

# DEVELOPMENT OF PARAMETER BASED COMPUTER MODELING TECHNIQUE FOR ONLINE FAULT DETECTION AND PREDICTION OF DAMPER AND SENSOR CONTROL FAULTS

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## ABSTRACT

Heating, Ventilation and Air Conditioning (HVAC) systems, often do not achieve the same level as it achieved at commissioning. An appropriate system analysis for Fault Detection and Diagnosis (FDD) can save material and energy significantly. FDD technology optimizes the use of the components of the system, so that they only be replaced or corrected when they are no longer useful. This paper presents a complete methodology of introducing warning signal component in building management system, which gets automatically activated as and when faults occur. The method is based upon Auto Regressive Exogenous (ARX) model and Recursive Parameter Estimation Algorithm. It is concluded that the method is robust and can detect faults in dampers, sensors and PID control.

## KEYWORDS

Fault detection and diagnosis, ARX model, VAV faults, AHU

## INTRODUCTION

There are several reasons behind malfunctioning of HVAC systems, falling short of levels achieved at commissioning stage. Usually, building management systems heavily rely on automated response mechanism, which compensates for the faults in the system. Thermal comfort of desired level is achieved by automatic change in operation parameters of HVAC unit subsystems. This is responsible for 20-30% higher energy consumption in commercial buildings (John, 1987). This methodology reduces energy efficiency and causes loss of materials. Often it leads to sudden breakdown of components, by the time faults are detected. The new requirement of the society for new technologies that improves the efficiency of the machines in order to save energy and reduce environmental impact of its activities, have further increased the importance of technique capable of early Fault Detection and Diagnosis (FDD). An early detection of faults would facilitate repair works at an appropriate time and schedule.

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 no 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, it is dominated by extensive use of sensors, and special monitoring instruments. The cost of application alone renders it enviable for application to building HVAC systems. Moreover, in nuclear and process industry, the process normally operates at steady state, and faults are detected as temperature or pressure deviate from the values of normal operation. High reliability requirements in these operations take precedence over cost of operation, which requires a well-trained staff of operators monitoring 24 hours a day besides employing several sensors. Nevertheless, the cost of operation and maintenance take precedence over high reliability and possibility of malfunctioning in common HVAC systems which are installed with the sole purpose of offering human comfort and usually do not operate in steady state condition. 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 (Osaka Sc. & Tech. Centre Report, 1990). Providing an adequate system for prompt detection of the cause of a breakdown and prompt repairs are more important than a highly reliable HVAC system. In other words, system availability, which is defined as the ratio of operable duration to the life span, is more important than spending considerable cost to attain high reliability.

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# PLAN

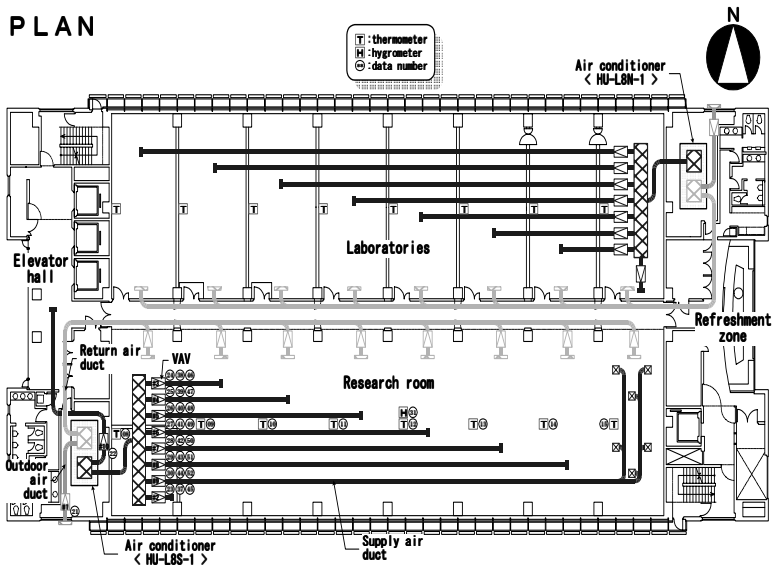


Fig. 1: Plan of the experimental area and position of the sensors

In this paper, an innovative way to detect faults in the system and its diagnosis is presented, which is based upon diagnosis of healthy and faulty behavior of the system. Dynamic system modeling is used to track the system on the basis of initial training data sets. The model changes itself to adopt the new situation. However, it generates warning signals, when deviations might be due to faulty behavior of the system. It would be possible to pinpoint several types of faults in HVAC systems by these signals.

## DATA ACCUMULATION

HVAC systems may have simultaneous faults with complex responses. Therefore, a need of data for known faults is strongly felt to assess the responses of the system due to individual and simultaneous faults. This data base can be obtained either by computer simulation or by measurement on a real system or testing bench. 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. To make an artificial fault by copying the symptoms of most typical faults or faulty component in real process is perceived suitable to develop real time FDD technique.

Various faults were introduced in HVAC systems artificially at VAV Air Handling Unit (AHU) system of Research and Development Center of Tokyo Electric and Power Company under actual use (Yoshida et al. 1997). Actual system layout plan is shown in fig 1. Various data at 80 points were collected at one minute interval for normal and faulty operating conditions. The R&D Center of Tokyo Electric Power Company is mainly office type with total floor Area  $38000 \text{ m}^2$  spread in 11 floors. The experimental site is located at 7<sup>th</sup> floor. Supply Air Fan Capacity is  $12,000 \text{ m}^3/\text{h}$ , 65 mm Aq, PID control with cooling capacity  $83,200 \text{ Kcal/h}$  @  $1,725 \text{ m}^3/\text{h}$  outside air intake.

## SYSTEM MODELING

Over the last decade, there has been considerable research activity in the field of model based reasoning for fault detection, which is specially suited for information poor process such as building systems. Usually, HVAC systems employ sensors for measuring the most basic parameters necessary for the control of the system in order to minimize cost of operation and possibility of sensor induced errors. Model based fault detection (MBD) is based upon behavior descriptions and interconnections of the separate components contained in the whole system. The kernel of model-

based FDD is the model, which describes the functionality of the concerned system. The principle can best be understood as a combination of observation and prediction. In the one hand, we have an actual device, in the other hand, we have a model of that device that can make predictions about its intended behavior. Observation indicate what the device is actually doing, prediction indicate what it is supposed to do. The difference between the system measurement and its model output is called residual and indicates malfunctioning of the monitored device or system. Unlike many diagnostic methods, MBD doesn't rely on a set of symptom-fault patterns. Since prediction of individual process behavior in a system is not the ultimate goal in fault detection, a simple model can well be used in most cases for the whole system. Even very simple "grey box" models can utilize the mathematical tools such as parameter estimation for fault detection and diagnosis in a system. The "grey box" models often consist of parameters, which can not be described and understood in physical terms. However, they are easier to set up and require much less detail information about the system to be modeled. Another advantage of the black box 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 be represented by a set of nearly constant parameters in dynamic modeling. Any change in the state of the system is likely to be reflected by a change in parameter values. This property can be utilized for fault detection in HVAC system.

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 a VAV sub-system is modeled using the aforementioned data base (Harunori Yoshida and Sanjay Kumar 1999).

$$\begin{aligned}
 \theta_n &= \theta_{n-1} + K_n (y_n - \hat{y}_n) \\
 \hat{y}(t) &= \varphi^T(t) \hat{\theta}(t-1) \\
 E[\omega(t)\omega^T(t)] &= R_1 \\
 K_n &= Q_n \varphi_n \\
 Q(t) &= \frac{P(t-1)}{R_2 + \varphi^T(t)P(t-1)\varphi(t)} \\
 P(t) &= P(t-1) - \frac{P(t-1)\varphi(t)\varphi^T(t)P(t-1)}{R_2 + \varphi^T(t)P(t-1)\varphi(t)}
 \end{aligned} \tag{1}$$

Here,  $\theta_n$  is the parameter vector estimated at step  $n$ , and  $y_n$  is the observed output at step  $n$ .  $\hat{y}_n$  is a prediction of the value  $y_n$  based on the observations up to step  $n-1$ . The gain  $K_n$  determines in what way the current prediction error,  $y_n - \hat{y}_n$  affects the update of the parameter estimate,  $\varphi_n$  is (an approximation of) the gradient with respect to  $\theta$  of  $\hat{y}(n|\theta)$ . The latter is the prediction of  $y_n$  according to the model described by  $\theta$ .  $Q_n$  is the matrix which determines the adaptation gain and the way parameters are updated. The regression vector  $\varphi_n$  contains old values of observed inputs and outputs.  $e_n$  is the noise source.  $\omega_n$  is assumed to be white Gaussian noise with covariance matrix,  $R_1$  is variation of the variance. Considering, underlying description of the observation, a linear regression, an optimal choice of  $Q_n$  can be computed from the Kalman filter. The above method is modified to discount old measurements so that the model adopts the changing situation dynamically. An observation that is  $\tau$  samples old carries a weight that is  $(R_2)^\tau$  of the weight of the most recent observation.  $R_2$  is the variance of the innovations  $e_n$  and also called forgetting factor. A typical choice of  $R_2$  is in the range of 0.97-0.995, which amounts to approximately remembering 33-200 last observations respectively.

## METHODOLOGY

The variation of Airflow Rate and Temperature with time corresponding to a normal and faulty VAV box on a typical normal day of operation is shown in fig. 2. Data Point 1 to 1440 represents 00:00 to 23:59 HRS. Operating period for the current analysis is considered from 10:01 AM to 6:30 PM. Let us consider a particular model description,

$$y_n = -\sum_{i=1}^p a_i y_{n-i} + \sum_{j=0}^q b_j z_{n-j} + \mu_n \quad (2)$$

where,  $y$  is output to be predicted,  $z$  is one or more inputs in vector form, which influences the output,  $\mu$  is random variable (normally distributed),  $a$  is AR parameters (order  $p$ ), and  $b$  is EX parameters (order  $q$ ) and are required to be determined by trial and error using training data sets. By evaluation the value of  $S$ , using the latest data, faults can be detected [Yoshida and Sanjay Kumar 1999],

$$S = L\sigma^2 = \sum_{k=n}^{n-L+1} \frac{(\hat{Y}_k - Y_k)^2}{N}$$

Where,  $L$  is the data window length for fault detection and  $\sigma$  is the standard deviation. The model developed can discount old data sets and could adopt the new situation arising out of slow and continuous change in the system such as continuous meteorological changes, change in the behavior pattern of the occupants etc. Therefore, the concept of forgetting factor to discounting old data sets in updating the model is used. Difference between room air temperature and room set point is used as input variable,  $z$  as,

$$z_n = T_{r,n} - T_{set} \text{ and } y_n = v_n - v_{n-1}$$

Where,  $T_{r,n}$  is actual room temperature recorded from the temperature sensors.  $T_{set}$  is temperature set point. 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 after having experience with other sampling times. Fig. 2 shows the input and output variable corresponding to a normal and faulty VAV box on a typical day of operation. RARX parameter orders are selected of 14<sup>th</sup> and 8<sup>th</sup> order AR- and EX - parameters with forgetting factor of 0.994, after having experience with the data and analyzing the results. Sixteen normal days are used five times to train the model and to stabilize the parameters. The Parameter matrix of the RARX model formed by the above methodology is preserved for further analysis and developing online FDD technique. The Parameter matrix created is preserved for further analysis based upon standard variation of complex frequency response [Harunori Yoshida and Sanjay Kumar 1999].

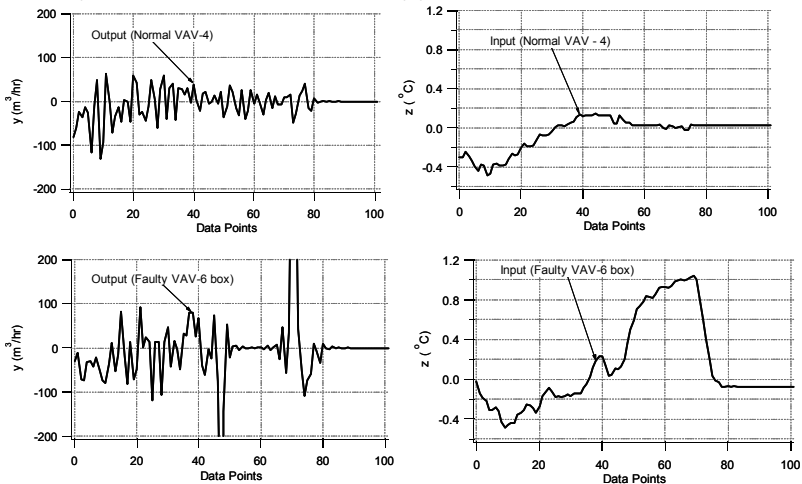


Fig. 2: Variation of change in Airflow Rate and Room air Temperature after subtracting actual set point with time under typical normal and faulty condition of operation (10:01 A.M. to 6:30 P.M.).

## RESULTS AND DISCUSSIONS

Present study shows that the frequency response of the model can be a good tool in diagnosing the fault besides detecting it. The methodology is based upon frequency response of all the AR & EX - parameters and preserves their properties. It was found suitable for all types of faults for which data were available. A few of them are included in this paper as representative ones. At first, damper faults are analyzed and thereafter, sensor faults are analyzed. Figure 3 shows the instantaneous frequency response of the model for all the VAVs before and after the fault is implemented. Three parts correspond to the timing 13:15 hrs, 14:15 hrs, and 15:15 hrs. The fault was introduced at 14:00 hrs. Aforementioned timing is chosen to avoid the exact timing of the fault for better representation of the results. However, any arbitrary time can be selected. The response of the fault remains approximately the same even after two hours of introduction. Similarly, other faults related to dampers have definite but different response at various frequencies. 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. Except in the case of PID fault, a few frequencies can be identified both for activating warning signals and identifying faults. In the present case, six such frequencies ( $f_1 = 13/128$ ,  $f_2 = 18/128$ ,  $f_3 = 23/128$ ,  $f_4 = 25/128$ ,  $f_5 = 27/128$  &  $f_6 = 29/128$ ) are identified out of 64 frequencies considered initially between 0 and 0.5. These frequencies lie in the range 0.1 - 0.3, where the fault responses are clearer.

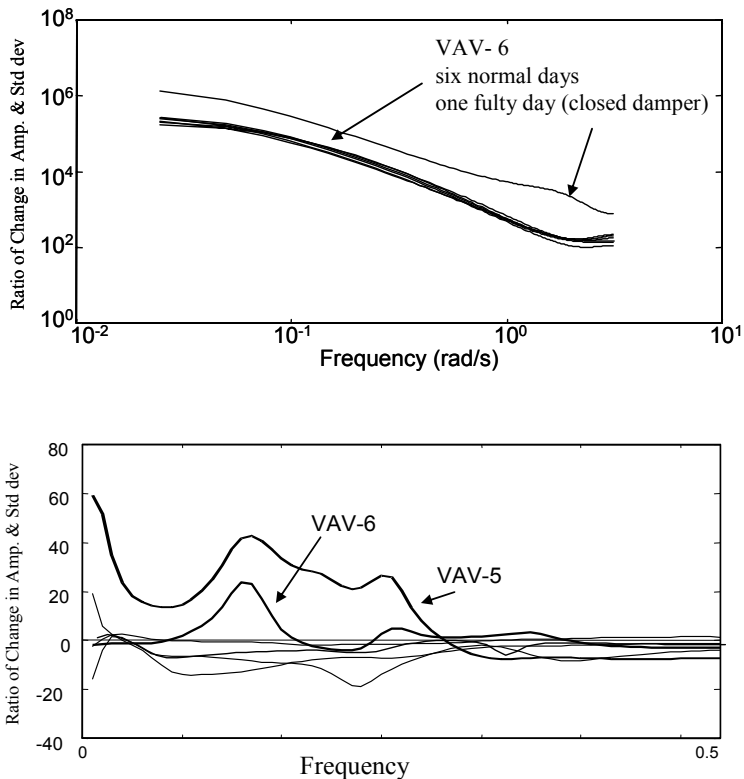


Fig. 3: Power spectrum of a VAV – 6 and 5 & 6 on six normal days and one faulty day of operation

Table 1: Threshold values and its effect on flashing of warning signal

Faulty VAV	Ratio = 4 Warning signal		Ratio = 5 Warning signal		Ratio = 6 Warning signal		Ratio = 8 Warning signal		Ratio = 10 Warning signal		Maximum Warning signals	
	Actual	False	Actual	False	Actual	False	Actual	False	Actual	False	Actual	False
	VAV-6	11	---	9	---	9	---	8	---	4	---	52
Others	---	27	---	---	---	---	---	---	---	---	---	41310
VAV-5	52	---	52	---	52	---	51	---	43	---	52	8210
VAV-6	51	---	14	---	5	---	1	---	1	---	52	8210
Others	---	34	---	---	---	---	---	---	---	---	---	33048
Sensor I	34	---	16	2	16	---	8	---	3	---	79	6376
Others	24	---	14	---	3	---	---	---	---	---	41	32648
Sensor II	45	---	36	---	24	---	8	---	4	---	117	7236
Others	54	24	16	3	3	---	---	---	---	---	100	40236

## CONCLUSION

The simple FDD tool presented can be easily be implemented in building management system to reduce energy and material wastages. Fault signatures for all types of damper faults, sensor faults and their identification demonstrate that technical implementation of the procedure in a BEMS is not a major problem.

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