STUDY ON FAULT DETECTION AND DIAGNOSIS OF WATER THERMAL STORAGE HVAC SYSTEMS

Song Pan and Mingjie Zheng
Research Laboratory, SANKO Air Conditioning Co, Ltd.
Nagoya+450-0003 - **JAPAN**
Nobuo Nakahara
Department of Architecture, Faculty of Engineering,Kanagawa University
Yokohama + 221-0802 - **JAPAN**

ABSTRACT

When some faults take place in a thermal storage HVAC system, changing pattern of the temperature profiles of the thermal storage tank is useful to infer where some faults exist. Authors designed some parameters calculated from the temperature profiles of the thermal storage tank in HVAC system and their Fourier Transform to detect the difference between the normal and faulty state. Further, present paper shows practicality of two methods of parameter optimization, a differentiation rate increment method and a variable selection method, with an actual application to a hospital.

INTRODUCTION

The thermal storage system has been widely used in Japan for the sake of power security, power demand shift, energy conservation, economy in construction and operation, and obtaining other advantages. In spite of its popularity, there are many cases where the design and/or operation are improper. Malfunction often takes place in control strategy in both heat pump side and in HVAC side. Therefore, the thermal stotrage system needs appropriate commissioning process over lifecycle. Authors have discussed how to detect and diagnose the control malfunctions using characteristic temperature profiles of the tank obtained from fault simulations [1][2]. Most important thing in this method is to find out optimal parameters corresponding to each object system. The present paper reports usability of this method in application to actual system and two methods of selecting optimal parameters for fault detection and diagnosis are introduced.

FAULT DETECTION AND DIAGNOSIS METHOD

(1) Creating data base

1) Data base in normal state

After modulating the thermal storage HVAC system well and making sure it is being operated normally, the water temperature distribution of each tank which compose so-called multi-connected complete mixing tanks shall be measured every hour to form the data base of temperature profiles in normal state.

2) Data base in various faulty states

① Method 1:Generate various faults in the same system as above and collect data to form data base of temperature profiles in faulty operation.

② Method 2:Run the dynamic type of thermal storage simulation program to calculate the temperature of each tank in normal state. After making sure the simulated results almost coincides with the normal data base gathered as above, run the program again in various kinds of faulty staes to form the faulty data base.

(2) Selecting optimal parameters

1) Analyzing both normal and faulty data in data base with Fourier Transform, the dynamic properties such as the phase and frequency can be recognized.

Two-dimensional Fourier Transform is expressed as equation (1).

$$[F_{kl}]=\begin{bmatrix}C\\S\end{bmatrix}\begin{bmatrix}C\\S\end{bmatrix}_{kl}=\begin{bmatrix}C_kC_l & C_kS_l\\S_kC_l & S_kS_l\end{bmatrix}=\frac{a_1a_2}{NM}\sum_{r=0}^{N-1}\sum_{s=0}^{M-1}x_{rs}\begin{bmatrix}\cos\frac{2\pi k_r}{N}\\ \sin\frac{2\pi k_r}{M}\end{bmatrix}\begin{bmatrix}\cos\frac{2\pi l_s}{N}\\ \sin\frac{2\pi l_s}{M}\end{bmatrix}$$

$$k=0,1,2\cdot\cdot N/2 \qquad l=0,1,2\cdot\cdot M/2$$

$$a_1=\begin{cases}2 & 0<k<N/2\\1 & k=0,\quad N/2\end{cases} \qquad a_2=\begin{cases}2 & 0<l<M/2\\1 & l=0,\quad M/2\end{cases} \qquad \cdots\cdots (1)$$

While,
F_{kl} : Fourier Transform of X with k and l for the number of Fourier transform along time and space.
X_{rs} : temperature of tanks in two-dimensional real cyclical function of s, the number of tank, and r, time
C, S : each cosine and sine parts of X.
N, M: the number of samples along time axis and tanks connected in a series.

2) Using statistical analysis, preliminary parameters are derived from the real temperatures of the tank and their Fourier Transform values. The cluster analysis will be then used ot classify parameters into groups with high correlation coefficient each other, thus

reducing to small number of independent parameters, which are the candidates of optimal parameters.

3) Generally, the more the number of parameters are, the higher rate of fault detection and diagnosis is expected. However, it is not smart way to use all the parameters. Although each parameter is effective to explain peculiar phemomena of fault operation, some other parameters which are in high corelation often play most part of roles. Therefore, it is necessary to find useful methods for selecting combination of optimal parameters.

In the present paper authors developed two programs to optimize parameters and number of dimension, i.e., ①differentiation rate increment method [3], and ② variable selection method [4]. The Fig.1 and Fig.2 shown later are the calculation flowcharts of the program of differentiation rate increment method and variable selection method, respectively.

①Differentiation rate increment method

It is generally understood that the more the number of parameters grows, the smaller the differentiation rate increment would be when a parameter is newly added. Therefore, the differentiation rate increment could be used to distinguish whether newly added parameter is effective or not. If eqution (2) is tenable,it is useful to add parameter from q to $q+r$. Judgement standard **a** is determined by the number of learning data.

$$P_{max1}^{(q+r)} - P_{max1}^{(q)} < a \qquad \text{-------(2)}$$

While,
$P_{max1}^{(q+r)}$ and $P_{max1}^{(q)}$ are the optimum rate of differentiation for q+r and q dimensions, respectively.

② variable selection method

Generally, the longer D^2_q, Mahananobis‘ generalized distance, equation(4), between the average values of parameter vector(y_1,y_2,・・・・,y_q) of both normal and faulty states, the lower the error differential rate becomes. The F-distribution for freedom(r,N-q-r+1) could be used to distinguish whether the increment of Mahananobis‘ generalized distance caused by adding parameters from q to $q+r$ is just the calculation error or the parameters‘ substantial differentiating effect.

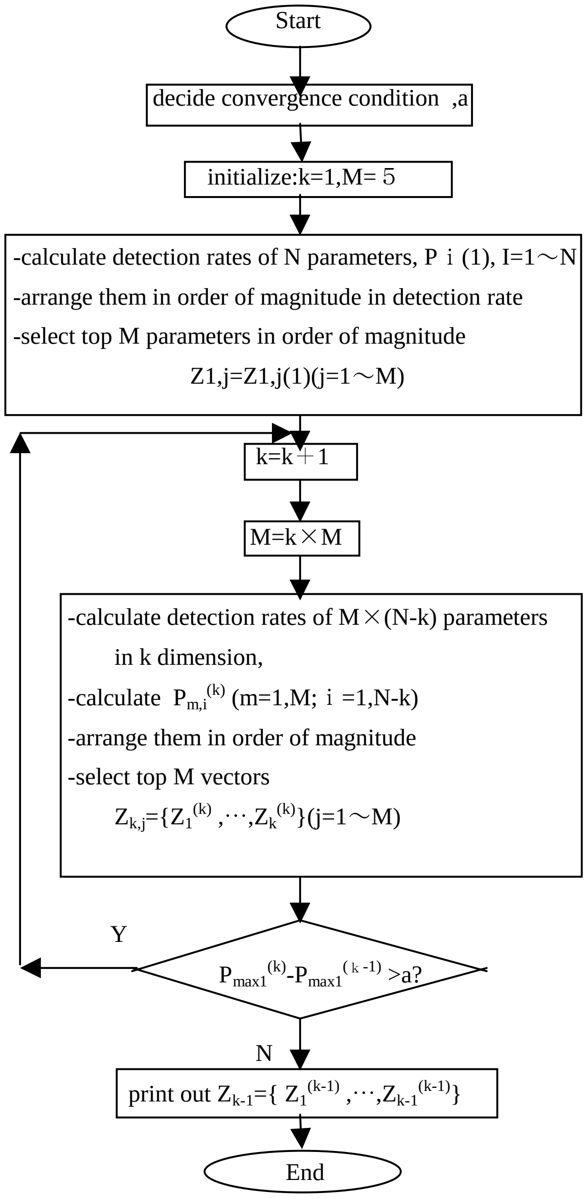
When the number of measured data is large, it is said appropriate to make judgement with F=2 standard [5].

$$F = \frac{N-q-r+1}{r}\,\frac{D_{q+r}^{\ 2} - D_q^{\ 2}}{\dfrac{N(N+2)}{N_1 N_2} + D_q^{\ 2}}$$

$$(N = N_1 + N_2 - 2)$$

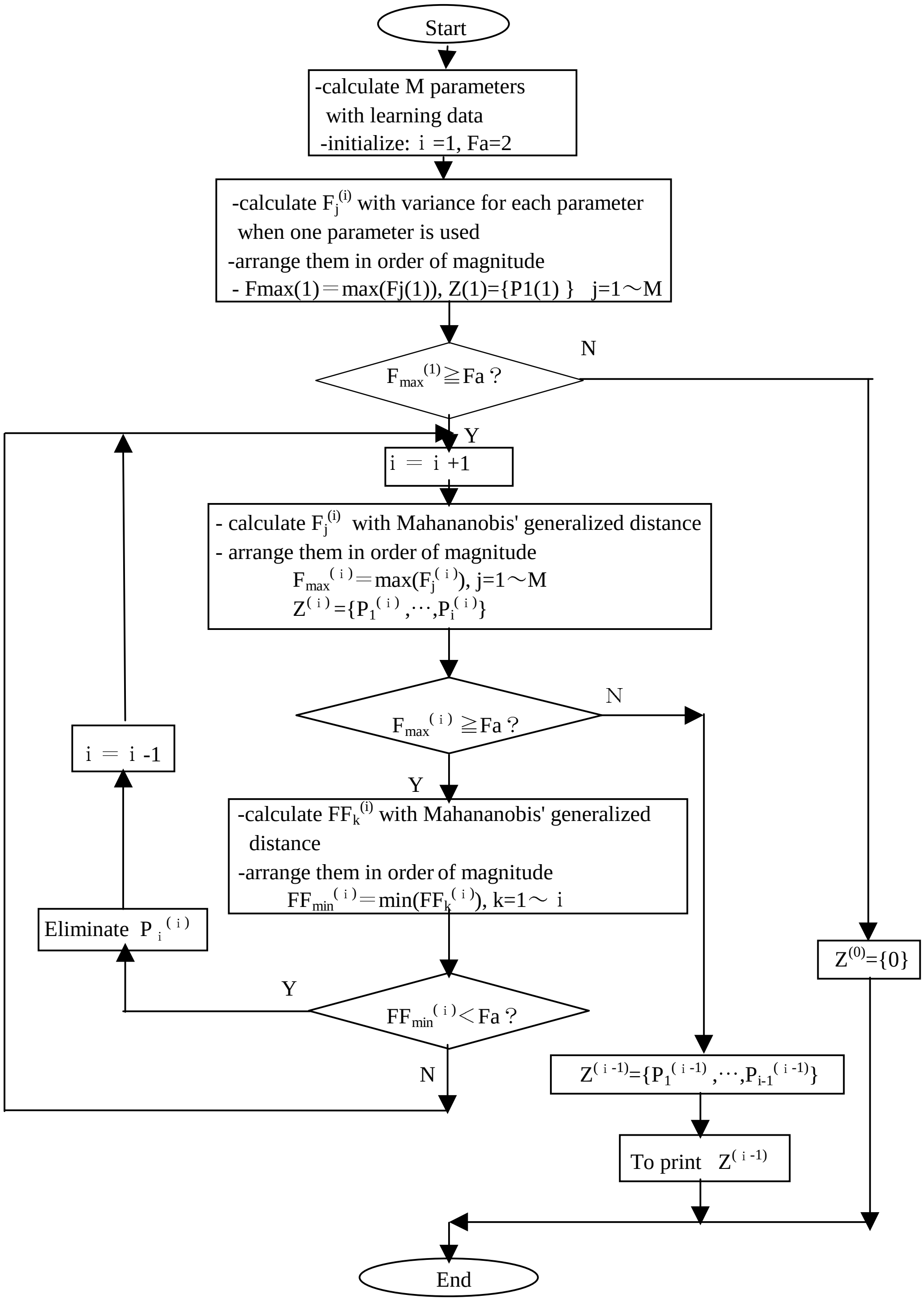
------(3)

Where, N_1, N_2 are the number of normal and faulty data, respectively.



a :condition for judging convergence
k : number of dimensions
M : number of vectors to be calculated in k-th dimension-
N : total number of parameters
$P_i^{(1)}$: detection rate in one dimension using i-th parameter
Pm,i(k) : detection rate in k dimensions obtained by combining i-th parameter with the selected m-th vector at stage of k-1 dimensions
Pmaxj(k) (j=1,M): top M detection rate in k dimensions vector, arranged in order of magnitude
Pmax1(k) : detection rate of optimal vector in k dimension
Zk,j : a vector consisted of the number of optimal parameters in k dimension
Zk(k) : number of k-th parameter in k dimension

Fig.1 Flowchart of optimization program for decting parameter with differentiation increment method



Fa : condition for judging convergence

i : number of parameter(i=1~M)

$FF_k^{(i)}$: index to evaluate contribution of Pk(i) in i optimal parameters {P1(i) ,⋯,Pk-1(i) ,Pk(i),⋯,Pi(i)} on the generalized distance calculated for other i-1 optimum parameters parameters

$FF_{min}^{(i)}$: minimum value of $FF_k^{(i)}$(k=1,i)

$F_j^{(i)}$, i>1: the index to evaluate contribution of newly added j-th parameter on the generalized distance calcualted for i-1 optimal parameters.
i=1: variance of j-th parameters.

$F_{max}^{(i)}$: maximum value of $F_j^{(i)}$ i (j= i ～M)

$P_k^{(i)}$: the number of i-th optimum parameter (k=1～ i)

$Z^{(i)}$: vector consisting of number of i optimum parameters

Fig.2 Flowchart of optimization program for decting parameter with variable selection method

(3) Fault detection/diagnosis with Mahananobis′ generalized distance

1) With Mahananobis' generalized distance based on optimum parameters vector selected, differentiation function for normal and faulty state shall be input into BEMS/BOFD computer as the knowledge data.

When parameter vector Y follows normal distribution, Mahananobis' generalized distance is calculated by equation (4).

$$D^2 = (y-\mu)^T \sum^{-1} (y-\mu)$$
$$y = [y_1 y_2 y_3 \cdot\cdot y_p]^T$$
$$\mu = [\mu_1 \mu_2 \mu_3 \cdot\cdot \mu_p]^T$$
$$\sum = \begin{bmatrix} \sigma_1^{\ 2} & \sigma_1\sigma_2 \cdots & \sigma_1\sigma_p \\ \sigma_2\sigma_1 & \sigma_2^{\ 2} \cdots\cdot & \sigma_2\sigma_p \\ \cdot\cdot & \cdot\cdot \ \ \cdots & \cdot\cdot \\ \sigma_p\sigma_1 & \sigma_p\sigma_2 \cdots & \sigma_p^{\ 2} \end{bmatrix} \qquad \text{------(4)}$$

Generally, if the number of measured data exceeds 50 and largest value of sample variance and covariance of all states is lower than twice of the smallest one, the mean value, variance and covariance may be calculated with measured data.

2) The optimal parameter vector calculated with data of instantaneous temperature distribution of the thermal storage tank to be maesured online is then evaluated using Mahananobis' generalized distance as follows whether the vector is distinguished as normal or fault.

The mean values of optimal parameters selected should be calculated first, which are to be the centers of distribution in various states. If all possible kinds fault data base have been prepared beforehand, the state distribution of which center is nearest from the any data is the one that data belongs. Thus all data differentiated, the state of storage operation is judged whether it is normal or any kind of fault.

APPLICATION TO A REAL SYSTEM

(1) Outline of the system and data measured

Table 1 and figure 3 show outline of the objective building and simplified diagram of the thermal storage HVAC system of it. The chilled water tank consistes of 20 complete mixing subtanks. The temperature of each tank and its changing profiles with time were measured from May 1995 to March 1996. In the early stage of measurements, from May 1 to July 21, 1995, a fault phenomenon was found, which was caused by improper operation of the three-way valve V1 shown in Figure 3, where the supply

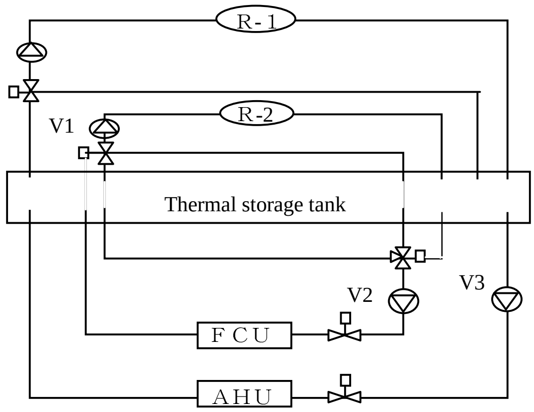


Figure 3 Simplified thermal storage HVAC system diagram

Table 1 Outline of the building and HVAC system

Site Structure Total area Stories Use	Tokyo R.C. 17,000 m^2 Six-stories,two-stories underground Hospital
Heat plant	Turbo-refrigerator(300USRT) ×2 Boiler(4800kg/h) ×2
HVAC	AHU+FCU(ward system) AHU(for fresh air)+ Terminal AHU(consulting room) AHU+reheater(operating room)
Thermal Storage tank	Multi-connected complete mixing style 20 subtanks,780m^3

water to the chiller was drawn only from the highest temperature tank.

The figure 4 shows temperature profile of the tank and Fourier transform of it during normal satate, while Figure 5 shows those in faulty state. As seen in these figures, temperature in the subtank of the low-temperature side is kept low during normal operation, while it becomes higher in faulty operation. The temperature variation is seen more frequent in normal operation along the time axis, as compared to that in faulty operation. It means that higher frequency component of Fourier transform C_kC_l is larger in normal state than that in fault state. Therefore, the maximum value C_1C_1 becomes smaller in normal state than that in fault state.

From the measured data it was recognized that almost no chilled water was used between October 28, 1995 and April 24, 1996, so that the data during this period are useless. As the result, data for 65 days between May 1 to July 21, 1995 were assumed as faulty and data for 257 days between July 22 and Sept. 30, 1995 plus those between April 25 and Sept. 30, 1996 were

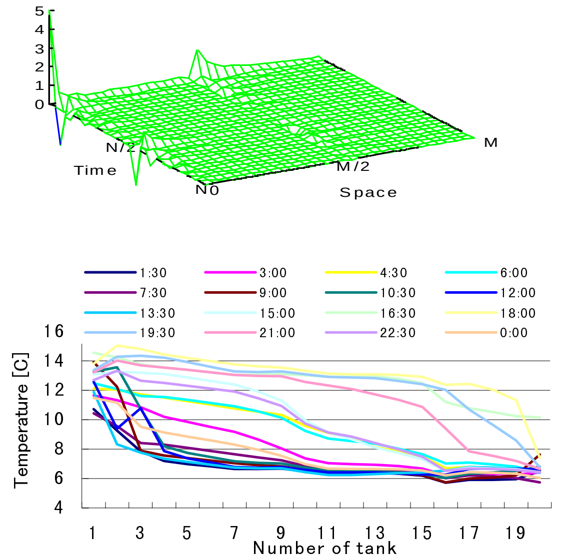


Figure 4 Temperature profile of tank and its Fourier transformation values in normal state(July 26,1995)

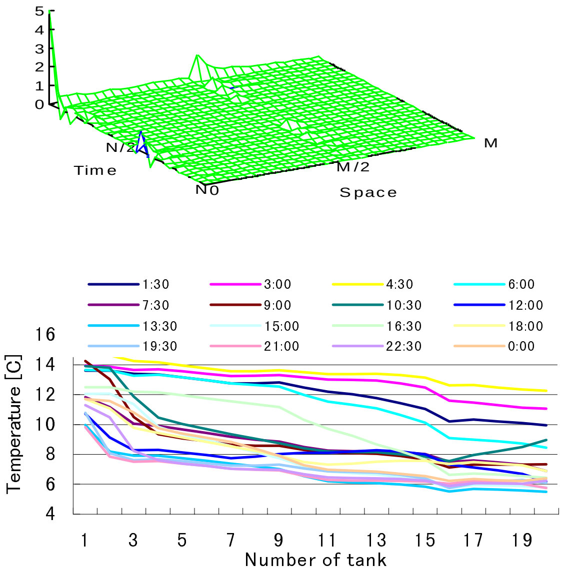


Figure 5 Temperature profile of tank and its Fourier transformation values in faulty state(July 15,1995)

assumed as normal in this study on fault detection and diagnosis, FDD, for actual system.

(2) Design parameters for FDD

As parameters representing characteristics of temperature profiles, following 24 parameters were designed. The suffixes in these equations are: i and j are time and the number of tank, respectively; k and l are the number of Fourier transform value along time space, respectively.

1) Minimum value of daily average temperature in each tank (P1)

$$P1 = \underset{j=1,M}{Min}\left(\sum_{i=1}^{N} X_{ij} / N\right) \quad \cdots\cdots (5)$$

2) Average value of daily maximum temperature difference in each tank (P2)

$$P2 = \sum_{j=1}^{M} (X_{\max i} - X_{\min i}) / M \quad \cdots\cdots (6)$$

$$X_{\max i} = \underset{i=1,N}{Max}(X_{ij}),\ X_{\min i} = \underset{i=1,N}{Min}(X_{ij})$$

3) Variance of average temperature of all tanks over all time (P3)

$$P3 = \left\{ \sum_{i=1}^{N}\left(\sum_{j=1}^{M} X_{ij}/M\right)^2 / N - \sum_{i=1}^{N}\left(\sum_{j=1}^{M} X_{ij}/MN\right)^2 \right\}^{1/2} \cdots\cdots (7)$$

4) Maximum value of average temperature of all tanks over all time (P4)

$$P4 = \underset{i=1,N}{Max}\left(\sum_{j=1}^{M} X_{ij} / M\right) \quad \cdots\cdots (8)$$

5) Minimum value of average temperature of all tanks over all time (P5)

$$P5 = \underset{i=1,N}{Min}\left(\sum_{j=1}^{M} X_{ij} / M\right) \quad \cdots\cdots (9)$$

6) Difference between maximum and minimum value of average temperature of all tanks over all time (P6)

$$P6 = \underset{i=1,N}{Max}\left(\sum_{j=1}^{M} X_{ij} / M\right) - \underset{i=1,N}{Min}\left(\sum_{j=1}^{M} X_{ij} / M\right) \cdots\cdots (10)$$

7) Variance of maximum temperature differences of all tanks at each time (P7)

$$P7 = \left\{ \sum_{i=1}^{N} (X_{mnj})^2 / N - \left(\sum_{i=1}^{N} X_{mnj} / N\right)^2 \right\}^{1/2} \quad \cdots\cdots (11)$$

$$X_{mnj} = \underset{j=1,M}{Max}(X_{ij}) - \underset{j=1,M}{Min}(X_{ij})$$

8) Maximum value of maximum temperature differences of all tanks at each time (P8)

$$P8 = \underset{i=1,N}{Max}\left[\underset{j=1,M}{Max}(X_{ij}) - \underset{j=1,M}{Min}(X_{ij})\right] \quad \cdots\cdots (12)$$

9) Minimum value of maximum temperature differences of all tanks at each time (P9)

$$P9 = \underset{i=1,N}{Min}\left[\underset{j=1,M}{Max}(X_{ij}) - \underset{j=1,M}{Min}(X_{ij})\right] \quad \cdots\cdots (13)$$

10) Difference between maximum and minimum values of maximum temperature differences of all tanks at each time (P10)

$$P10 = \underset{i=1,N}{Max}\left[\underset{j=1,M}{Max}\left(X_{ij}\right) - \underset{j=1,M}{Min}\left(X_{ij}\right)\right] - \underset{i=1,N}{Min}\left[\underset{j=1,M}{Max}\left(X_{ij}\right) - \underset{j=1,M}{Min}\left(X_{ij}\right)\right] \cdots\cdots \quad (14)$$

11) Sum of Fourier transformation (P11)

$$P11 = \sum_{k=1}^{N}\sum_{l=1}^{M} F_{kl} \quad \cdots\cdots \quad (15)$$

12) Norme $\| F \|^2$ of Fourier transformation (P12)

$$P12 = \sum_{k=1}^{N}\sum_{l=1}^{M} F_{kl}^{2} \quad \cdots\cdots \quad (16)$$

13) Maximum value in C_kC_l components of Fourier transformation (P13)

$$P13 = Max\left(F_{kl}\right) \quad k = 1, N/2 \quad l = 1, M/2 \cdots\cdots \quad (17)$$

14) Maximum value in C_kS_l components of Fourier transformation (P14)

$$P14 = Max\left(F_{kl}\right) \quad k = N/2, N \quad l = 1, M/2 \quad \cdots\cdots \quad (18)$$

15) Maximum value in S_kC_l components of Fourier transformation (P15)

$$P15 = Max\left(F_{kl}\right) \quad k = 1, N/2 \quad l = M/2, M \quad \cdots\cdots (19)$$

16) Maximum value in S_kS_l components of Fourier transformation (P16)

$$P16 = Max\left(F_{kl}\right) \quad k = N/2, N \quad l = M/2, M \quad \cdots\cdots \quad (20)$$

17) Average value of maximums in each component of Fourier transformation (P17)

$$P17 = \left(P13 + P14 + P15 + P16\right)/4 \quad \cdots\cdots \quad (21)$$

18) Sum of average value of cycles which exceed threshold value b (P18)

$$P18 = \sum_{k=1}^{N}\sum_{l=1}^{M} Fl_{kl} \quad \begin{pmatrix} Fl_{kl} = (k+l)/2 & |F_{kl}| > b \\ Fl_{kl} = 0 & |F_{kl}| \le b \end{pmatrix} \cdots\cdots (22)$$

$$\begin{pmatrix} k = k - (N/2) & k \ge N/2 \\ k = k & k < N/2 \end{pmatrix} \begin{pmatrix} l = l - (M/2) & l \ge M/2 \\ l = l & l < M/2 \end{pmatrix}$$

19) Norme $\| Fl \|^2$ of average value of cycles which exceed threshold value b (P19)

$$P19 = \sum_{k=1}^{N}\sum_{l=1}^{M} Fl_{kl}^{2} \quad \begin{pmatrix} Fl_{kl} = (k+l)/2 & |F_{kl}| > b \\ Fl_{kl} = 0 & |F_{kl}| \le b \end{pmatrix} \cdots\cdots (23)$$

$$\begin{pmatrix} k = k - (N/2) & k \ge N/2 \\ k = k & k < N/2 \end{pmatrix} \begin{pmatrix} l = l - (M/2) & l \ge M/2 \\ l = l & l < M/2 \end{pmatrix}$$

20) Frequency for the magnitude of cycles to exceed threshold value b (P20)

$$P20 = \sum_{k=1}^{N}\sum_{l=1}^{M} Fl_{kl} \quad \begin{pmatrix} Fl_{kl} = 1 & |F_{kl}| > b \\ Fl_{kl} = 0 & |F_{kl}| \le b \end{pmatrix} \cdots\cdots \quad (24)$$

21) Maximum value of cycles varied along time axis which exceed threshold value b (P21)

$$P21 = Max\left(Fa_{kl}\right) \quad \cdots\cdots \quad (25)$$

$$Fa_{kl} = \begin{pmatrix} \begin{pmatrix} k & k > N/2 \\ k - N/2 & k < N/2 \end{pmatrix} & |F_{kl}| > b \\ 0 & |F_{kl}| \le b \end{pmatrix}$$

22) Maximum value of cycles varied along space axis which exceed threshold value b (P22)

$$P22 = Max\left(Fb_{kl}\right) \quad \cdots\cdots \quad (26)$$

$$Fb_{kl} = \begin{pmatrix} \begin{pmatrix} l & l > M/2 \\ l - M/2 & l < M/2 \end{pmatrix} & |F_{kl}| > b \\ 0 & |F_{kl}| \le b \end{pmatrix}$$

23) Thermal quantity of storage tank (P23)

$$P23 = \sum_{j=1}\sum_{i=1}\left(X_{i+1,j} - X_{j,i}\right) \quad \sum_{i=1}\left(X_{i+1,j} - X_{j,i}\right) < 0 \cdots (27)$$

24) Thermal quantity of heat dissipated (P24)

$$P24 = \sum_{j=1}\sum_{i=1}\left(X_{i+1,j} - X_{j,i}\right) \quad \sum_{i=1}\left(X_{i+1,j} - X_{j,i}\right) \ge 0 \cdots (28)$$

(3) Selecting optimal detecting parameters

Table 2 and Table 3 show the procedure of selecting optimal parameters for FDD with both variable selection method and differentiation rate increment method ,respectively. The FF in Table 2 is an index for releasing useless parameters, with which the degree of contribution of each parameter on the other parameters is evaluated. In order to test if the result is optimal, another method, exhaustion method[3], which needs much more time for calculation but more correct, was also applied.

The table 4 shows detecting rate about the data for 1995 and diagnosing rate about the data for 1996 using three optimal detecting parameters selected by the above-mentioned procedure. It also compares the calculation time with a mainframe high performance computer. It should be noted that the fault detection and diagnosis model is formed with normal and faulty data for 1995, that detecting rate means a proportion of faulty data successfully cllasified at the data period when the model was established, i.e. 1995 in this case, and that diagnosing rate is a proportion of normal data successfully classified at the following data time period, i.e. 1996 in this case. The table 4 illustrates the following.

1) Detecting rate and diagnosing rate calculated with parameter vector (P1,P13) selected by differentiation rate increment method is a bit higher than that

Table 2 Calculation procedure of variable selection method

One dimension :

parameter	1	5	13	16	21	19	24	22	23	10	8	14	11	9	2	17
$F_j^{(1)}$	39.9	22.0	14.8	10.0	7.7	4.3	3.0	2.9	2.6	1.6	1.2	1.1	0.8	0.6	0.6	0.3

Two dimension :

P1,	17	13	14	21	16	2	22	24	9	19	10	23	8	5	11	parameter	17,1	1,17
$F_j^{(2)}$	11.2	9.5	4.8	3.7	2.7	2.3	1.1	1.0	0.8	0.8	0.8	0.7	0.2	0	0	$FF_k^{(2)}$	55.2	11.2

Three dimension :

P1+17,	2	13	5	9	16	8	11	10	24	23	22	19	21	14	parameter	17+2,1	1+2,17	1+17,2
$F_j^{(3)}$	3.3	2.0	1.7	1.3	1.3	1.3	1.2	1.1	1.0	0.9	0.7	0.6	0.2	0.1	$FF_k^{(3)}$	56.1	12.2	3.3

Four dimension :

P1+17+2,	9	13	14	10	21	16	22	8	17	5	24	23	11	parameter	17+2+9,1	1+2+9,17	1+17+9,2	1+17+2,9
$F_j^{(4)}$	4.0	3.2	2.3	2.1	1.2	1.1	1.0	0.3	0.3	0.1	0.1	0.1	0.0	$FF_k^{(4)}$	60.5	15.6	6.0	4.0

Five dimension (end)**:**

P1+17+2+9,	21	13	5	22	23	14	16	10	8	19	24	11
$F_j^{(5)}$	1.8	1.3	1.0	0.8	0.8	0.8	0.8	0.8	0.8	0.7	0.6	0.3

Table 3   Calculation procedure of differentiation rate increment method

One dimension	parameter	P1	P5	P8	P13	P19	P24	P11	P21	P10
	differentiation rate	0.91	0.80	0.77	0.76	0.71	0.68	0.67	0.67	0.66
Two dimension	parameter	P1+P13	P1+P17	P1+P14	P1+P24	P1+P2	P1+P8			
	differentiation rate	0.962	0.942	0.936	0.923	0.917	0.917			
	differentiation rate increment	0.052	0.032	0.026	0.013	0.007	0.007			
Three dimension (end)	parameter	P1+P13+P2	P1+P13+P9	P1+P13+P14	P1+P13+P16					
	differentiation rate	0.962	0.962	0.962	0.962					
	differentiation rate increment	0.0	0.0	0.0	0.0					

Table 4 Comparison of three optimum methods

Method	Detection/ Diagnosis Parameter	5/1～10/27,1995		4/25～9/30,1996		Calculation* time [minutes]
		Number	Differentiation rate	Number	Diagnosis rate	
Variable selection method	P1,P2,P9,P17	149	0.955	110	0.748	1. 5
Differentiation rate increment method	P1,P13	150	0.962	137	0.932	2.0
Exhaustion method	P1,P2,P13,P14	151	0.968	139	0.946	60

* with a high performance mainframe computer

calculated with parameter vector (P1,P2,P9,P17) selected by variable selection method. It is because, in case of variable selection method, the degree of contribution for newly added parameter to the optimal vector, merely pays attention to the one which was selected at the preceding step. It means that some other combinations of parameters, which had been released at the preceding step as non-optimal due to lower detecting rate, may become more optimal by adding new parameter.

2) Detecting rate and diagnosing rate of parameter vector determined by differentiation rate increment method is a little lower than the optimal parameter vector selected by exhaustion method, however, the calculation time of the former is far shorter than the latter, i.e. two minutes vs. sixty minutes, so that the differentiation rate increment method is considered more practical.

3) The diagnosing rate for the data for 1996 with the two parameter vectors, selected by differentiation rate increment method and exhaustion method, is only a little smaller than the detecting rate for learning data of 1995. It means that the differnce of diagnosing rate is little between the two models in spite of the difference of cooling load pattern between two years, once the FDD model is properly identified. .

(4) Discussion on FDD mapping for a case

Fig.6 shows the detecting result for 1996 data with parameter (P1,P13). The ovals shown are boundaries of 1.5 times σ in Mahananobis' generized distances from the centers of both normal and fault data groups for 1995.

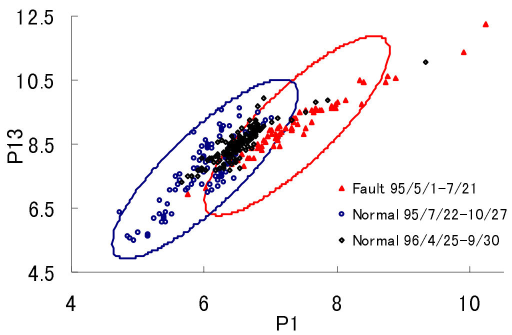


Figure 6 Fault detection/diagnosis mapping with parameter (P1,P13)

1) While most of parameter values calculated with normal data for 1996 are in the overlapping range between normal and faulty state space ovals which were constructed with data for 1995, most of them are correctly classified as the normal, for they are in the closest distance from the center of the normal space. That means, the parameter vector (P1,P13) could express the difference of temperature variation property in low-temperature between normal state and faulty one.

2) A few vector plots calculated with normal data for 1996 disribute apart from normal and faulty state space. It may be because some other abnormal phenpmena other than a fault in the present attention, the fault in three way valve in suction line of heat pump have taken place.

CONCLUSION

The summary of the present fault detection/diagnosis methods for application to actual HVAC thermal storage system is as follows.

1) In order to apply present methods effectively, it is necessary to prepare database for each type of normal and faulty states and to design parameters properly for each state.

2) The differentiation rate increment method may not be the best method of choosing optimal parameters, but it seems to be an optimal method considering that the detecting and diagnosing rate is sufficiently high and that calculation time is much shorter, compared with more correct but time-consuming exhaustion method.

3) The most effective parameters can be selected automatically by the present fault detection and diagnosis methods, however, it should be noted that each state space is classified statistically and that errors are naturally probable for fault detection and diagnosis.

ACKNOWLEDGEMENT

The authors acknowledge Mr. Miyasaka, Yamatake Buiding Systems Co. Ltd. for his efforts in preparing temperature data, and Prof. Sagara, Mie University and FDD Working Group members of the Thermal Storage Optimizaion Committee in SHASE.

REFERENCES

[1]Mingjie Zheng and Nobuo Nakahara : Study on Fault Detection and Diagnosis of Thermal Storage Control Systems with Pattern Recognition, Transactions of the Society of Heating, Air-Conditioning and Sanitary Engineers of Japan, No.63, Oct., 1996

[2]Nobuo Nakahara, Mingjie Zheng and Yoshihiko Nishitani: Simulation and Fault Detection of the Thermal Storage Systems, Proceedings of BUIDING SIMULATION '87,Sept.,1997, Prague

[3] Mingjie Zheng, Song Pan and Nobuo Nakahara: Study on Fault Detection of Thermal Storage System with Pattern Recognition (part 5 Online Detecting Method and Optimization of Detecting Vector). Proceedings of AIJ Academic Meeting , 1998, Fukuoka, in Japanese

[4] Song Pan ,Mingjie Zheng and Nobuo Nakahara: Study on Fault Detection of Thermal Storage System with Pattern Recognition (part 4 Development of Optimum Program for Detecting Parameter), Proceedings of AIJ Tokai Chapter Academic Meeting, 1998, Nagoya, in Japanese

[5]Takaiti Sugiyama: Elementary Course of Maltiple Variable Analysis, 1983, Asakusa Bookstore, in Japanese.