ELSEVIER

Computers and Chemical Engineering 24 (2000) 743–748

Computers & Chemical Engineering

www.elsevier.com/locate/compchemeng

Robust alarm generation strategy

Chii-Shang Tsai [a], Chuei-Tin Chang [b,*], Shuh-Woei Yu [c], Chen-Shan Kao [c]

[a] *Far East College, Tainan, Taiwan, ROC*

[b] *National Cheng Kung University, Tainan, Taiwan, ROC*

[c] *Center for Industrial Safety and Health Technology, Hsinchu, Taiwan, ROC*

Abstract

A novel alarm-system design strategy, which takes full advantage of the inherent hardware and spatial redundancy in a process network, is proposed in this paper. Specifically, systematic procedures have been developed to identify independent methods for evaluating any alarm variable in the process and to synthesize corresponding alarm generation logic. In order to implement this logic, the error models in data reconciliation and the formulas for evaluating conditional probabilities of type I and II mistakes have also been derived. The results of simulation studies show that it is indeed superior to any of the existing design techniques. This is because the resulting alarm system is appropriately tailored to minimize the expected loss. More importantly, it is robust in the sense that the system performs satisfactorily even under the influence of various sensor malfunctions.

Keywords: Alarm logic; Spatial redundancy; Data reconciliation

1. Introduction

Alarm generation is a basic function of the protective system in any chemical process plant. The current practice in the industry is simply to compare measurement data of the variable of interest with a pre-determined threshold value. The decision concerning whether or not to set off an alarm is then made accordingly. Naturally, all sensor measurements are subject to errors, i.e. the random and/or gross errors. Thus, two types of mistakes may be committed in the above decision making process. First of all, spurious alarms may be produced due to measurement errors when the variations of the process variables are actually within acceptable limits (type I mistakes). Secondly, the system may fail to detect the existence of hazardous operating conditions and thus no alarms are generated (type II mistakes).

One possible way to improve the current operation is to make use of the *spatial redundancy* embedded in any process network. The hardware redundancy built in a traditional alarm system can actually be viewed as a special case of spatial redundancy in the sensor network of the overall process. Consequently, the reconciled data, rather than the raw measurement data, are adopted in this study for alarm generation purpose. In a previous study (Tsai & Chang, 1997), a systematic method for synthesizing the optimal *flow* alarm logics has been developed according to the design criterion of minimizing expected loss. Although this method was demonstrated to be cost effective if only random errors exist, the problems caused by gross errors were not discussed in sufficient detail. Thus, in order to address the issue of alarm resilience and to extend the approach to all measurable variables in the process network, i.e. the flow rates, the temperatures and the concentrations, it is necessary to perform a more comprehensive study.

2. The error models

In order to explore the structural characteristics of chemical processes, it is convenient to represent the process flow diagrams with *process networks* (Mah, 1990). On each arc in a process network, the variables of interest are the total flow rate, the temperature and the component concentrations. In this paper, they are referred to as the process variables. The true values of these variables can be viewed as

* Corresponding author.

0098-1354/00/$ - see front matter © 224 Elsevier Science Ltd. All rights reserved.
PII: S0098-1354(00)00341-0

$$v_j^t = v_j^d + \Delta_j \quad (1)$$

where, v_j^t denotes the true value of the jth process variable, v_j^d represents its design value and Δ_j is the corresponding difference resulting from unknown disturbances. In this study, Δ_j is assumed to be a normally-distributed random variable with *time-variant* mean. Specifically, its expected value is zero when the system is operated at normal steady state and otherwise when faults occur. Notice that, Eq. (1) is equally applicable to the temperatures, concentrations and total flow rates.

Next, let us assume that, the measurement errors are related to their true values according to the following constraint

$$v_j = v_j^t + e_j \quad (2)$$

where, v_j represents the measurement value of the jth variable and e_j denotes the corresponding error. In this study, e_j is treated as a normally distributed random variable with zero mean. It should be reasonable to believe that the variance of each measurement error can be acquired from the vendor or an analysis of its historical data.

3. The reconciliation errors

In this work, the reconciled values of the process variables are utilized in the alarm generation process. Consequently, the corresponding estimation errors must also be analyzed. It should be noted that the choice of constraint equations used in the reconciliation calculation is dependent upon the variables involved in alarm logic. For example, it is only necessary to consider mass balance in the flow-alarm algorithm, but both mass and energy balance must be included in a temperature-alarm system. Let us express these constraint equations in a general form, i.e.

$$\mathbf{\Phi}(\mathbf{v}^t, \mathbf{u}^t, \boldsymbol{\eta}^t) = 0 \quad (3)$$

where, $\mathbf{\Phi}$ denotes the vector of constraint functions, $\mathbf{v}^t$ and $\mathbf{u}^t$ represent respectively the true values of the measured and unmeasured process variables and $\boldsymbol{\eta}^t$ is the vector of unknown parameters, e.g. the reaction extent and the split fraction.

If the constraint equations in Eq. (3) are linear, then the reconciled values of process variables can be determined analytically (Crowe, Garcia Campos & Hrymak, 1983). Otherwise, an iterative computation procedure is needed (Crowe, 1986). Notice that the intention for installing an alarm is usually to protect the process against certain hazards. Prompt remedial actions must be taken if such emergency situations occur. Thus, the standard reconciliation algorithm for nonlinear (or bilinear) systems is really inappropriate in alarm generation applications due to its iterative nature. In this study, a linearized version of the constraint equations is adopted to produce estimates of the process variables. In particular, let us linearize Eq. (3) with respect to the measurement values, i.e.

$$\mathbf{A}^{(1)}\Delta\mathbf{v} + \mathbf{A}^{(2)}\Delta\mathbf{u} + \mathbf{A}^{(3)}\Delta\boldsymbol{\eta} = -\boldsymbol{\delta} \quad (4)$$

where $\Delta\mathbf{v} = \mathbf{v}^t - \mathbf{v}$, $\Delta\mathbf{u} = \mathbf{u}^t - \mathbf{u}$, $\Delta\boldsymbol{\eta} = \boldsymbol{\eta}^t - \boldsymbol{\eta}$ and $\boldsymbol{\delta} = [\mathbf{\Phi}_1(\mathbf{v}, \mathbf{u}, \boldsymbol{\eta}), \mathbf{\Phi}_2(\mathbf{v}, \mathbf{u}, \boldsymbol{\eta}), \cdots, \Phi_{N_E}(\mathbf{v}, \mathbf{u}, \boldsymbol{\eta})]^T$. It is assumed that the values of u_ks and η_ls can be determined by solving various subsets of the constraint equations in Eq. (3) on the basis of the measurement values v_js. As a result, the coefficient matrices in Eq. (4) can also be evaluated accordingly.

In order to derive an explicit formula to estimate reconciliation errors, it is often necessary to rearrange the order of variables in vector $\mathbf{v}$ and partition $\mathbf{A}^{(1)}$ accordingly into two matrices:

$$\mathbf{A}^{(1)} = [\mathbf{A}^{(11)} \quad \mathbf{A}^{(12)}] \quad (5)$$

Furthermore, this partition must be done in such a way that a nonsingular matrix $\mathbf{T}$ can be constructed with $\mathbf{A}^{(12)}$, $\mathbf{A}^{(2)}$ and $\mathbf{A}^{(3)}$, i.e.

$$\mathbf{T} = [\mathbf{A}^{(12)} \quad \mathbf{A}^{(2)} \quad \mathbf{A}^{(3)}] \quad (6)$$

By premultiplying $\mathbf{T}^{-1}$, Eq. (4) can be transformed into

$$\begin{bmatrix} \mathbf{C}_1 & \mathbf{I}_1 & 0 & 0 \\ \mathbf{C}_2 & 0 & \mathbf{I}_2 & 0 \\ \mathbf{C}_3 & 0 & 0 & \mathbf{I}_3 \end{bmatrix} \begin{bmatrix} \Delta\mathbf{v}_1 \\ \Delta\mathbf{v}_2 \\ \Delta\mathbf{u} \\ \Delta\boldsymbol{\eta} \end{bmatrix} = -\begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \end{bmatrix} \quad (7)$$

where, $\Delta\mathbf{v}_1$ and $\Delta\mathbf{v}_2$ is vectors corresponding to the columns of $\mathbf{A}^{(11)}$ and $\mathbf{A}^{(12)}$, respectively. On the basis of Eq. (7), it can be shown that the reconciled values of the measured variables $\hat{\mathbf{v}}$ can be expressed as

$$\hat{\mathbf{v}} = \mathbf{v} - \mathbf{Q}\mathbf{B}^T(\mathbf{B}\mathbf{Q}\mathbf{B}^T)^{-1}\boldsymbol{\delta}_1 \quad (8)$$

where $\mathbf{Q}$ is the covariance matrix associated with $\hat{\mathbf{v}}$ and $\mathbf{B} = [\mathbf{C}_1 \quad \mathbf{I}_1]$. Let us now define the vector of estimation errors $\mathbf{d}$ as $\mathbf{d} = \hat{\mathbf{v}} - \mathbf{v}^t$. Then, by substituting this definition and the first part of Eq. (7) into Eq. (8), one can produce the following result:

$$\mathbf{d} = \mathbf{e} - \mathbf{Q}\mathbf{B}^T(\mathbf{B}\mathbf{Q}\mathbf{B}^T)^{-1}\mathbf{B}\mathbf{e} = \lfloor \mathbf{I} - \mathbf{Q}\mathbf{B}^T(\mathbf{B}\mathbf{Q}\mathbf{B}^T)^{-1}\mathbf{B} \rfloor \mathbf{e} \quad (9)$$

Thus, the error of every reconciled value can be estimated by a linear combination of the measurement errors of all sensors.

4. The threshold limits

In a chemical plant, a subset of the measured process variables may be selected as the alarm variables on the basis of process considerations. More specifically, each of these variables must satisfy one or more operational constraint. A typical constraint can be written as

$$v_A^t - v_A^L \geq 0 \quad \text{or} \quad v_A^U - v_A^t \geq 0 \tag{10}$$

where, v_A^t represents the true value of the Ath process variable and v_A^L and v_A^U denote, respectively, the lower and upper threshold limit. For convenience, the operational constraint can be expressed in an alternative general form as:

$$G(v_A^t) \geq 0 \tag{11}$$

where G is referred to a *performance function* in this study.

Obviously, an alarm is set off as an indication of constraint violation. Since the true process state can never be determined, one has to rely on the measurement data to evaluate the performance function. In other words, the values of *indicator function* $G^{(s)}$ ($s = 1, 2, \ldots, N_A$) must be computed according to

$$G^{(s)} = G(v_A^{(s)}) \tag{12}$$

where, $v_A^{(s)}$ denotes the value of alarm variable obtained with the sth independent method.

Apparently, the alarm variable can be monitored *directly* with a sensor. Although there is at most one sensor for each variable on any arc in the process network, it is still possible to identify more than one independent method to determine the alarm variable indirectly according to the measurement data of other process variables. These indirect methods can be identified mainly by exploiting the inherent spatial redundancy implied in the mass, component and energy balance relations. Due to measurement errors, the values of indicator function evaluated with data obtained from different methods are in general not consistent with one another. Nonetheless, one is still required to make a decision concerning whether or not to set off an alarm with these data. Thus, let us now turn our attention to the development of an optimal alarm generation strategy.

5. The optimal alarm generation logic

As indicated above, there may be several different evaluation methods available for the purpose of monitoring the same variable of interest. Let us express these methods with a set of evaluation functions $\Psi_A^{(s)}$ ($s = 1, 2, \ldots, N_A$), i.e.

$$v_A^{(s)} = \Psi_A^{(s)}(\mathbf{v}) \tag{13}$$

where each $\Psi_A^{(s)}$ is derived from a subset of the constraint equations in Eq. (3) and $\mathbf{v}$ is the vector of measurement values of all measured process variables. The explicit forms of these evaluation functions can be identified with the procedures described in the next section. Assuming that such functions are available, one should be able to compute $v_A^{(s)}$s on-line and then substitute them into the performance function G to assess the current operation status. On the basis of these results, a set of binary indicator variables y_s can be determined accordingly, i.e.

$$y_s = \begin{cases} 1 & \text{if } G^{(s)} < 0 \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

where, $G^{(s)}$ is the indicator function defined in Eq. (12).

The system alarm should then be generated on the basis of these indicators. The logic for setting off the alarm can be explicitly expressed with an alarm function $f(\mathbf{y})$, i.e.

$$f(\mathbf{y}) = \begin{cases} 1 & \text{if the system is generating an alarm} \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

Obviously, the values of the indicator variables y_ss in $\mathbf{y}$ may not be consistent with the true state v_A^t. Let us consider the true value of the performance function, G^t. There are two kinds of mistakes that can be identified accordingly, i.e. y_s is set to be 1 when $G^t \geq 0$ (type I mistake) or y_s is set to be 0 when $G^t < 0$ (type II mistake). Similarly, the mistakes committed in generating the *system alarm* can also be classified into type I and II. Since both types of mistakes result in financial losses, there are incentives for developing an optimal alarm generation logic which minimizes the expected loss. This loss function L can be written as,

$$L = C_a(1 - P_F)P_a + C_bP_FP_b \tag{16}$$

where P_a and P_b, respectively, denote the probabilities of type I and II mistakes in alarm generation, C_a and C_b are the corresponding costs. Also, P_F is the demand probability which is defined as the probability of violating the constraint. It can be shown (Tsai & Chang, 1997) that the expected loss is minimized if the alarm function is chosen such that

$$f(\mathbf{y}) = \begin{cases} 1 & \text{if } h(\mathbf{y}) > 0 \\ 0 & \text{if } h(\mathbf{y}) \leq 0 \end{cases} \tag{17}$$

where $h(\mathbf{y}) = C_bP_F\Pr\{\mathbf{y}|G^t < 0\} - C_a(1 - P_F)\Pr\{\mathbf{y}|G^t \geq 0\}$ After obtaining the values of $f(\mathbf{y})$ for all possible $\mathbf{y}$, its functional form can be constructed accordingly. With the functional form given, the logic associated with $f(\mathbf{y})$ can be implemented as a hard-wired circuit or as a computer program. Finally, it should be noted that, in order to carry out the proposed alarm strategy, the demand probability and the two conditional probabilities in $h(\mathbf{y})$ must be obtained first. Since the means of unknown disturbances defined in Eq. (1) are unpredictable, these probabilities cannot be evaluated directly. On the other hand, from the assumption that the means of measurement errors defined in Eq. (2) are negligible, an alternative estimation method can be developed according to the reconciled value of the alarm variable (Tsai & Chang, 1997). Thus, the resulting alarm generation procedure is really time-variant.

6. Independent evaluation methods

Let us first consider the flow alarm installed on one particular arc, say a, in a process network. It has been well established that all the different ways of indirectly evaluating the same mass (or molar) flow are given by the cut sets that contain arc a in which the total mass (or molar) flow of every other arc is measured (Ali & Narasimhan, 1993, 1995). However, since some of the elements may appear in more than two of these cut sets, the corresponding evaluation methods are statistically dependent. Consequently, it is necessary to select out cut sets that do not contain common arcs other than a. Tsai and Chang (1997) proposed a simple digraph-based procedure to perform this task:

1. Consider the original process network. Merge the input and output nodes of every arc on which the flow sensor is not installed. Let the resulting process graph be the current digraph and also $i = 1$.
2. Find a cut set $\mathbf{K}^{(i)}$ of the current digraph which contains arc a.
3. Merge the input and output nodes of every arc in $\mathbf{K}^{(i)}$ except those of arc a. Let the resulting graph be the current digraph and $i = i + 1$.
4. Repeat steps 2 and 3 until arc a itself forms a loop.

It should be noted that the evaluation methods obtained with this approach might not be unique. This is due to the fact that more than one cut set can usually be found in any given graph. Conceivably, other candidate measurement methods may be identified if different cut sets are adopted in step 2.

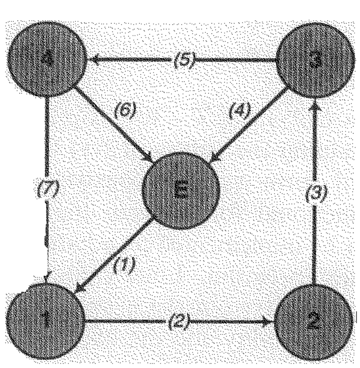

Fig. 1. Process network of ammonia process.

Let us next consider the problem concerning the temperature alarm on arc a. Notice that the connection between the cut sets and the evaluation methods in a mass-flow network is still valid in an energy-flow network. On the basis of this insight, a similar procedure can be developed to identify a set of independent temperature evaluation methods. Finally, it should be noted that, without reactors and splitters, the equation form of component-flow constraint in a process network is really identical to that of mass-flow or energy-flow constraint. Consequently, another modified version can also be developed to identify indirect independent concentration (or component flow) evaluation methods (Chu, 1999). For the sake of brevity, these two procedures are not described in the present paper.

7. Case studies

Let us consider the ammonia synthesis process (Fig. 1) which was first studied by Crowe et al. (1983). In this process network, node 1 is associated with a mixer, node 2 a reactor, node 3 a separator and node 4 a splitter. A simple reaction $N_2 + 3H_2 = 2NH_3$ takes place in the reactor and there are at most four species, i.e. nitrogen, hydrogen, ammonia and argon, in each process stream. It is assumed that an alarm system must be installed on arc 2 to protect against the undesirable outcomes caused by low hydrogen flow rate. Consequently, it is more convenient to formulate the constraint equations in terms of component flows which are products of concentrations and total flow rates. In particular, these products should be replaced by a set of new variables n_{li}s representing the component flows. Then the *apparent* measurement error covariance matrix corresponding to these variables should be block diagonal even if the measurement errors of flow rates and concentrations are independently distributed.

Under normal operating conditions, the system is assumed to be at its original steady state and can be described with the statistical parameters presented in Table 1. The means and variances of every 'true' component flow rate in each stream can be found in the third and fourth column of Table 1. Notice that, in almost every stream, the data associated with one or more component flow are not included. This is due to the assumption that these components are not present in the corresponding stream. As mentioned previously, the difference between the true value of a process variable and its design value is treated in this work as a random variable with zero mean during normal operation. Thus, the mean values listed in Table 1 are also used as the design values in the present example. In this process network, all component flow rates are measured except n_{2,N_2}, n_{7,N_2} and n_{7,H_2}. The variance of each

Table 1
Statistical parameters of component flows under normal operating conditions

Stream number (l)	Component (i)	$E[n^t_{li}]$	$\text{var}[n^t_{li}]$	$\text{var}[e_{nli}]$
1	N_2	39.74	0.1579	0.03947
	H_2	113.0	1.334	0.3335
	Ar	2.526	0.-164	0.2416
2	N_2	101.0	15.67	N.A.
	H_2	253.4	6.704	1.676
	Ar	20.20	0.04111	0.01028
3	N_2	70.02	17.27	4.318
	H_2	160.4	2.686	0.6716
	Ar	20.20	0.04111	0.01028
	NH_3	61.98	0.4013	0.1003
4	NH_3	61.98	0.4013	0.1003
5	N_2	70.02	17.27	4.318
	H_2	160.4	2.686	0.6716
	Ar	20.20	0.04111	0.01028
6	N_2	8.753	0.2699	0.06747
	H_2	20.05	0.04197	0.01049
	Ar	2.526	0.74864	0.00016
7	N_2	61.27	13.22	N.A.
	H_2	140.3	2.057	N.A.
	Ar	17.68	0.03148	0.00787

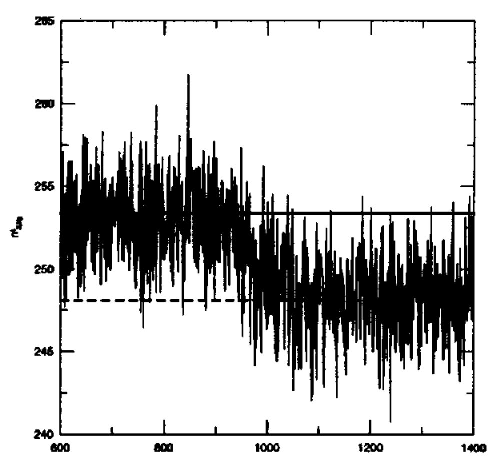

Fig. 2. Results of the true component flow n^t_{2,H_2}.

Table 2
The performance of optimal alarm strategy (fault origin: a decrease in H_2 supply)

Alarm strategies	C_b/C_a	Proportion of mistakes	
		Type I	Type II
Traditional		0.06752	0.13680
Approach A		0.02971	0.06551
Approach B	30.0	0.07562	0.01541
	60.0	0.08373	0.00963
	100.0	0.09386	0.00771

measurement error can also be found in Table 1 (column 5). The covariance values of each pair of measurement errors associated with the ith and jth components within the same stream (say stream l) are assigned according to the following formula:

$$\text{cov}[n_{li}, n_{lj}] = \frac{\sqrt{\text{var}[n_{li}]\text{var}[n_{lj}]}}{2} \tag{18}$$

The reconciled values of component flow rates can be obtained with Eq. (8). The threshold limit n^L_{2,H_2} selected in the simulation studies is 248.1 mol/s. The first independent evaluation method is naturally associated with the sensors for directly measuring arc 2, i.e. when $s = 1$

$$n^{(1)}_{2,H_2} = \Psi^{(1)}(n_{2,H_2}) = n_{2,H_2} \tag{19}$$

The indirect evaluation methods adopted in this study can be expressed as:

$$n^{(2)}_{2,H_2} = \Psi^{(2)}(n_{1,H_2}, n_{5,H_2}, n_{6,H_2}) = n_{1,H_2} + n_{5,H_2} - n_{6,H_2} \tag{20}$$

$$n^{(3)}_{2,H_2} = \Psi^{(3)}(n_{3,H_2}, n_{3,NH_3}) = n_{3,H_2} + n_{3,NH_3} \tag{21}$$

The effectiveness of the proposed alarm generating strategy can be demonstrated with simulation studies. The variation in the true flow rate n^t_{2,H_2} due to a sudden decrease in H_2 supply from environment, i.e. n_{1,H_2}, was first simulated. Initially, $E[n^t_{2,H_2}]$ was kept at its design value, i.e. 253.4 mol/s. The fault occurs at time $900\Delta t$ and Δt is the sampling interval. As a result, the mean value of n^t_{2,H_2} decreases gradually and reaches a new steady level of 248.2 mol/s after time $1100\Delta t$. A total of 2000 sets of data have been generated in this case. Only half of them, i.e. from sample number 600 to 1400, are shown in Fig. 2. Next, the measurement values were simulated. This was done by adding the measurement errors to the corresponding true component flow rates. The values of measurement errors were again created with a random number generator according to the given covariance matrix $\mathbf{Q}$. Using the measurement data, one can then compute the reconciled component flow rates with Eq. (8).

In this study, the traditional approach, i.e. using the raw measurement data n_{2,H_2}, was taken first to set off alarm. The proportions of type I and II mistakes in this case were determined to be 0.06752 and 0.13680, respectively. On the other hand, by adopting the reconciled data as the basis for alarm generation, it was found that the chances of making these mistakes can be lowered significantly to 2.97% (type I) and 6.55% (type II).

Each time a new set of measurement data and the corresponding reconciled component flow rates are obtained, an optimal alarm logic can be constructed online with the proposed synthesis procedure. The time needed to construct one of these logics was found to be less than one second on a Pentium PC. The results of adopting the proposed alarm policy (approach B) with

Table 3
The performance of optimal alarm strategy in additional case studies ($C_b/C_a = 30$)

Case number	Alarm strategies	Proportion of type II mistakes
1	Traditional	0.13680
	Approach A	0.12524
	Approach B	0.04817
2	Traditional	0.22667
	Approach A	0.14667
	Approach B	0.06667

different C_b/C_a ratios are summarized in Table 2. In particular, the proportions of type I and II mistakes are presented in this table. For comparison purpose, the results of using only the direct measurement data (the traditional approach) and the reconciled data (approach A) are also included. From these results, it is clear that the proposed alarm system is superior in the sense that the corresponding loss due to misjudgment reaches a minimum. Also notice that type II mistakes can be reduced to a negligible level by increasing the C_b/C_a ratio. This is usually the first priority in most cases since the purpose for installing an alarm is almost always to protect against certain catastrophic consequences.

Due to the fact that more independent evaluation methods are adopted for alarm generation purpose, it is our belief that the proposed strategy should outperform the traditional practice even under the influence of gross errors. In order to demonstrate the resilience of the proposed approach, the alarm strategy was tested with various additional scenarios. A brief description of two of these cases is presented in the sequel:

1. *Case 1*. In addition to the fault simulated in the above studies, i.e. a decrease in hydrogen supply, an additional sensor failure on stream 1 is also introduced in this case. Specifically, the mean of the measurement values of n_{1,H_2} was kept at it 'normal' level, i.e. 113.0 mol/s, when disturbances enter the system.
2. *Case 2*. The effects of a leakage in stream 4 are studied in this case. It is assumed that 2% of the ammonia flow is released to the environment.

The results of these additional case studies are presented in Table 3. One can see clearly that approach B performs better than the other two methods in all scenarios.

8. Conclusions

From the above discussions, it is clear that the proposed alarm-logic design strategy is indeed superior to any of the existing techniques. Not only the resulting alarm system is optimal, but also robust. These desirable features are brought about mainly by integrating the intrinsic characteristics of process network, i.e. the spatial redundancy, into system design. Furthermore, from experiences obtained in solving the example problem, one can also conclude that the demand for on-line computation is reasonable especially when the sampling interval is in the range of seconds or longer.

References

Ali, Y., & Narasimhan, S. (1993). Sensor network design for maximizing reliability of linear processes. *American Institute of Chemical Engineering Journal, 39*, 820.

Ali, Y., & Narasimhan, S. (1995). Redundant sensor network design for linear processes. *American Institute of Chemical Engineering Journal, 41*, 2237.

Chu, S. H. (1999). The design of alarm system in multi-component process networks, MS Thesis, National Cheng Kung University, Tainan, Taiwan.

Crowe, C. M. (1986). Reconciliation of process flow rates by matrix projection: II. The nonlinear case. *American Institute of Chemical Engineering Journal, 32*, 616.

Crowe, C. M., Garcia Campos, Y. A., & Hrymak, A. (1983). Reconciliation of process flow rates by matrix projection: I. The linear case. *American Institute of Chemical Engineering Journal, 29*, 881.

Mah, R. S. H. (1990). *Chemical process structures and information flows*. Boston: Butterworths.

Tsai, C. S., & Chang, C. T. (1997). Optimal alarm logic design for mass flow networks. *American Institute of Chemical Engineering Journal, 43*(11), 3021.