International Journal of Emerging Engineering Research and Technology
Volume 3, Issue 1, January 2015, PP 56-62
ISSN 2349-4395 (Print) & ISSN 2349-4409 (Online)

Online Fault Detection Technique: Innovative Way to Energy Conservation

Saurabh Kumar
Dept. of Physics
Ranchi University, Ranchi
Jharkhand

Sanjay Kumar
Univ. Department of Physics
BRA Bihar University, Muzaffarpur
Bihar, India

Abstract: *Timely and accurately detection and diagnosis of fault in Heating, Ventilation and Air Conditioning (HVAC) systems may significantly reduce energy consumption. To develop model based FDD technique, artificial faults were introduced in real time operation of HVAC unit and data were collected for analysis. Parameter based mathematical model is developed to analyze the trend and behavior of data to predict sudden faults in damper and sensors of the system. The method is based upon Auto Regressive Exogenous (ARX) model and Recursive Parameter Estimation Algorithm. These parameters have no physical significance but changes in them can be tracked to predict faults. It is shown that even diagnosis of faults is possible. It is concluded that the method is robust and can detect faults in dampers, sensors and PID control.*

Keywords: *Fault Detection and Diagnosis (FDD), Recursive Auto Regressive Exogenous (RARX), Energy Conservation, Auto Regressive Exogenous (ARX)*

1. 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 [1]. 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 [2]. 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.

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 generates warning signals, when deviations are due to faulty behavior of the system.

2. 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.

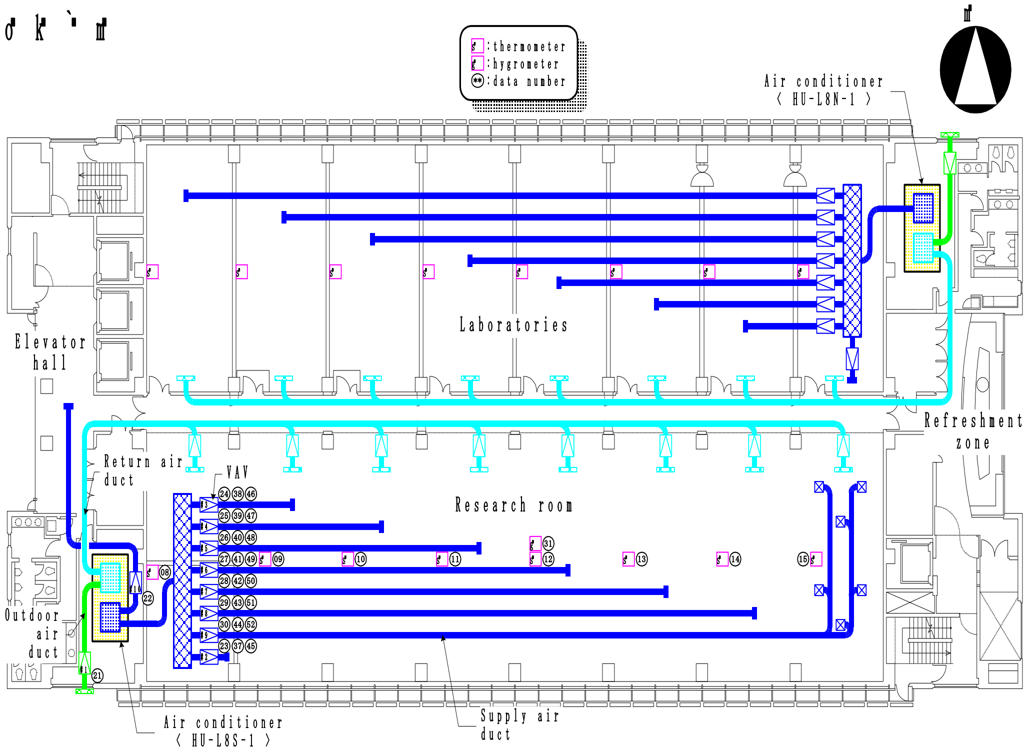

Fig1. *Plan of the experimental section*

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 [3]. Actual system layout plan is shown in fig 1 & 2. 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 m^2 spread in 11 floors. The experimental site is located at 7th floor. Supply Air Fan Capacity is 12,000 m^3/h, 65 mm Aq, PID control with cooling capacity 83,200 Kcal/h @ 1,725 m^3/h outside air intake

3. SYSTEM IDENTIFICATION

It is better to estimate a model in 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 [4 & 5]. 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 at their normal values. If some physical changes in the system causes deviation from the normal state, some or all of the parameters will deviate from those normal values. Therefore, the faulty condition can be identified. 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. A typical recursive identification algorithm [6] is,

$$\theta_n = \theta_{n-1} + K_n(y_n - \hat{y}_n) \tag{1}$$

Here, θ_n is the parameter vector estimated at step *n*, and y_n is the observed output at step *n*. $\tilde{y}_n$ is a prediction of the value y_n based on the observations up to step *n-1* and the current model. K_n determines the way current prediction error, y- $\tilde{y}_n$ affects the update of the parameter estimate. Typically,

$$K_n = Q_n \varphi_n \tag{2}$$

Where, φ_n is (an approximation of) the gradient with respect to θ of $\tilde{y}$ (n|θ). The latter is the prediction of y_n according to the model described by θ. Q_n is the matrix which determines the

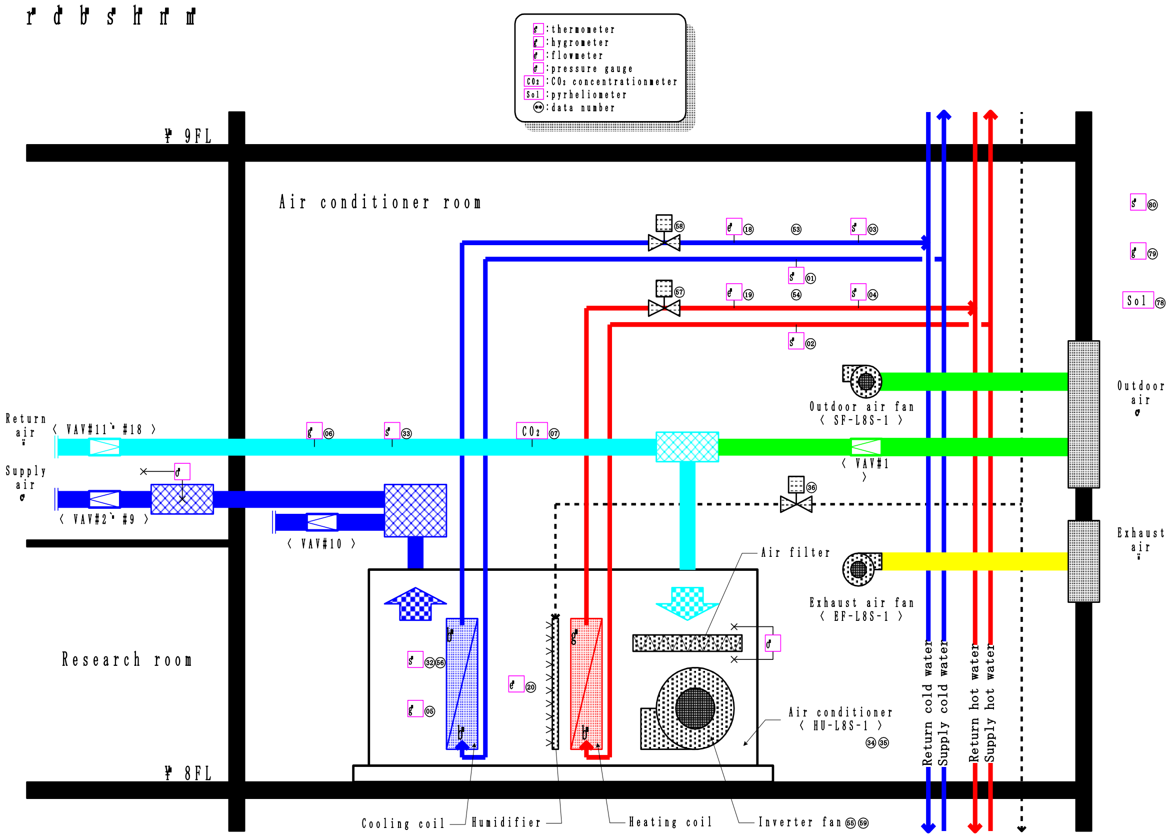

Fig2. *Sectional Plan of the experimental site*

Adaptation gain and the way parameters are updated. The model structure that correspond to linear regression can be written as,

$$y_n = \varphi_n^T \theta_n + e_n \tag{3}$$

Where, the regression vector φn contains old values of observed inputs and outputs. en is the noise source. The most logical approach to the adaptation problem is to assume a certain model for how "true" parameter θn changes. A typical choice is to describe these parameters as a random walk,

$$\hat{\theta}(t) = \hat{\theta}(t-1) + \omega(t) \tag{4}$$

Here, ωn is assumed to be white Gaussian noise with covariance matrix,

$$E[\omega(t)\omega^T(t)] = R_1 \tag{5}$$

Where, R1 is variation of the variance. Considering, underlying description of the observation, a linear regression, an optimal choice of Qn in eq. 1 and 2 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 Γ samples old carries a weight that is R1τ of the weight of the most recent observation. The complete algorithm becomes,

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

$$\hat{y}(t) = \varphi^T(t)\hat{\theta}(t-1)$$

$$K_n = Q_n\varphi_n \tag{6}$$

$$Q(t) = \frac{P(t-1)}{R_2 + \varphi^T(t)P(t-1)\varphi(t)}$$

$$P(t) = P(t-1) - \frac{P(t-1)\varphi(t)\varphi^T(t)P(t-1)}{R_2 + \varphi^T(t)P(t-1)\varphi(t)}$$

Here, 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.

4. 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. 3. Data Point 1 to 1440 represents 00:00 to 23:59 HRS. Let us consider a particular model description,

$$y_n = -\sum_{i=1}^{p} a_i y_{n-i} + \sum_{j=0}^{q} b_j z_{n-j} + \mu_n \tag{7}$$

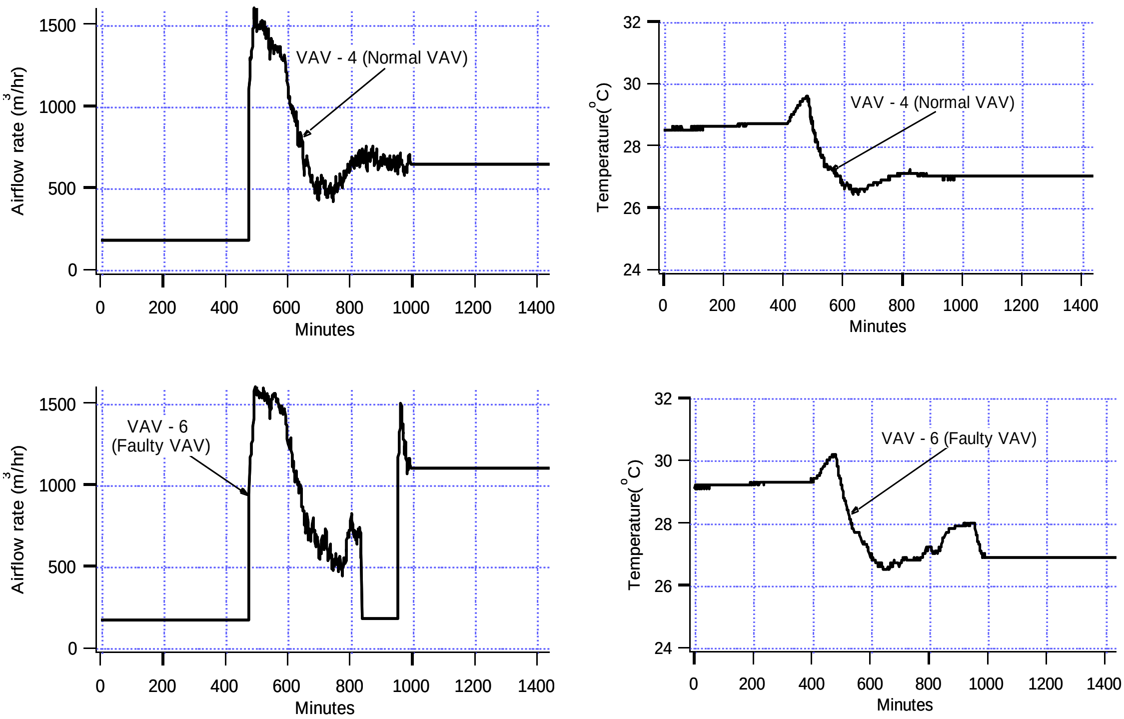

Fig3. *Variation of Airflow Rate and Temperature with time under normal and faulty condition of operation*

where, y is output to be predicted, z is one or more inputs in vector form, which influences the output, μ 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 (defined by Eq. 8), using the latest data, faults can be detected [9],

$$S = L\sigma^2 = \sum_{k=n}^{n-L+1} \frac{(\hat{Y}_k - Y_k)^2}{N} \tag{8}$$

where, L is the data window length for fault detection. 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,

$$z_n = T_{r,n} - T_{set} \text{ And } y_n = v_n - v_{n-1} \tag{9}$$

Where, Tr,n (Tset) is actual room temperature recorded (set point) from the temperature sensors. Where, υn is airflow rate at time n and υn-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. RARX parameter orders are selected of 14th and 8th 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 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 [6].

4.1. Complex Frequency Response

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

$$A(f) = \left| \frac{b_1 + b_2 e^{-j2\pi f} + \ldots\ldots.. b_{q+1} e^{-jq2\pi f}}{a_1 + a_2 e^{-j2\pi f} + \ldots\ldots.. b_{p+1} e^{-jp2\pi f}} \right| \tag{10}$$

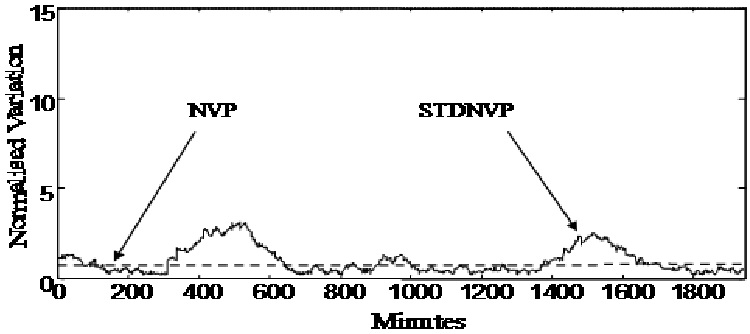

Fig4. *Variation of NVP and STDNVP with time for 16 normal days, one faulty day and two normal days in sequence for a typical normal VAV Box*

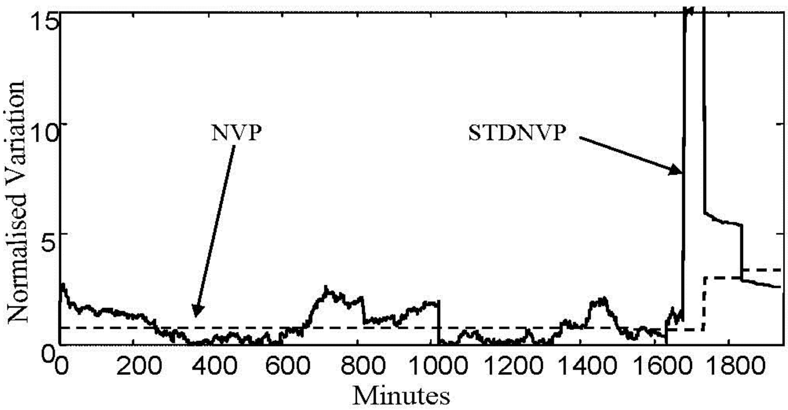

Fig5. *Variation of NVP and STDNVP with time for 16 normal days, one faulty day and two normal days in sequence for a typical faulty VAV Box*

Where, a represents autoregressive parameters and b represents exogenous parameters. P and q are respective orders. 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. Corresponding amplitude A(f) corresponding to each VAV subsystems is found to have definite but different patterns in normal cases of operation. When a fault occurs, variation in change in amplitudes is found to have different responses at different frequencies. This property is used to diagnose the faults. Another variable RAV is further defined to keep the average magnitude near to zero as in the case of computing STDNVP.

$$RAV = \frac{A(f) - \overline{A(f)}}{\sigma(A)} \tag{11}$$

5. RESULTS AND DISCUSSIONS

The Parameter matrix of the RARX model formed by the above method, are found to be very sensitive. For further analysis, another matrix NVP is computed as follows,

$$NVP = \frac{ParamValue - Avr.\,ParamValue\,of\ last\,15\,days}{Std.\,Deviation\,of\ param\,of\ last\,15\,days}$$

Ratio of NVP and STDNVP (15 days standard deviation in NVP)) is used for analysis. Based upon the experience, a static threshold is proposed for automatic flashing of warning signal. This can be used as a starting point in any automatic FDD system and based upon further experience of the particular HVAC system, it can be refined. Figure 4 shows the variation of NVP and STDNVP for the first AR-parameter for a typical normal VAV Box (VAV-4) under actual conditions of operation. For clarity of results, two normal days are added after a faulty day. The total number of data points represent nineteen days (sixteen normal days + one faulty day + two normal days). Since the operating period considered is 10:01-18:30 hrs (510 minutes) and data is sampled at five minutes' interval, one day of operation is represented by 102 data points. Data points 1633 to 1734 represents faulty day. From the figure it can be seen that STDNVP has quite stable value near zero. This is due to a relatively longer period of fifteen days for which standard deviation has been taken. Stability in the behavior of STDNVP due to small external influences (an essential part of the HVAC system operation) is incorporated automatically. Threshold value for automatic fault detection is computed as a ratio of NVP and STDNVP value. Fig. 5 shows the variation of NVP and STDNVP for the first AR-parameter for a typical faulty VAV Box (VAV-6) under actual conditions of operation. Similarly, other faults can also be detected visually. To use the method for online application, threshold checking is applied by computing 'Ratio' (= NVP / STDNVP).

Table 1 shows the number of the warning signals flashed every five minutes for Ratios 4, 5, 6, 8 & 10. In the table typical damper faults and sensor faults are included to show that the method is robust for automatic detection. However, further work is required for its integration as diagnostic tool into BMS of large and complex buildings. Maximum number of expected actual warning signals during faulty period operation and false warning signals during normal period of operation are also shown. Absolute value of warning signals are considered instead of relative value since false warning signals even though large for Ratio=4 has a very low relative value due to eighty normal days (sixteen normal days used five times to train the model) of operation and doesn't represent actual situation. For example, 27 false warning signals out of 33048 possible false warning signals seems to be very low.

Table1. *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 Others	11 ---	--- 27	9 ---	--- ---	9 ---	--- ---	8 ---	--- ---	4 ---	--- ---	52 ---	8210 41310
VAV-5 VAV-6 Others	52 51 ---	--- --- 34	52 14 ---	--- --- ---	52 5 ---	--- --- ---	51 1 ---	--- --- ---	43 1 ---	--- --- ---	52 52 ---	8210 8210 33048
Sensor I Others	34 24	---	16 14	2 ---	16 3	--- ---	8 ---	--- ---	3 ---	--- ---	79 41	6376 32648
Sensor II Others	45 54	--- 24	36 16	--- 3	24 3	--- ---	8 ---	--- ---	4 ---	--- ---	117 100	7236 40236

But it may represent a fault if it occurs continuously for a single VAV box on the last day. After a fault occurs, the parameter changes from its previous value for rest of the day while STDNVP, calculated on the basis of last fifteen days of operation has no effect. Therefore, warning signals are flashed for the consecutive period of operation during the day. However, the next normal day has a relatively higher STDNVP value due to the effect of last faulty day. Therefore, 'Ratio' goes down and the present methodology is capable of detecting the fault even consecutive day. Further, As evident from the table, lower threshold (Ratio) is not desirable. For example, Ratio=4 activates false warning signal in all the cases considered. Similarly, a higher threshold reduces the confidence level since number of warning signal reduces sharply and small faults might not be detected in the process. An static threshold of 'Ratio = 5' seems to be ideal for all the cases in the present study since it detects all the faults and practically, no false alarm is activated. The proposed approach can be applied to practical problems with normal sets of training data obtained in two to three week's time. These data need not be in continuation. Further analysis based upon frequency response is undertaken to automatically recognize the fault at the same time of its detection.

6. Conclusion

The objective of the methodology developed consists of creating suitable and simple FDD tool, which can be easily implemented. 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. The representative cases of damper and sensor fault detection and their validation by real time data, demonstrate the flexibility and robustness of the scheme.

Acknowledgment

Part of the investigations described in this article had been financially support by the JSPS. Findings are also a part of IEA Annex-34 activity. The work is partially published in International journal.

References

[1] John, R. (1987) Operating Experience of Building Management System. Proceedings, 3rd Int. Congress on Building Energy Management, USA,.

[2] Osaka Science and Technology and Engineering Center (1990) Report of Maintenance System with artificial Intelligence for Intelligent Buildings, Osaka, Japan.

[3] Yoshida, H. Tsubota, Y. Suzuki, T. and Kamimura, K. (1997) Implementing Faults in a VAV System of R/D Center of TEPCO, IEA Annex 34, Computer Aided Fault Detection and Diagnosis (Working paper), Colorado, USA,.

[4] EITIJ, Digital Signal Processing Handbook, Tokyo: OHM Publishing Company, Japan, 1993.

[5] Ljung, L. and Glad, T. (1994) Modeling of Dynamic Systems, Prentice Hall Information and System Sciences Series,.

[6] Harunori Yoshida and Sanjay Kumar (1999) ARX and AFMM model-based on-line data base diagnosis of sudden fault in AHU of VAV system. Energy Conversion and Management; Vol. 40 pp 1191:1206

Authors' Biography

Saurabh Kumar, Msc. Physics, I.I.T Delhi, M.tech (Computer Science), worked as lecturer In St. Xavier's College, Ranchi. Currently Managing Director, Sigma Kappa Education Solutions Private Limited (Ranchi).

Sanjay Kumar Academician, Researcher and Consultant with 20 years of experience in the field of Energy, Environment and Meteorology. 190 research papers in high impact factor Journals and Conferences; seven books/book chapters (two by International publishers) are to my credit. I am empanelled to review papers of international journals from *Elsevier* and *Springer* on Energy and Environment. My work is recognized by prominent international bodies in Japan (JSPS, CAPS, NEF); Canada (International Energy Foundation, Alberta) and International Desert Council.