely to be reflected by a change in parameter values.

A lot of activities in the field of Fault Detection and Diagnosis (FDD) have been coordinated by the "Annex 25" (Building Optimization and Fault Detection, 1992-1996), of the International Energy Agency (IEA) with the main objective to develop methodological process, within a defined concept, for the real-time and automatic performance optimization, diagnosis and fault detection of HVAC process [3]. Most recently, IEA has been coordinating research under its frame work of Annex 34, "Computer Aided Fault Detection and Diagnosis" to devise an appropriate computer tool for online fault detection and diagnosis. The number of different components, subsystems and systems in a building are large. Therefore, attention must converge on the most important faults in terms of some (inevitable subjective) evaluation criteria, i.e., the fault modes and ways in which faults appear [4]. The best way to solve a problem is to decompose it in simpler problems. Following this strategy recurrently, until the problems obtained are simple enough to solve them with an accuracy as much as desired. As investigated by the Japanese researchers participating in IEA Annex-25, VAV faults are widely considered as one of the most important faults. This work is undertaken in continuance of the earlier findings and as part of the IEA ANNEX-34 guidelines to develop online FDD technique for VAV subsystems [5]. Real time data were obtained from a real building under actual use and are used to validate the model.

DATA ACQUISITION

Fault implementation is a central issue for testing the feasibility and robustness of the FDD method. Data for artificial and natural faults are hardly available and data generated by simulated faults may not give accurate results in an emulated and real process. Previous studies were limited to and based upon computer simulated data and their robustness vis-a-vis real time data is yet to be established. To make an artificial fault by copying the symptoms of most typical faults or faulty component in real process can be perceived suitable to develop real time FDD technique. This can be achieved by changing and modifying the control set points of a sub-system or manually disconnecting control signals or mechanical parts with a faulty one.

To develop and evaluate automatic online FDD technique for one of the most widely used Variable Air Volume (VAV) HVAC systems, faults were introduced in a VAV Air Handling Unit (AHU) system of Research and Development Center of Tokyo Electric and Power Company under actual use. Hitherto, the most significant technical problem perceived in these systems is interaction among VAV units equipped with a control loop, where information exchange takes place between several control strategies. This interaction must be carefully analyzed and measured for achieving optimal control and therefore, in development of any FDD technique. However, present approach do not require any prior knowledge of the interaction and results show that it is capable of detecting the faults.

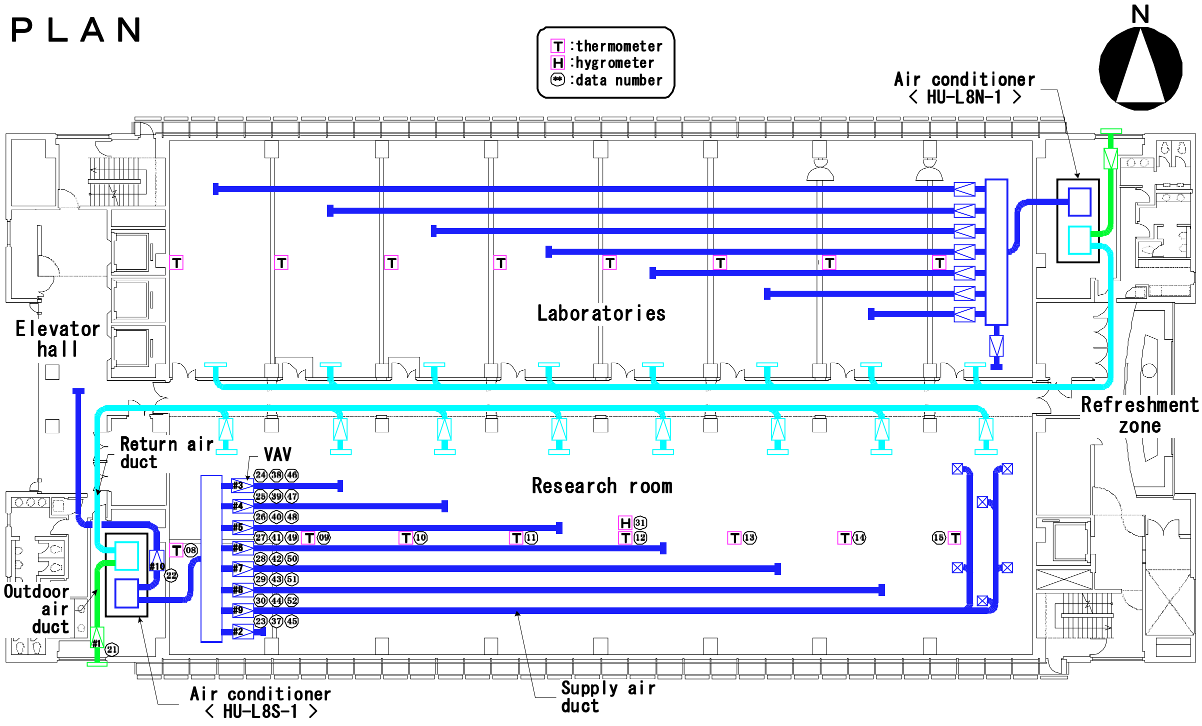

Fig. 1 System layout diagram of 7th floor of Tokyo Electric Power Company FDD test (Japan)

System layout diagram of the 7th floor where faults were introduced are shown in Fig. 1. The VAV subsystem consists of dampers, controller, airflow rate and temperature sensors, controllers etc. Various data (80 types) were collected at one minute interval for normal and faulty condition operations in July-August, 1998. Locations of some of the sensors are shown in the Fig. 1. In the present study data collected from airflow rate measuring sensors of the VAVs 3 to 9 corresponding to the points 24-30, and temperature sensor of these VAVs corresponding to the points 9-15 are only used. The three types of faults and their simultaneous combinations used for the present study are stuck damper at 1) fully opened position, 2) fully closed position and 3) half opened position. Specifications of the faults implemented are given in Table 1.

Table 1 Specifications of faults implemented

No.	Date and Time of fault implementation	Type of faults
1	31.7.98 at 14:00 hrs	VAV-6 Damper opening is fixed
2	3.8.98 at 14:00 hrs	VAV-5 & VAV-6 Dampers kept fully open
3	4.8.98 at 14:00 hrs	VAV-5 & VAV-Dampers kept fully closed
4	5.8.98 at 14:00 hrs	VAV-5 Damper kept fully closed & VAV-6 fully open
5	6.8.98, whole day	VAV-6 Damper kept fully open
6	7.8.98 at 14:00 hrs	VAV-6 Damper kept fully closed

The outline of the building and the VAV system are as follows,

Building Outline

Name	R&D Center of Tokyo Elec. Power Comp.
Type	Mainly Office (Including Res. Space)
Location	Kawasaki City (Japan)
Floor Area	38000 m^2
Floors	+11 F (1 BF)
Completion	Oct. 1994

VAV AHU System Outline

Location of the floor	7th floor
Supply Air Fan Capacity	12,000 m^3/h, 65mm Aq
Cooling Capacity	83,200 Kcal/h
Heating Capacity	37,200 Kcal/h
Design Outside Air Intake	1,725 m^3/h
Control	PID

DYNAMIC SYSTEM IDENTIFICATION

It is better to estimate a model in online FDD technique at the same time as the input-output data is received to make some decisions as in adaptive control, adaptive filtering, or adaptive prediction. Possible time variation in the system's properties during the collection of data can be investigated online and faults can be detected. Recursive identification, adaptive parameter estimation, sequential estimation, and online algorithms are used for such algorithms [5 & 6]. To adjust the parameters of the model to represent the system is called System Identification. When a process operates under normal operating conditions, the parameters in a continuously updated model of the process will be within small changes around their normal values. If some physical changes in the system causes deviation from the normal state, some or all of the parameters will significantly deviate from those normal values. Therefore, the faulty condition can be identified.

Model Structure

In this study, a Single Input / Single output (SISO) Recursive Auto Regressive Exogenous (RARX) system identification methodology with forgetting factor is used and the dynamic performance of VAV sub-systems are modeled using the aforementioned data base. A typical difference equation "black box" model algorithm can be expressed as,

$$y_n = -\sum_{i=1}^{p} a_{n-i} y_{n-i} + \sum_{j=0}^{q} b_j z_{n-j} + e_n \qquad (1)$$

where,
y = output to be predicted,
z = one or more inputs in vector form, which influ ences the output,
e = random variables (normally distributed),
a = autoregressive parameters,
p = autoregressive parameter order,
b = exogenous parameters and
q = exogenous parameter order

The variables y and z must be measured in actual situations. The model represents the causality between the input and output. In the present analysis, deviation of room air temperature from the set point is used as input variable, and change in airflow rate is considered output variable as explained in the methodology section. The model can be written as,

$$y_n = \varphi_n^T \theta_n + e_n \qquad (2)$$

Where, the regression vector φ_n contains old values of observed inputs and outputs. e_n is the noise source. $\hat{\theta}$ represents a set of parameters representing the system as follows [6],

$$\hat{\theta} = (a_{n-1}, a_{n-2}, ... a_{n-p}, b_1, b_2, ... b_q) \qquad (3)$$

Recursive Parameter Estimation : The above method is modified to discount old measurements so that the model adopts the changing situation dynamically. An observation that is τ samples old carries a weight that is R^τ of the weight of the most recent observation. and the complete algorithm becomes,

$$\hat{\theta}_n = \hat{\theta}_{n-1} + K_n(y_n - \hat{y}_n)$$

$$\hat{y}_n = \varphi_n^T \hat{\theta}_{n-1}$$

$$K_n = Q_n \varphi_n \tag{4}$$

$$Q_n = \frac{P_{n-1}}{R + \varphi_n^T P_{n-1} \varphi_n}$$

$$P_n(t) = P_{n-1} - \frac{P_{n-1}\varphi_n \varphi_n^T(t) P_{n-1}}{R + \varphi_n^T P_{n-1}\varphi_n}$$

Here, R is the variance of the innovations e_n and also called the forgetting factor. A typical choice of R is in the range of 0.97-0.995 which amounts to approximately remembering 33-200 last observations respectively.

Frequency Response : n-Point complex frequency response $H(f)$ of the model can be computed from the Autoregressive and Exogenous parameters by the following transformation equation,

$$A(f) = \left| \frac{b_1 + b_2 e^{-j2\pi f} + \ldots\ldots. b_{q+1} e^{-jq2\pi f}}{a_1 + a_2 e^{-j2\pi f} + \ldots\ldots. a_{p+1} e^{-jp2\pi f}} \right| \tag{5}$$

Where, a_i represents autoregressive parameters and b_i represents exogenous parameters. p and q are respective orders.

METHODOLOGY

The variation of airflow rate and temperature with time corresponding to a normal and faulty VAV box on a typical day of operation is shown in Fig. 2. Data were collected at one minute interval. Data Point 1 represent 00:00 HRS and data point 1440 represent 23:59 HRS. Since the principle used for the present study requires that the system must be stable and in continuous state, operating period for the current analysis is chosen from 10:01 AM to 6:30 PM. The starting period of operation from 9:00 to 10:00 is avoided since the system could not stabilized in this period. To develop a methodology for system identification, fault detection and diagnosis, and flashing of warning signal when a fault occurs, following process is adopted,

1) Deviation of room air temperature from the set point is used as input variable and computed as follows,

$$y_n = T_{r,n} - T_{set} \tag{6}$$

Where, $T_{r,n}$ is actual room temperature recorded from respective temperature sensors of the VAV subsystems and T_{set} is temperature set point.However, average room air temperature is found to be deviating from the actual room temperature set point T_{set}. Performance of a model depends upon well-chosen input and output variables which should be quite sensitive to the system characteristics. Therefore, an average of last day room temperature is used as room temperature set point. Data is

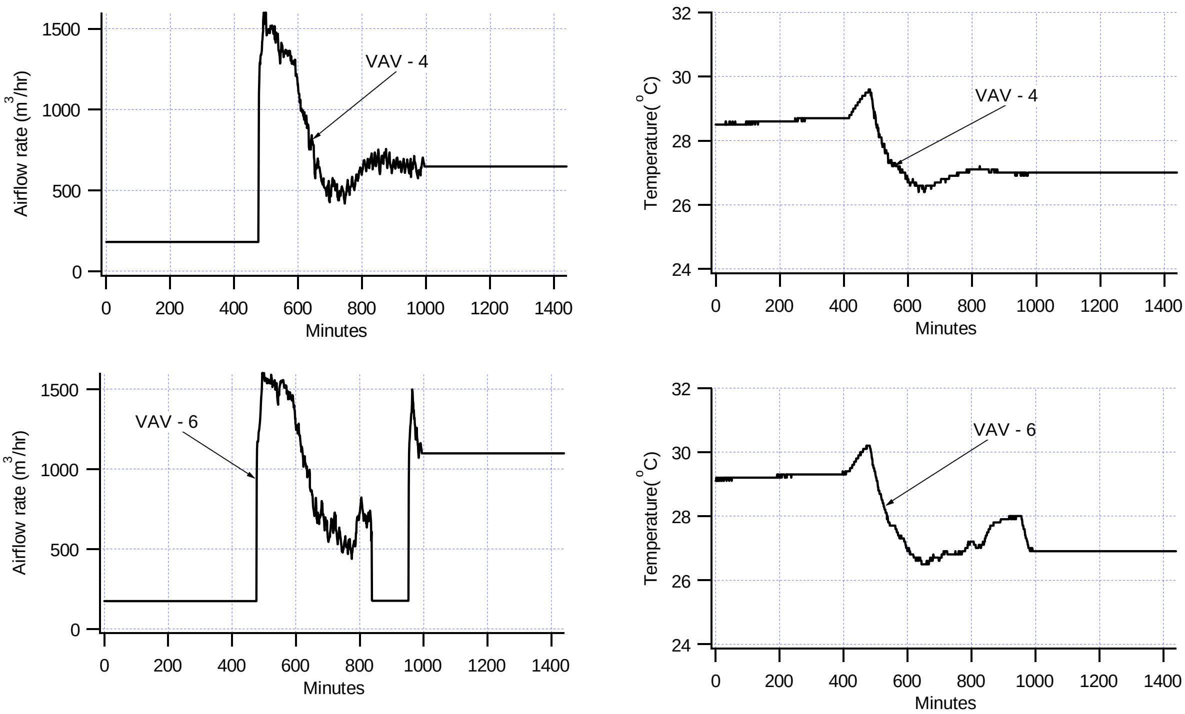

Fig. 2 : Variation of airflow rate and room temperature for a typical normal (VAV - 4) and faulty (VAV -6) unit under normal conditions of operation

further filtered by a high frequency cut off digital filter and sampled at five minutes' interval to remove high frequency noise after having experience with several other sampling time. The above method is preferred to simple sampling ie., picking up data at an interval of five minutes. It preserves the charecteristics of the system more precisely and therefore, parameters reflect more consistency in system identification and fault detection.

2) Present setup of VAV sub-system uses PID controller which controls increase or decrease in airflow rate. Therefore, change in airflow rate is considered as output variable,

$$z_n = V_n - V_{n-1} \tag{7}$$

Where, V_n is airflow rate at time n and V_{n-1} is airflow rate at time $(n-1)$. This imparts a physical meaning to the model. The data is further sampled at five minute interval as in the case of output parameters. Fig. 3 shows the corresponding input and output variable corresponding to a normal and faulty VAV box on a typical normal day of operation.

3) RARX parameter orders are selected after having experience with the data and analyzing the results. Considering computational requirements and effect on results, AR - and EX- parameter are chosen of eighth and fourth order respectively. Though, there exist AIC criteria [7] to exactly determine the order of the parameters, very often the optimum value is quite high which requires a lot of computational time and may not deem suitable for the FDD application. Experience show that a relatively small order may also give results which is nearly optimum from application point of view.

4) Similarly forgetting factor of 0.997 is chosen as the most suitable one after experimenting and analyzing the result.

5) Data corresponding to normal operation of sixteen days during July and August excluding Saturday and Sundays were chosen for the present analysis. These are used five times to train the model and to stabilize the parameters.

6) Faulty day data are applied after sixteen normal days in the final loop to validate the model and to check the behavior of the model parameters.

7) The parameter matrix is preserved for evolving frequency response based fault detection and diagnosis technique.

8) Complex frequency responses corresponding to Nyquist frequency 0.5 (actual unit = 1/600 Hz) are computed at 64 equal intervals from parameter matrix every one hour. Amplitudes are computed from the complex frequency responses for further analysis.

9) Amplitudes corresponding to each VAV subsystems are found to have definite but different patterns in normal cases of operation. Similarly, when a fault occurs,

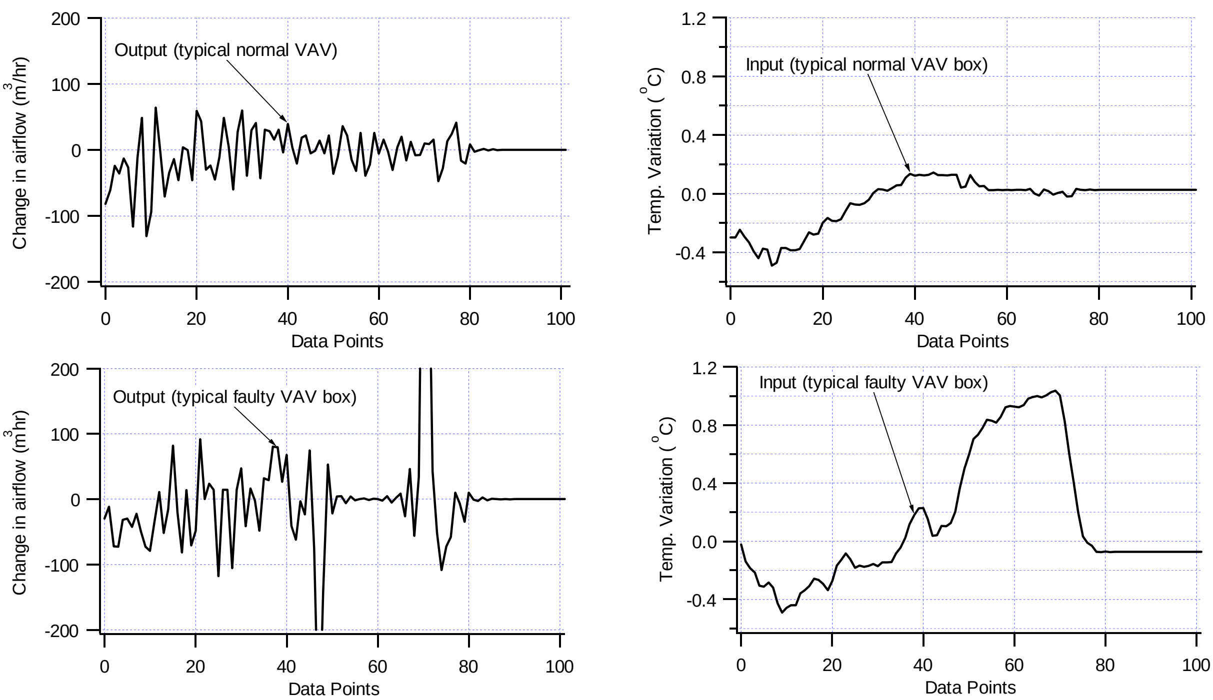

Fig. 3 : Variation of change in airflow rate and room temperature (from set temperature) for a typical normal (VAV - 4) and faulty (VAV - 6) unit under normal conditions of operation

variation in change in amplitudes with time are found to have different responses at different frequencies which can be used not only to detect the fault but also diagnose the fault. Therefore, another matrix is formed by subtracting the average mean value of the amplitude corresponding to each frequencies for last five normal days and dividing it by standard deviation (called hereafter RAV),

$$RAV = \frac{A(f) - \overline{A(f)}}{\sigma(A)} \qquad (8)$$

Where, $A(f)$ is amplitude of the complex frequency response; $\overline{A(f)}$ is average mean value of the corresponding amplitude for last 5 days; and $\sigma(A)$ is standard deviation of the corresponding amplitude for last 5 days. The methodology keeps the average magnitude near to zero of all the parameters. Average mean value of more than 5 days are found to be unsuitable due to insensitivity and less than five days are found to be very sensitive.

10) RAV are analyzed for fault detection and diagnosis application.

RESULT AND DISCUSSION

If some physical change in the equipment causes a deviation from the normal state, the model parameter of the process would also deviate from the normal values and faults may be detected when a specified threshold is exceeded [8]. However, experiences accrued from using real data sets show that identification of faults is not possible by analyzing the patterns of variation of parameters [9]. On the other hand, present study shows that the frequency response of the model can be a good tool in diagnosing the fault besides detecting. As explained in methodology, sixteen normal days are used for training the model and optimizing number of parameters, forgetting factor and sampling time. Faulty day data is used in succession. Besides, the methodology is based upon frequency response of all the Autoregressive and Exogenous parameters and preserves their properties.

The operating period considered is 10:01 - 18:30 hrs (510 minutes). The data points are filtered and sampled at five minutes' interval. Therefore, 102 data points represent one day of operation. The faults include, 1) stuck damper at fully opened position, 2) fully closed position and 3) half opened position; and their simultaneous combinations (as explained in Table 1). Figure 4 shows the instantaneous frequency response of the model for all the VAVs before and after the fault (No. 6) is implemented. Three parts correspond to the timing 13:15 hrs, 14:15 hrs, 15:15 hrs. Aforementioned timing is chosen to avaoid the exact timing of the fault for better representation of the results. However, any arbitrary time can be selected. Further, results are obtained at one

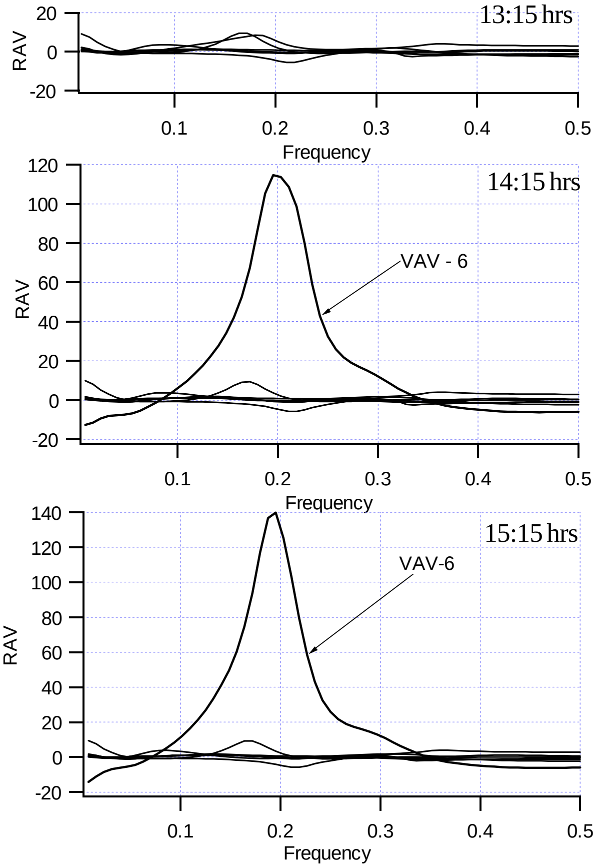

Fig. 4 : Variation of RAV with frequency on 7.8.1998

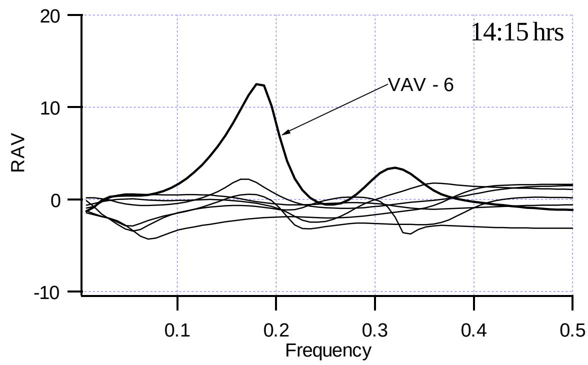

Fig. 5 : Variation of RAV with frequency on 6.8.1998

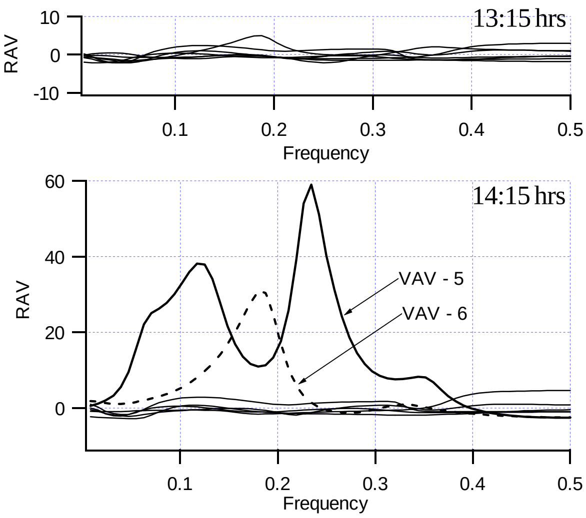

Fig. 6 : Variation of RAV with frequency on 5.8.1998

hour interval. As shown in Table 1, the fault was introduced at 14:00 hrs. The response of the fault remains approximately the same even after nearly two hours after the fault was introduced. Figure 5 shows the frequency response corresponding to the fault (No. 5) at 14:15 hours. However, the response was nearly the same for the whole day because the fault continued for the whole day. Similarly, Fig. 6-8 shows the frequency response just before (13:15 hrs) and after (14:15 hrs) the faults (No. 4, 3 & 2). However, a soft fault like damper stuck between fully opened and fully closed position (No. 1) is difficult to detect as shown in Fig. 9. A close look at the data shows that the temperature variation inside the room due to this fault is very small and remains near to the set point temperature. This may be one of the reasons as temperature data is input variable in the present model. Moreover, since temperature remains near to the set point, it may not be considered fault from performance of HVAC point of view.

On the basis of results, a threshold value of 10 can be identified for activating warning signal. Further, it is not necessary to compute frequency response at all points. A few frequencies can be identified both for activating warning signals and identifying faults. In the present case, five such frequencies (f_1 = 18/128, f_2 = 23/128, f_3 = 25/128, f_4 = 27/128 & f_5 = 30/128) are identified out of 64 frequencies considered initially between 0 and 0.5, as shown in the fig. 8. These frequencies lie in the range 0.1 - 0.3, where the fault responses are more clear. Moreover, these frequencies are identified on the basis of results obtained in the present study and to set up a broad and precise criteria for selection of exact frequencies, more data and case variations are required. Data collected for the present analysis include four cases of fully opened dampers and four cases of fully closed dampers, as explained in the Table 1. While, a fault corresponding to closing of damper has signature at all the frequencies, a fault of damper opening has signature at no more than two frequencies. The method can be further refined after accumulating experiences and adjusting the threshold value. Though, present methodology and analysis is quite specific and needs further validation with other types of data and buildings, the concept put forth is quite robust and may be an effective tool for evolving FDD technology in future.

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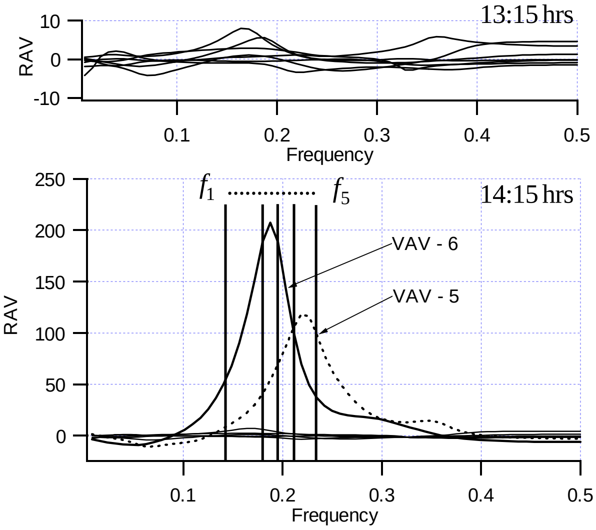

Fig. 7 : Variation of RAV with frequency on 4.8.1998

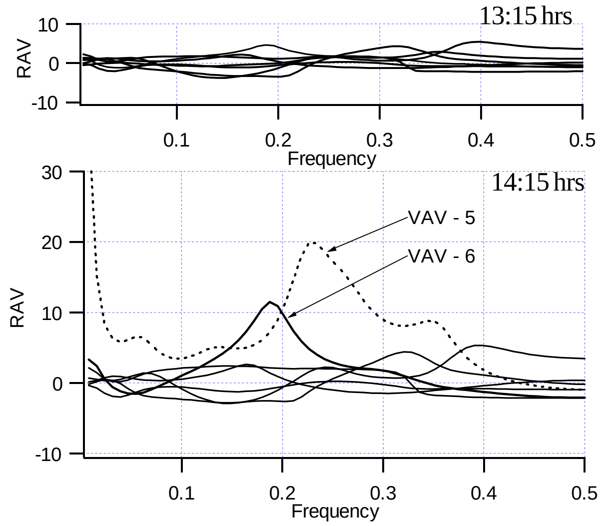

Fig. 8 : Variation of RAV with frequency on 3.8.1998

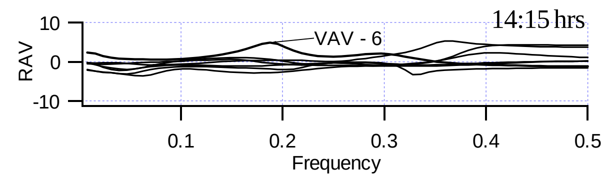

Fig. 9 : Variation of RAV with frequency on 31.7.1998

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