Model-Based Approach for Fault Diagnosis. 1. Principles of Deep Model algorithm

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Model-Based Approach for Fault Diagnosis. 1. Principles of Deep Model Algorithm

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Equation types of deep models are often employed in fault diagnosis. Upon diagnosis this quantitative process knowledge is utilized as a criterion for satisfaction/violation in a Boolean or non-Boolean manner. Therefore, the resolution of equation-oriented fault diagnosis systems is often limited to, at most, fault isolation at a qualitative level. A deep model algorithm (DMA) is proposed to improve diagnostic resolution. First, tolerances of model equations are defined for each model equation with respect to each fault origin. Following the new definition of tolerance, degree of fault is defined to detect the level of fault and a consistency factor is used to evaluate the consistency given by different model equations. A CSTR example is used to illustrate the resolution of DMA. Results show that the proposed method is effective in identifying fault origins.

1. Introduction

Fault diagnosis has received a great deal of attention recently (Willsky, 1976; Himmeblau, 1978; Venkatasubramanian and Rich, 1979; Mah and Tamhane, 1982; Isermann, 1984; Iri *et al.*, 1985; Kramer and Palowitch, 1987; Ramesh *et al.*, 1988; Davis, 1988; Ulerich and Powers, 1988; Petti *et al.*, 1990; Hoskins *et al.*, 1991; Yu and Lee, 1992; Gertler and Anderson, 1992; Ungar and Psichogios, 1992; Chang *et al.*, 1993). The reason for this is obvious, since chemical plants are operated, if not optimally, at least safely from an operating point of view. Furthermore, most modern chemical plants are controlled with distributed control systems (DCS). This implies that the availability of process data poses little technical problems for online fault diagnosis. The only problem remaining is an appropriate methodology for utilizing these process data in a real-time environment. Quantrille and Liu (1991) give a good review on process fault diagnosis.

From the rigorousness of the process model employed, the diagnostic systems can be classified into quantitative model-based approach. The Kalman filter approaches (Mah and Tamhane, 1982; Himmeblau, 1978; Fathi *et al.*, 1992), the neutral network approaches (Ungar and Psichogios, 1992; Himmeblau, 1989; Hoskins *et al.*, 1991; Fan *et al.*, 1993), expert systems (Dhurjati *et al.*, 1987; Davis *et al.*, 1988), and equation-oriented model-based approaches (Reiter, 1987; Kramer, 1987; Petti *et al.*, 1990; Frank, 1990; Isermann, 1991a and 1991b; Gertler and Anderson, 1992) fall into this category. The signed directed graph (SDG) methods (Kramer and Palowitch, 1987; Chang and Yu, 1990), qualitative simulation (QSIM) approaches (de Kleer and Brown, 1984; Kuipers, 1986; Kramer and Oyeleye, 1988), order-of-magnitude (O[M]) approach (Mavrovouniotis and Stephanopoulos, 1988), and qualitative process theory (QPT) approaches (Forbus, 1984; Grantham and Ungar, 1991) belong to the qualitative model-based diagnosis. Hybrid systems (semiquantitative model-based) are also proposed (Ulerich and Powers, 1988; Yu and Lee, 1992; Chang *et al.*, 1993).

However, from the resolution point of view, the resolution of a diagnostic system can be up to the quantitative level or the qualitative level. By quantitative level, we mean that the diagnostic system can isolate the fault from the quantitative differences. In other words, if the patterns of two faults are exactly the same on the basis of the analysis of the signs (e.g., the directions (sign) of the deviations are exactly the same) and differ in magnitude (e.g., the sizes of the deviations are different), then we call the resolution of the system up to the quantitative level. For example, the SDG approach of Kramer and Palowitch (1987) and Chang and Yu (1990), the qualitative physics approach of Kuipers (1986), and the equation-oriented model-based approach of Kramer (1987) and Petti *et al.* (1990) are diagnostic systems with the resolution up to the qualitative level. On the other hand, the parameter estimation method of Park and Himmeblau (1983), the Kalman filter method of Fathi *et al.* (1992), and the fault detection, isolation, and accommodation (FDIA) method of Frank (1990), Willsky (1976), and Gertler and Anderson (1992) are the diagnostic systems of the quantitative level.

As far as the knowledge representation is concerned, the model-based diagnostic system can be further classified into equation-oriented (Himmelblau, 1978; Willsky, 1984; Himmelblau et al., 1989; Kramer, 1987; Petti *et al.*, 1990) and graphics-oriented approaches (SDG; Kramer and Palowitch, 1987; Ulerich and Powers, 1988; Chang and Yu, 1990; Yu and Lee, 1992). The advantage of the graphics-oriented approach, e.g., SDG approach, is that the user can *visualize* the process knowledge. However, at present stage, most process engineers are more familiar with equation-oriented approaches. That is, most process engineers utilize (or were taught) equations to solve engineering problems. Therefore, from the familiarity and maintenance point of view, the equation-oriented approach is an attractive alternative for online fault diagnosis.

The purpose of this series of papers is to investigate and extend the equation-oriented approaches for online fault diagnosis. In part 1, the potential problems for equation-oriented approaches, specifically DMP of Petti *et al.* (1990), are explored and appropriate remedial actions are also proposed. This paper is organized as follows. Section 2 discusses previous works on model-based diagnosis and illustrates the current problems of equation-oriented diagnostic systems. DMA is proposed in section 3. In section 4, a CSTR example is used to illustrate the consecutive and diagnosis of DMA and a procedure is summarized. A conclusion is given in section 5.

2. Model-Based Diagnosis

Model-based diagnosis systems are fundamentally different from heuristic knowledge-based (rule based) systems

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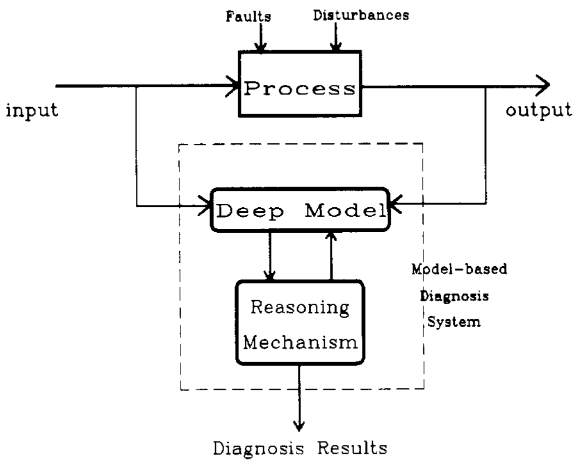

Figure 1. Structure of model-based diagnosis system.

because they rely on the structured knowledge which comes directly from the first principle. Figure 1 illustrates the general concept of model-based diagnosis systems. A fault diagnosis system consists of two major components: a deep model and a reasoning mechanism. In the deep model, the knowledge, either quantitative or semiquantitative, is represented in the form of model equations or in a graphical form (e.g., in the form of SDG). In this stage, any inconsistencies between process model and process measurements are generated. For example, residuals are generated from model equations (Gertler and Anderson, 1992; Petti *et al.*, 1990) or consistencies of specific branches are generated in terms of membership function of the fuzzy set (Yu and Lee, 1992). Typically, the inconsistency measures can be represented in a Boolean (yes or no answer) or non-Boolean (degree of inconsistency) form. The non-Boolean representation receives a great deal of attention. These include the probability assignment (Gertler and Luo, 1989; Gertler and Anderson, 1992), the belief function (Kramer, 1987; Petti *et al.*, 1990), and the fuzzy measure of Yu and Lee (1992). Once an inconsistency is observed, a reasoning mechanism is activated to find the possible fault. In this stage, generally, statistical testing (Gertler and Luo, 1989), evidential reasoning (Dampster-Shafer reasoning, Bogler, 1987; Gertler and Anderson, 1992; Fathi *et al.*, 1993), constraint satisfaction (Kramer, 1987; Petti *et al.*, 1990), and fuzzy reasoning (Yu and Lee, 1992) are employed.

2.1. Equation-Oriented Fault Diagnosis. A fault is understood as any kind of malfunction in the actual dynamic system, the plant, that leads to an unacceptably anomaly in the overall system performance. Such malfunctions may occur either in the sensors, actuators, and process variables or in the components of the process. Fault diagnosis based on static *quantitative* model equations was introduced in the 1970s in the chemical (Himmelblau, 1978) and aerospace (Deckert *et al.*, 1977) industries. Generally, the equation-oriented diagnosis system is formulated in such a way that, initially, the quantitative mathematical model (equations) is abstracted from the first principle. In normal operation, this set of model equations gives zeros for the right-hand-side of the equations' "parity equation". In other words, this set of equations is satisfied with normal conditions. Residuals are generated when a process fault occurs. A predetermined tolerance is used to indicate possible faulty conditions. Generally, a set of satisfaction factors is generated to give an indication of the violation of model equations (Kramer, 1987; Petti *et al.*, 1990). Following the satisfaction checking, fault discrimination and consistency criterion are applied to isolate the fault. Figure 2 illustrates the general concept of equation-oriented fault diagnosis.

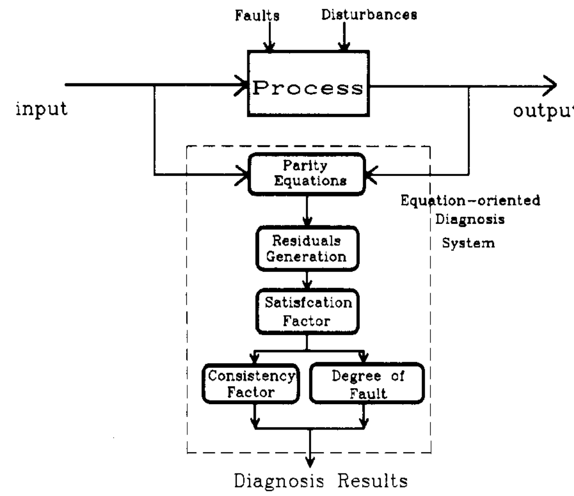

Figure 2. Structure of equation-oriented fault diagnosis system.

Each component of the diagnostic system is discussed in detail, and resolution and potential problems in this type of diagnostic system are discussed. The development and notations of the system follow the work of DMP (Petti *et al.*, 1990).

2.1.1. Parity Equations. Parity equations constitute the core of the equation-oriented fault diagnosis system. They are generally derived from the material balances and energy balances describing the physical system. Prior to the formulation of the parity equations two sets of parameters have to be specified. One is the "fault" to be diagnosed which is denoted as a vector $\mathbf{a} = [a_1, a_2, ..., a_n]^T$. The fault set $\mathbf{a}$ include sensor failure, actuator failure, external disturbances, degradation of equipment, etc. The other is the set of process measurements available which is denoted as $\mathbf{m} = [m_1, m_2, ..., m_k]^T$. Notice that if the failure of a particular process measurement, e.g., sensor failure, is to be diagnosed, that process measurement is included in the $\mathbf{a}$ vector. Following the definition of $\mathbf{a}$ and $\mathbf{m}$, a set of parity equations can be expressed as

$$\begin{aligned} c_1(a_1, a_2, a_3, ..., a_n, m_1, m_2, ..., m_k) &= e_1 \\ c_2(a_1, a_2, a_3, ..., a_n, m_1, m_2, ..., m_k) &= e_2 \\ c_j(a_1, a_2, a_3, ..., a_n, m_1, m_2, ..., m_k) &= e_j \\ c_m(a_1, a_2, a_3, ..., a_n, m_1, m_2, ..., m_k) &= e_m \end{aligned} \tag{1}$$

or, in a more compact form,

$$\mathbf{c}(\mathbf{a}, \mathbf{m}) = \mathbf{e} \tag{2}$$

Typically, this is a nonlinear set of equations, and at nominal operating conditions the RHS of eq 1 is zero, i.e., $e_1 = e_2 = ... = e_m = 0$ for $\mathbf{a}^s = [a_1^s, a_2^s, ..., a_n^s]^T$, where the superscript s denotes the nominal steady-state and a set of linear algebraic equations can be derived:

$$\begin{aligned} p_{11}a_1 + p_{12}a_2 + ... + p_{1i}\,a_i + ... + p_{1n}\,a_n + k_1 &= e_1 \\ p_{21}\,a_1 + p_{22}\,a_2 + ... + p_{2i}\,a_i + ... + p_{2n} + a_n + k_2 &= e_2 \\ p_{j1}\,a_1 + p_{j2}\,a_2 + ... + p_{ji}\,a_i + ... + p_{jn}\,a_n + k_j &= e_j \\ p_{m1}\,a_1 + p_{m2}\,a_2 + ... + p_{mi}\,a_i + ... + p_{mn}\,a_n + k_m &= e_m \end{aligned} \tag{3}$$

or in a matrix form

$$\mathbf{Pa} + \mathbf{k} = \mathbf{e} \tag{4}$$

where $\mathbf{P}$ is an $m \times n$ matrix with the entry p_{ji} and $k = [k_1, k_2, ..., k_m]^T$. Notice that p_{ji}, k_j, and a_i are functions of process measurements and system parameters. Here p_{ji} can be viewed as the sensitivity of the ith fault (a_i) with respect to the jth parity equation at nominal steady-state. Mathematically, this is

$$p_{ji} = \left(\frac{\partial c_j}{\partial a_i}\right)_s \tag{5}$$

It should be emphasized that at nominal operation, the residuals of the parity equations (eq 1 or 3) are zero ($e_1 = e_2 = ... = e_m = 0$). That is, when nominal steady-state values are substituted for the fault set ($a_i = a_i^s$) and process measurements ($m_i = m_i^s$), the equations yield zero residuals.

$$\mathbf{P}(\mathbf{m}^s)\mathbf{a}^s + \mathbf{k}(\mathbf{m}^s) = 0 \tag{6}$$

2.1.2. Residual Generation. When a fault occurs (e.g., $a_i = a_i^s + \delta a_i$), this leads to a new set of process measurements ($\mathbf{m}$). Obviously, at this point we do not have any knowledge about which a_i's constitute the fault (deviate from its nominal value a_i^s). All we can do is substitute $\mathbf{a}^s$ and $\mathbf{m}$ into the parity equations. That leads to inconsistency in the parity equations, and residuals are generated.

$$\mathbf{P}(\mathbf{m})\mathbf{a}^s + \mathbf{k}(\mathbf{m}) = \mathrm{e} \neq 0 \tag{7}$$

The reason is that at this new (faulty) steady-state, a consistent set of process variables are $\mathbf{m}$ and $\mathbf{a}^*$, ($\mathbf{a}^* = \mathbf{a}^s + \delta\mathbf{a}$). That is,

$$\mathbf{P}(\mathbf{m})\mathbf{a}^* + \mathbf{k}(\mathbf{m}) = 0 \tag{8}$$

Without any knowledge about the fault ($\mathbf{a}^*$ or $\delta\mathbf{a}$), residuals are, thus, generated as shown in eq 7. As for the case of sensor failure, a_i itself is a process measurement; the explanation is a little different. The correct process measurement, a_j^*, is

$$a_i^* = a_{i,\mathrm{meas}} + \delta a_i \tag{9}$$

where $a_{i,\mathrm{meas}}$ is the measurement reading and δa_i is the bias. Again, the substitution of $a_{i,\mathrm{meas}}$ into eq 7 generates residual.

Notice that faulty conditions, e.g., $a_i^* = a_i^s + \delta a_i$, are not the only source of the residuals. Measurement noises, modeling error, e.g., $\mathbf{P} = \mathbf{P}^s + \delta\mathbf{P}$, where $\delta\mathbf{P}$ stands for modeling error, etc. all can contribute to the residuals of the parity equations. In order to achieve robustness in fault diagnosis, some type of checking for satisfaction/violation in parity equations is necessary.

2.1.3. Satisfaction Factor. Since the residuals arise from not only the fault itself but also from noise effect or modeling error, tolerances (τ_j's) are used to evaluate the violation of corresponding parity equation c_j in a Boolean manner (Venkatasurramanian and Chan, 1989). Kramer (1987) proposes a non-Boolean measure, sf (satisfaction factor), to evaluate the degree of satisfaction to each parity equation. The belief function of Kramer (1987), sf, is defined as

$$\mathrm{sf} = \mathrm{sgn}(e/\tau)\frac{(e/\tau)^4}{1 + (e/\tau)^4} \tag{10}$$

where $\mathrm{sgn}(e/\tau)$ is the sign of e/τ which takes the value of

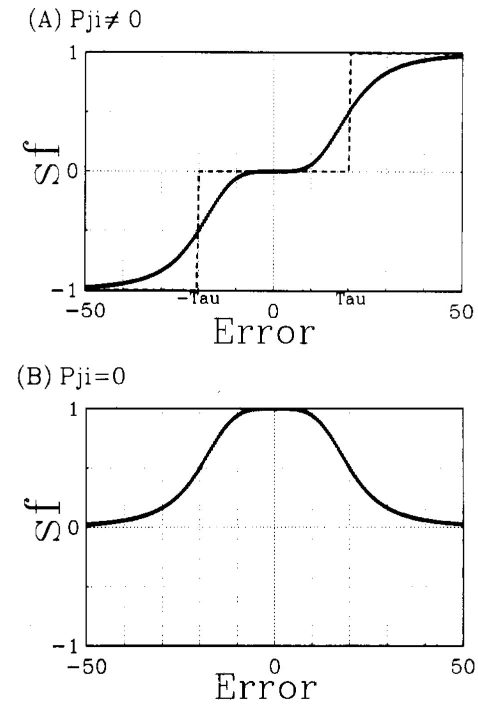

Figure 3. Non-Boolean type of satisfaction factor for (A) $p_{ji} \neq 0$ and (B) $P_{ji} = 0$.

+1 when $e/\tau > 0$ and becomes −1 when $e/\tau < 0$. Therefore, the value of sf falls between −1 and 1 (Figure 3). The non-Boolean type of sf (solid line of Figure 3) avoids *abrupt* changes from satisfaction to violation of parity equations (compared to Boolean type of sf as shown in Figure 3, dashed line) which, in turn, is more robust to noise effects as well as modeling errors. In the work of Kramer (1987) and Petti *et al.* (1990), the tolerances (τ_j's) are defined for each parity equation. Therefore, for a system with parity equations, m tolerances ($\tau_1, \tau_2, ..., \tau_m$) are defined for satisfaction checking. Little emphasis is placed on the selection of τ_j's. The selection of τ_j's is by no means a trivial matter for fault isolation, as will be discussed in detail later. As pointed out by Kramer (1987) and Petti *et al.* (1991), the tolerances for the upper bound (τ_j^H) and lower bound (τ_j^L) violations do not have to be symmetric, i.e., $\tau_j^H \neq \tau_j^L$. This is helpful for nonlinear chemical processes. The formal definition of sf's is given as follows.

Definition. The vector of satisfaction factor $\mathbf{sf} = [\mathrm{sf}_j] = [\mathrm{sf}_1, \mathrm{sf}_2, ..., \mathrm{sf}_m]$ is the collection of satisfaction factors for each parity equation defined by a belief function (Kramer, 1987) as (a) for high violation

$$\mathrm{sf}_j = \mathrm{sgn}(e_j/\tau_j^H)\frac{(e_j/\tau_j^H)^4}{1 + (e_j/\tau_j^H)^4} = +\frac{(e_j/\tau_j^H)^4}{1 + (e_j/\tau_j^H)^4} \tag{11}$$

and (b) for low violation

$$\mathrm{sf}_j = \mathrm{sgn}(e_j/\tau_j^L)\frac{(e_j/\tau_j^L)^4}{1 + (e_j/\tau_j^L)^4} = -\frac{(e_j/\tau_j^L)^4}{1 + (e_j/\tau_j^L)^4} \tag{12}$$

Figure 3 shows the sf for the case of $\tau_j^H = \tau_j^L$. The shape of the belief function is smooth for one to one mapping to prevent an unstable diagnostic situation.

2.1.4. Fault Isolation. As shown in Figure 2, in the fault isolation stage, an ideal equation-oriented fault diagnosis system consists of two steps: fault discrimination (to find the most likely fault) and consistency checking (to check whether the isolated fault is determined consistently from each parity equation). Most of the works

(Kramer, 1987; Petti *et al.*, 1990) isolate the fault solely on the basis of the first step, fault discrimination. The consistency checking is considered, at most, in an indirect manner (Petti *et al.*, 1990).

Consider a set of m parity equations with n faults to be isolated (eq 1 or 3). Once the satisfaction factors, sf, are available (from the previous stage in Figure 2), the fault can be isolated in the following way. The supportability of Kramer (1987) for the ith fault (a_i) is defined as

$$q_i = [\prod_{j=1}^{r} |\mathrm{sf}_j|][\prod_{j=1}^{m-r}(1 - |\mathrm{sf}_j|)] \tag{13}$$

where q_i is the supportability for the ith fault, r is the number of equations that depends on a_i, and $(m - r)$ is the number of equations that are independent on a_i. When q_i approaches unity, the result of the reasoning supports the fault assumption. That implies

$$p_{1i}, p_{2i}, p_{3i}, ..., p_{ri} \neq 0 \tag{14}$$

and

$$p_{r+1,i}, p_{r+2,i}, p_{r+3,i}, ..., p_{mi} = 0 \tag{15}$$

In other words, the only way to discriminate a fault depends on the zero/non-zero configuration in the **P** matrix. Petti *et al.* (1990) go a step further, using the concept of weighting to improve the diagnostic resolution. The most likely fault is isolated using the failure likelihood (Petti *et al.*, 1990). For the ith fault (a_i), the failure likelihood $\mathcal{F}_i$ is defined as

$$\mathcal{F}_i = \frac{\check{p}_{1i}\mathrm{sf}_1 + \check{p}_{2i}\mathrm{sf}_2 + ... + \check{p}_{mi}\mathrm{sf}_m}{|\check{p}_{1i}| + |\check{p}_{2i}| + ... + |\check{p}_{mi}|} \tag{16}$$

where $\check{p}_{ji}$ is the normalized parameter with respect to the tolerance τ_j, i.e., $\check{p}_{ji} = p_{ji}/\tau_j$. Equation 16 implies that $\mathcal{F}_i$ is the normalized weighted sum of sf_j's from all the parity equations. When $\mathcal{F}_i$ approaches +1 (or −1), the reasoning concludes that a_i is the most likely fault with a positive (or negative) deviation. Despite the fact that the concept of weighting is more appropriate than the fault isolation using zero/non-zero configuration, it may have difficulties in discriminating the fault even when the faults are qualitatively isolable.

2.2. Resolution. The resolution of equation-oriented diagnostic systems (Kramer, 1987; Petti *et al.*, 1990) is investigated. Let us take a simple set parity equation as an example. Consider a system with two parity equations and three possible faults:

$$\begin{cases} c_1(\mathbf{a}, \mathbf{m}) = p_{11}a_1 + p_{12}a_2 + p_{13}a_3 + k_1 \\ c_2(\mathbf{a}, \mathbf{m}) = p_{21}a_1 + p_{22}a_2 + p_{23}a_3 + k_2 \end{cases} \tag{17}$$

For the sake of clarity in the illustration, all three faults (a_1, a_2, and a_3) are assumed to be sensor failure. That implies p_{ji}'s and k_i's are constants in eq 17. In order to evaluate DMP in a consistent manner, the tolerances are defined as

$$\tau_j^{\mathrm{H}} = \tau_j^{\mathrm{L}} = \tau_j = \min(p_{j1}{\cdot}10\%, p_{j2}{\cdot}10\%, p_{j3}{\cdot}10\%) \tag{18}$$

Here a_i's are assumed to be unity for all t's. This means that 10% deviation in a_i from its nominal value is considered as a fault. Three numerical examples are used to illustrate the resolutions for supportability and failure likelihood.

Example 1. Qualitatively Isolable Faults with Competitive Model Coefficients (p_{ji}'s). Consider the following set of parity equations:

$$e_1 = 2a_1 + 2a_2 + 0a_3 - 4 \tag{19}$$

$$e_2 = 2a_1 - 2a_2 + 2a_3 - 2 \tag{20}$$

From the parity equations (eqs 19 and 20), it is obvious that the faults a_1, a_2, and a_3 are isolable in a qualitative manner, since the sign pattern for example 1 is

	a_1	a_2	a_3	
e_1	+	+	0	
e_2	+	−	+	(21)

For example, if both eqs 19 and 20 deviate positively (or negatively) then, on the basis of this qualitative observation, we can say that a_1 is the fault origin. If e_1 and e_2 in the parity equation deviate toward different directions, then a_2 is the fault. A similar argument can be applied to the fault a_3. Therefore, in our classification the resolution of this system is to the qualitative isolable level. The supportability of Kramer (1987) and the failure likelihood of DMP (Petti *et al.*, 1990) are tested on this example. Table 1A shows the diagnostic results using supportability and failure likelihood with 20% positive deviation in the fault origins a_1, a_2, and a_3, respectively. Results show that the supportability (q_i's) is not able to distinguished the faults a_1 and a_2 even when the sign patterns (eq 21) of these two faults are different. The supportability can, however, isolate the fault a_3 since the zero, non-zero configuration for a_3 is different from that of a_1 or a_2. The failure likelihood of DMP, on the other hand, cannot distinguish the faults between a_1 and a_3 (or a_2 and a_3) when the failure occurs in a_1 (or a_2) as shown in Table 1A. This simple example shows that despite the fault that *quantitative* parity equations are employed in the fault diagnosis, the fault isolation approaches using supportability and/or failure likelihood are not able to isolate the fault even when the fault can be isolated from a purely qualitative argument, e.g., eq 21.

Example 2. Qualitatively Isolable Faults with Drastically Different Model Coefficients.

$$e_1 = 1a_1 + 10a_2 + 0a_3 - 11 \tag{22}$$

$$e_2 = 10a_1 - 1a_2 + 10a_3 - 19 \tag{23}$$

The sign pattern of this system is exactly the same as that of example 1 (eq 21). That is, the faults a_1, a_2, and a_3 can be isolated simply on the basis of qualitative observation of e_1 and e_2. Again, the diagnostic results for 20% positive deviation in a_1, a_2, and a_3, respectively, are shown in Table 1B. A similar interpretation of faults is found using the supportability. That is, the supportability is exactly the same for the faults a_1 and a_2. The ability to discriminate faults using failure likelihood deteriorates for example 2 as shown in Table 1B. For example, when the fault a_1 occurs, the most likely fault interpreted by $\mathcal{F}_i$'s is a_3. That means the ability of the approach of failure likelihood to isolate faults for systems with different orders of magnitude in the coefficients decreases. More importantly, it produces erroneous interpretation, e.g., fault origin a_1 or a_2 in Table 1B. It should be emphasized that the faults in example 2 can be isolated simply on the basis of *qualitative* observation.

Example 3. Qualitatively Nonisolable System. Consider another system with two parity equations and three faults:

$$e_1 = 1a_1 + 10a_2 + 10a_3 - 21 \tag{24}$$

Table 1. Resolutions for Different Model-Based Diagnostic Algorithms

	errors		statisf.		supportability			DMP likelihood			this approach		
fault origin	e_1	e_2	sf_1	sf_2	q_1	q_2	q_3	F_1	F_2	F_3	$(d_1)_{\mathrm{cf1}}$	$(d_2)_{\mathrm{cf2}}$	$(d_3)_{\mathrm{cf3}}$
					(A) $e_1 = 2a_1 + 2a_2 + 0a_3 - 4$			$e_2 = 2a_1 - 2a_2 + 2a_3 - 2$					
a_1	0.4	0.4	0.94	0.94	0.88	0.88	0.5	0.94	0	0.94	$(0.94)_1$	$(0)_{-1}$	$(0.47)_0$
a_2	0.4	−0.4	0.94	−0.94	0.88	0.88	0.05	0	0.94	−0.94	$(0)_{-1}$	$(0.94)_1$	$(-0.47)_0$
a_3	0	0.4	0	0.94	0	0	0.94	0.47	−0.5	0.94	$(0.47)_0$	$(-0.47)_0$	$(0.97)_{0.94}$
					(B) $e_1 = 1a_1 + 10a_2 + 0a_3 - 11$			$e_2 = 10a_1 - 1a_2 + 10a_3 - 19$					
a_1	0.2	2	0.94	0.99	0.94	0.94	0.05	0.82	0.95	0.99	$(0.94)_1$	$(-0.5)_0$	$(0.5)_{0.062}$
a_2	2	−0.2	0.99	0.94	0.94	0.94	0	0.94	0.82	0.94	$(0.5)_0$	$(0.94)_1$	$(0)_{-0.004}$
a_3	0	2	0	−0.99	0	0	0.99	0.9	0.09	0.99	$(0.47)_0$	$(-0.5)_0$	$(0.97)_{0.94}$
					(C) $e_1 = 1a_1 + 10a_2 + 10a_3 - 21$			$e_2 = 1a_1 + 11a_2 + 1a_3 - 13$					
a_1	0.2	0.2	0.94	0.94	0.88	0.88	0.88	0.94	0.94	0.94	$(0.94)_1$	$(0.013)_{0.68}$	$(0.47)_0$
a_2	2	2.2	1	1	1.0	1.0	1.0	0.99	0.99	0.99	$(1)_1$	$(0.94)_1$	$(0.97)_{0.94}$
a_3	2	2	1	0.94	0.94	0.94	0.94	0.97	0.97	0.97	$(0.97)_{0.94}$	$(0.47)_0$	$(0.94)_1$

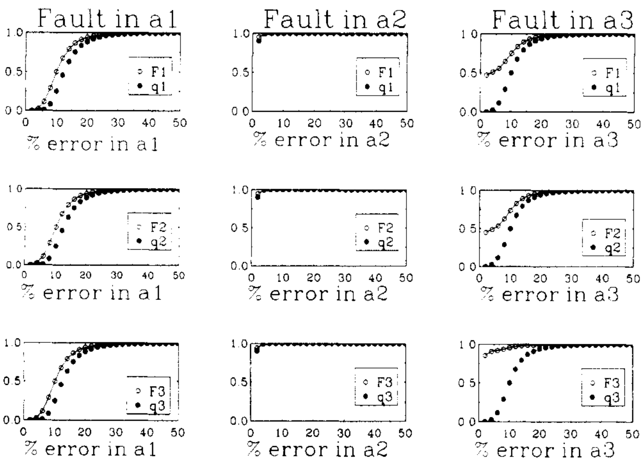

Figure 4. Diagnosis results using supportability (q_i) and likelihood (F_i) for example 3.

$$e_2 = 1a_1 + 11a_2 + 1a_3 - 13 \tag{25}$$

The sign pattern for this example is

	a_1	a_2	a_3	
e_1	+	+	+	
e_2	+	+	+	(26)

This means that the propagations of the fault based simply on qualitative observations are exactly the same. Obviously, we do not accept that the approaches of supportability and failure likelihood can discriminate the faults in this example. The results (Table 1C) show that all three faults are indistinguishable for 20% deviation in the fault origin a_i. Figure 4 shows the diagnosis results using q_i's and $\mathcal{F}_i$'s for a range of deviations in a_1, a_2, and a_3, respectively. As expected, the supportability and failure likelihood are not able to discriminate the fault for a range of faults.

All three examples show the resolution problems associated with the supportability or failure likelihood. More importantly, the knowledge level of the diagnostic system is up to the *quantitative* level. Therefore, some modifications have to be made to improve the resolution in the equation-oriented approach.

3. Deep Model Algorithm (DMA)

An algorithm for fault diagnosis, the deep model algorithm (DMA), is proposed to overcome the problems of diagnostic resolution associated with an equation-oriented diagnosis system.

3.1. The Structure. The structure of DMA is shown in Figure 2. The core of the knowledge base for DMA consists of a set of parity equations (e.g., eq 1 or 3). The parity equations can be either linear or nonlinear. As the process measurements become available, the residuals (e_j's) are generated and satisfaction factors (sf's) are computed. The fault can be isolated on the basis of the fault discrimination and consistency checking once sf's are available (Figure 2).

3.2. Tolerance. Despite the fact that most works in equation-oriented diagnosis systems define the tolerance (threshold) for each individual equation (Gertler and Anderson, 1992; Kramer, 1987; Petti *et al.*, 1990), part of the problem in diagnostic resolution comes from the threshold selection; it was clearly shown in example 2. For example, in an equation with imbalance coefficients, the selected tolerance can be too large for one fault and too small for the other. Therefore, a fundamental approach to improve the diagnostic resolution is to define the tolerance on individual equation as well as individual fault basis. For a system with m parity equations and n faults to be diagnosed, $m \times n$ tolerance τ_{ji} ($j = 1, 2, ..., m$ and $i = 1, 2, ..., n$) is defined. For example, for a fault origin a_i, the upper bound violation $(1 + \bar{\alpha}_i)a_i^s$ and a lower bound violation $(1 - \underline{\alpha}_i)a_i^s$ are the recognized fault, and the upper and lower bound tolerances for the jth parity equation become

(a) violation high

$$\tau_{ji}^{\mathrm{H}} = c_j(a_1^s, a_2^s, ..., (1 + \bar{\alpha}_i)a_i^s, a_{i+1}^s, ..., a_n^s, \mathbf{m}) - 0 \tag{27}$$

(b) violation low

$$\tau_{ji}^{\mathrm{L}} = 0 - c_j(a_1^s, a_2^s, ..., (1 - \underline{\alpha}_i)a_i^s, a_{i+1}^s, ..., a_n^s, \mathbf{m}) \tag{28}$$

If the linearized version of the parity equations (eq 3) is employed, then the tolerance becomes

(a) violation high

$$\tau_{ji}^{\mathrm{H}} = \bar{\alpha}_i p_{ji} a_i^s \tag{29}$$

(b) violation low

$$\tau_{ji}^{\mathrm{L}} = \underline{\alpha}_i p_{ji} a_i^s \tag{30}$$

Since the linearized parity equations are used and the upper and lower bound violations are assumed to be the same for clarity, we have

$$\tau_{ji} = \tau_{ji}^{\mathrm{H}} = \tau_{ji}^{\mathrm{L}} \tag{31}$$

Nonetheless, it should be clear that, in this work, the tolerance (τ_{ji}) is defined for each fault in each parity equation.

3.3. Satisfaction Factor. With the tolerance (τ_{ji}) defined, the satisfaction factor (sf_{ji}) can be calculated once the residual in each parity equation (e_j) is generated. Unlike the previous approaches, DMA finds a vector of satisfaction factors for a fault origin. For example, for the fault a_i, the vector of satisfaction factor is

$$\mathbf{sf}_i = [sf_{1i}, sf_{2i}, sf_{3i}, ..., sf_{mi}]^T \quad (32)$$

Since the zero/non-zero configuration can be identified by a Kramer approach (Kramer, 1987), a distinction is made between the system with zero and non-zero coefficients. The satisfaction factor is defined for zero ($p_{ji} = 0$) coefficients. A new belief function is also defined for the sf with zero coefficient.

The belief function for the fault with non-zero coefficient is defined as follows:

(a) for $p_{ji} \neq 0$

$$sf_{ji} = \mathrm{sgn}(e_j/\tau_{ji})\frac{(e_j/\tau_{ji})^4}{1 + (e_j/\tau_{ji})^4} \quad (33)$$

where sf_{ji} is the satisfaction factor of the ith fault on jth parity equation, e_j is the residual value of the jth parity equation, τ_{ji} is the tolerance of the ith fault on the jth parity equation, and $\mathrm{sgn}(e_j/\tau_{ji})$ takes the value of +1, 0, or −1 for positive, zero, or negative elements, respectively. This definition is exactly the same as that of Kramer (1987) except that m sf's are computed for a fault. For the case of zero coefficient, the belief function is modified to

(b) for $p_{ji} = 0$

$$sf_{ji} = \mathrm{sgn}^*\left[1 - \frac{(e_j/\tau_{j,\min})^4}{1 + (e_j/\tau_{j,\min})^4}\right] \quad (34)$$

with

$$\tau_{j,\min} = \min\{|\tau_{jr}|\} \quad \text{for all } r \text{ with } p_{jr} \neq 0 \quad (35)$$

where $\tau_{j,\min}$ is the smallest (in the absolute sense), non-zero tolerance in the jth parity equation and sgn* define the sign of sf_{ji}, which can be found from

$$\mathrm{sgn}^* = \begin{cases} \mathrm{sgn}(sf_i^*) & \text{for } |sf_i^*| \geq 0.1 \\ 1 & \text{for } |sf_i^*| < 0.1 \end{cases} \quad (36)$$

where sf_i^* is the largest sf (in absolute sense) for the ith fault in different parity equations with non-zero coefficients. The reason for going through eqs 35 and 36 to find sf_{ji} (when $p_{ji} = 0$) is that process measurement noises can be misleading to the sign of the sf_{ji} when $p_{ji} = 0$. This is typically true when a_i is not the fault origin. Therefore, a positive sign is assigned to sf_{ji} when the largest sf for that particular fault (sf_i^*) does not exceed the threshold (0.1 in eq 36). The belief function with a positive sign is shown in Figure 5. Notice that when sgn* = −1, the belief function is simply the mirror image of that in Figure 5. With this definition, we are able to distinguish the zero/non-zero configuration.

The characteristic of the proposed method is illustrated in the following example. Consider the set of parity equations in eq 3 with all non-zero p_{ji}'s. For a given a_i, the tolerance (τ_{ji}'s) can be calculated. That is,

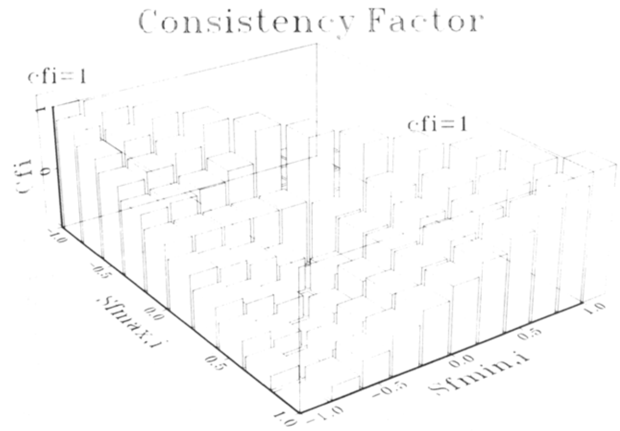

Figure 5. Relationship between ranges of sf_{ji} ($sf_{i,\min} \sim sf_{i,\max}$) and consistency.

$$\tau_{ji} = \alpha_i p_{ji} a_i^s \quad (37)$$

Now, consider that fault a_1 occurs, with a positive deviation of α_1; the residual in each parity equation is

$$e_j = \alpha_1 p_{j1} a_1^s \quad \text{for } j = 1, 2, ..., m \quad (38)$$

With e_j's available, we can find the vector of $\mathbf{sf}_1 = [sf_{11}, sf_{21}, ..., sf_{m1}]^T$.

$$sf_{j1} = \mathrm{sgn}(e_j/\tau_{j1})\frac{(e_j/\tau_{j1})^4}{1 + (e_j/\tau_{j1})^4} = \frac{\left(\frac{\alpha_1 p_{j1} a_1^s}{\alpha_1 p_{j1} a_1^s}\right)^4}{1 + \left(\frac{\alpha_1 p_{j1} a_1^s}{\alpha_1 p_{j1} a_1^s}\right)^4} = 0.5 \quad (39)$$

We have $\mathbf{sf}_1 = [0.5, 0.5, ..., 0.5]^T$. This implies that we are not only able to find the degree of the fault (e.g., 0.5) but also to measure the consistency for the fault. By consistency we mean that the indication of the fault arises from each parity equation, based on $\mathbf{sf}_1$. In theory, the vector of sf's can be utilized to give better diagnostic resolution.

3.4. Fault Isolation. As shown in Figure 2, the fault isolation stage consists of two steps: to find the degree of the fault and to check the consistency of the assumed fault from each parity equation. Two measures are computed for a specific fault, a_i: one is the degree of fault d_i, and the other is the consistency factor cf_i once that vector of satisfaction factor, $\mathbf{sf}_i$, is available.

3.4.1. Degree of Fault. Since the evidence of fault is generated from the residuals, the method of combination of evidences (e.g., certainty factor in MYCIN, Shortliffe, 1976) is useful in finding the likelihood of the failure a_i once the sf_{ji}'s are available. Because the residuals are generated from independent parity equations and are further transformed into sf's, a rule for the combinations sf_{ji}'s can be helpful in discriminating the fault.

Petti *et al.* (1990) utilize the weighted sum of sf's to find the likelihood of failure. This is quite similar to the mechanism of combining evidence in the expert system MYCIN (Shortliffe, 1976; Cendrowska and Kramer, 1984). Before the degree of fault is defined, it should be emphasized that the sf_{ji}'s defined in this work are already *weighted* by its coefficient (p_{ji}) (eqs 29, 30, 33, 34). The degree of fault in a_i is

$$d_i = \left(\sum_{j=1}^{m} sf_{ji}\right)/m \quad (40)$$

d_i ranges from −1 to 1 and d_i approaching 1 (or −1) implies that the errors in the parity equations are significant enough to support the hypothesis, failure in a_i with a positive (or negative) deviation. This definition is very similar to the failure likelihood of Petti *et al.* (1990) except that the weighting is not necessary in this work since sf's are defined differently. Notice that this index d_i only indicates the degree of the fault (a_i), e.g., how close to the threshold the errors are.

3.4.2. Consistency Factor. Since the sf's are defined for the fault in every parity equation, we can utilize this to improve the diagnostic resolution. That is, for a fault a_i and a vector of sf, i.e., sf_{1i}, sf_{2i}, ..., sf_{mi}, one can use sf_{ji}'s (j = 1, 2, ..., m) to further discriminate the fault. A consistency factor cf_i is employed to check the consistency in sf_{ji} (j = 1, 2, ..., m) generated from the parity equations. Ideally, a complete measure of the likelihood of failure a_i is

$$(d_i)_{cf_i} \tag{41}$$

where d_i is the degree of fault for a_i and cf_i is the consistency factor (similar to the certainty factor in MYCIN, Shortliffe, 1976) for d_i.

The consistency factor is defined as

$$cf_i = 1 - \left[\frac{sf_{max,i} - sf_{min,i}}{\max(|sf_{1i}|, |sf_{2i}|, ..., |sf_{mi}|)}\right] \tag{42}$$

where $sf_{max,i}$ and $sf_{min,i}$ are the largest and the smallest satisfaction factors, respectively. $sf_{max,i}$ and $sf_{min,i}$ are defined as

$$sf_{max,i} = \max(sf_{1i}, sf_{2i}, ..., sf_{mi}) \tag{43}$$

$$sf_{min,i} = \min(sf_{1i}, sf_{2i}, ..., sf_{mi}) \tag{44}$$

Appendix A gives the derivation of cf_i. Notice that cf_i ranges from −1 to 1. A positive cf_i of unity indicates that the sf_{ji}'s (j = 1, 2, ..., m) are consistent, and a cf_i of −1 reveals that the results from sf_{ji} (j = 1, 2, ..., m) are completely inconsistent. cf_i decreases as the consistency between sf_{ji}'s decreases. More importantly, *qualitatively inconsistent* sf_{ji}'s (e.g., $sf_{1i} > 0$ and $sf_{2i} < 0$) lead to a *negative* value in cf_i. Figure 5 shows the characteristic of the consistency factor (cf_i). cf_i's are positive for sf_{ji}'s with the same sign, and a $sf_{max,i} > 0$ and $sf_{min,i} = 0$ (or $sf_{max,i} = 0$ and $sf_{min,i} < 0$) gives a zero cf_i. When the range covered by $sf_{max,i}$ and $sf_{min,min}$ crosses zero, the cf_i becomes negative and equal strength sf_{ji}'s (i.e., $|sf_{max,i}| = |sf_{min,i}|$) with opposite sign give $cf_i = -1$, as shown in Figure 5.

With the introduction $(d_i)_{cf_i}$ one can use it to isolate the failure. It should be emphasized that since sf's are defined differently from that of Petti *et al.* (1990) or Kramer (1987), we are now able to utilize cf_i to give a better diagnostic resolution.

3.5. Example Revisited. The resolution of the proposed DMA is examined using the three examples studied. Consider the system in eq 17; the tolerances τ_{ji}'s are defined for each parity equation with respect to different faults. For $p_{ji} \neq 0$, we have

$$\tau_{ji} = p_{ji} \cdot 10\% \tag{45}$$

For the cases with $p_{ji} = 0$, $\tau_{j,min}$ is found using eq 35. With the definition of τ_{ji}'s, sf_{ji}'s can be calculated according to eqs 33 and 34. Once sf_{ji}'s are available, one can proceed to calculate d_i and cf_i from eqs 40 and 42, according to the procedure in Figure 2.

Consider the example with qualitatively isolable faults in example 1. The satisfaction factors for a +20% deviation in a_1 are

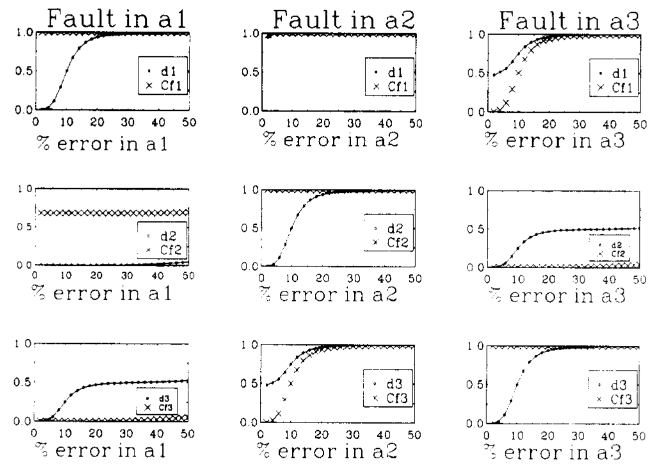

Figure 6. Diagnosis results using degree of fault (d_i) and consistency factor (cf_i).

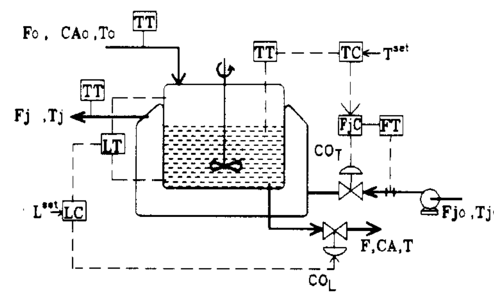

Figure 7. CSTR example.

	a_1	a_2	a_3	
e_1	0.94	0.94	0	
e_2	0.94	−0.94	0.94	(46)

The sf_{ji}'s indicate inconsistency when a_2 (or a_3) is the assumed fault (e.g., e_1 indicating a positive deviation in a_2 and e_2 indicating a negative deviation in a_2). The degrees of fault (d_i's) are 0.94, 0, and 0.47 for a_1, a_2, and a_3 with this perturbation (Table 1A). The consistency factors cf_i's also indicate the inconsistency for the fault assumptions a_2 and a_3 ($cf_2 = -1$ and $cf_3 = 0$) as shown in Table 1A. Clearly, DMA is able to isolate the fault (as opposed to the spurious solutions generated from supportability and failure likelihood). Similar results can also be found for the fault originated from a_2 and a_3 (Table 1A).

For example 2, an example with qualitatively isolable fault, DMA clearly discriminates the fault using $(d_i)_{cf_i}$ for all three possible fault origins, as shown in Table 1B. The results from the second example show the advantages of the DMA over the failure likelihood of DMP and the supportability (Table 1B) without incorporating additional process knowledge.

The limitation of the proposed method is illustrated by example 3. Consider the qualitatively indistinguishable example, example 3. That is, the faults give exactly the same pattern qualitatively (e.g., eqs 24 and 25). Obviously, for given fault, all three fault assumptions (a_1, a_2, and a_3) are possible fault origins (e.g., spurious solutions) from the supportability and failure likelihood analysis (Table 1C). The DMA also gives spurious solutions, as shown in Table 1C (e.g., fault occurring in a_2). Despite the fact that spurious interpretation is minimized to a certain degree (e.g., by comparing the cases for failures in a_1 and a_3 with these three methods in Table 1C), the results clearly indicate the limitation of the proposed method. Figure 6 shows the resolution of DMA for different degrees of faults.

Table 2. Steady-State Operating Conditions for CSTR

$F = 40\ \mathrm{ft^3/h}$	$U = 150\ \mathrm{BTU/h\ ft^3\ °R}$
$V = 48\ \mathrm{ft^3}$	$A = 250\ \mathrm{ft^2}$
$C_{A_0} = 0.50\ \mathrm{mol/ft^3}$	$T_{j0} = 530\ \mathrm{°R}$
$C_A = 0.245\ \mathrm{mol/ft^3}$	$\Delta H = -30\,000\ \mathrm{BTU/mol}$
$T = 600\ \mathrm{°R}$	$c_p = 0.75\ \mathrm{BTU/lb_m\ °R}$
$T_j = 594.6\ \mathrm{°R}$	$c_{pj} = 1.0\ \mathrm{BTU/lb_m\ °R}$
$F_j = 49.9\ \mathrm{ft^3/h}$	$\rho = 50\ \mathrm{lb_m/ft^3}$
$V_j = 3.85\ \mathrm{ft^3}$	$\rho_j = 62.3\ \mathrm{lb_m/ft^3}$
$k_0 = 7.08 \times 10^{10}\ \mathrm{h^{-1}}$	$R = 1.987\ \mathrm{BTU/mol\ °R}$
$E = 30\,000\ \mathrm{BTU/mol}$	$A_h = 19.6\ \mathrm{ft^2}$
$L^{set} = 0.192\ \mathrm{ft}$	$T^{set} = 600\ \mathrm{°R}$
$k_{c1} = 32$	$k_{c2} = 10$
$\tau_{I1} = 0.9\ \mathrm{h}$	$\tau_{I2} = 0.6\ \mathrm{h}$
$F_{max} = 96\ \mathrm{ft^3/h}$	$\mathrm{bias_1} = 12\ \mathrm{psi}$
$\mathrm{bias_2} = 9\ \mathrm{psi}$	

Table 3. Process Measurements for Fault Diagnosis

symbol	measured variables
T	reactor temp
T_0	reactor inlet temp
L	reactor level
T_j	cooling water outlet temp
F_j	cooling water flow rate in the jacket
F	reactor outlet flow rate

Table 4. Fault Origins

symbol	fault origin
F_0	changes in the feed flow rate
C_{A_0}	changes in the feed concentration
k_0	changes in the preexponential factor of the rate constant
U	changes in the overall heat transfer coefficient
T_j	sensor failure in cooling water outlet temp

4. DMA and Diagnosis Results

A CSTR example (Luyben, 1973; Chang and Yu, 1990; Yu and Lee, 1992) is used to illustrate the formulation and diagnosis of DMA. Comparisons are made between the DMA and the deep model processor (DMP) of Petti *et al.* (1990).

4.1. Process Description. An irreversible, exothermic reaction is carried out in a perfectly mixed CSTR, as shown in Figure 7. The reaction is first order in reactant A.

$$A \xrightarrow{k} B \tag{47}$$

The heat generated from the reaction is removed using a cooling water jacket. Reactor temperature (T) is controlled by changing the set point of a cooling water flow controller (F_{jc}), and the reactor level (L) is controlled by changing the outlet flow rate (F). Tuning constants for these two PI controllers are $k_{c1} = 32$ and $\tau_{I1} = 0.9$ h for the temperature loop and $k_{c2} = 10$ and $\tau_{I2} = 0.6$ h for the level loop, respectively. In modeling negligible heat losses, constant densities and perfect cooling water flow control are assumed. Equations describing the system are

$$\frac{dV}{dt} = F_0 - F \tag{48}$$

$$\frac{dVC_A}{dt} = F_0 C_{A_0} - FC_A - k_0 e^{-E/RT} C_A V \tag{49}$$

$$\frac{dVT}{dt} = F_0 T_0 - FT - \frac{\Delta H}{\rho c_p} k_0 e^{-E/RT} C_A V - \frac{UA}{\rho c_p}(T - T_j) \tag{50}$$

$$\frac{dV_j T_j}{dt} = F_j (T_{j0} - T_j) + \frac{UA}{\rho_j c_{pj}}(T - T_j) \tag{51}$$

Table 2 gives the steady-state operating conditions. Process variables employed for diagnosis include (1) process measurements and (2) process parameters inferred from control outputs, as shown in Table 3. Faults to be diagnosed include external disturbance (changes in F_0 or C_{A_0}), equipment degradation (changes in k_0 or U), and sensor failure (measurement failure in T_j), as shown in Table 4.

4.2. Formulation of Parity Equations. The formulation of parity equations is one of the most important steps in the construction of DMA. For a given system, a straightforward way to formulate the parity equations is to include all governing equations. However, in any realistic situation, not all process variables are measured (or measured online). Therefore, unmeasured variables have to be removed from governing equations.

4.2.1. Elimination of Unmeasured Variables. Frequent composition measurements, e.g., measuring C_A, is generally not available in an operating environment. Unfortunately, C_A plays an important role in the system

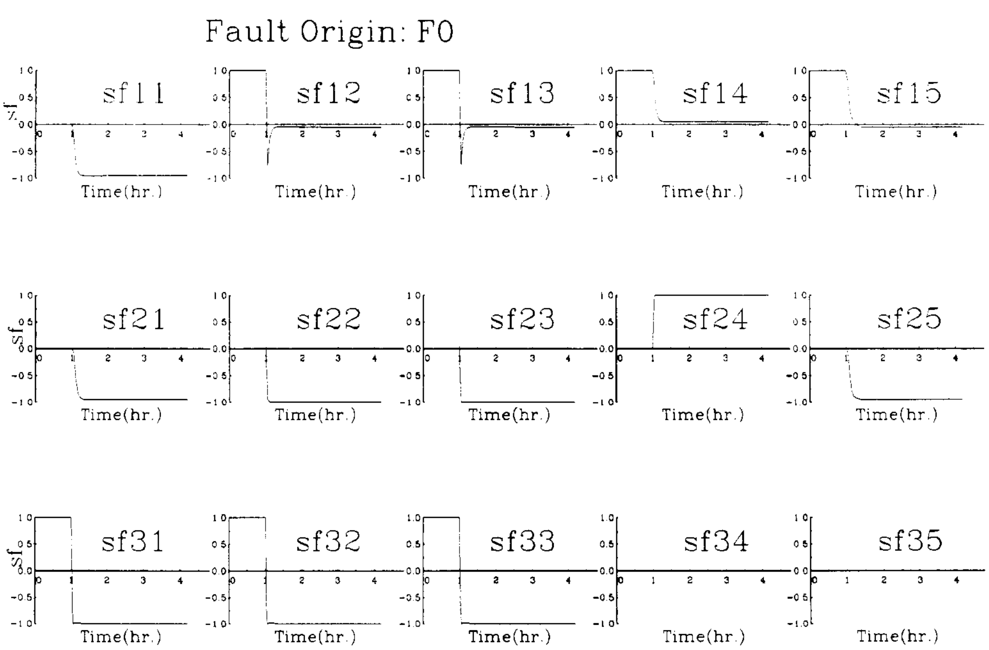

Figure 8. Satisfaction factors (sf$_{ji}$'s) of CSTR example for fault in F_0 failure with perfect measurements.

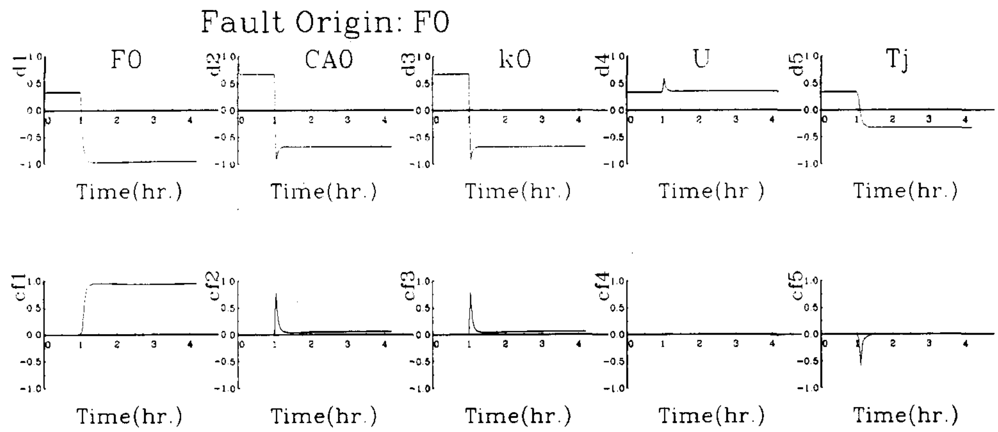

Figure 9. Diagnostic results of CSTR example for fault in F_0 failure with perfect measurements.

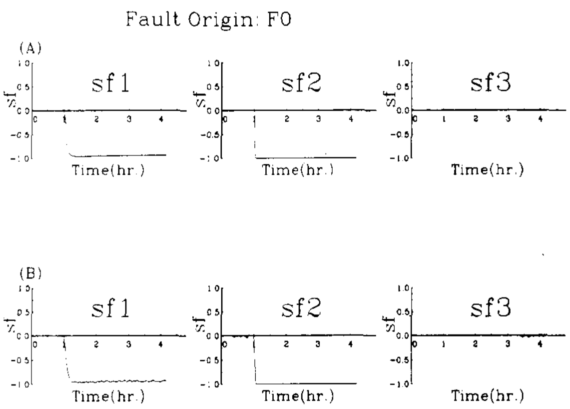

Figure 10. Satisfaction factors of DMP approach with (A) perfect measurements and (B) measurement corrupted with noises.

equations (eqs 49 and 50). Therefore, C_A has to be eliminated from the parity equation. Since only a static diagnostic system is considered, a simple way to remove C_A is to express C_A in terms of measured variables. From eq 49, C_A becomes

$$C_A = \frac{F_0 C_{A_0}}{F + k_0 e^{-E/RT} V} \tag{52}$$

Substituting eq 52 into eq 50 gives the complete set of nonlinear equations describing the CSTR with known variables:

$$F_0 - F = 0 \tag{53}$$

$$F_0 T_0 - FT - \frac{\Delta H F_0 V C_{A_0} k_0 e^{-E/RT}}{\rho c_p (F + k_0 e^{-E/RT} V)} - \frac{UA}{\rho c_p}(T - T_j) = 0 \tag{54}$$

$$F_j (T_{j0} - T_j) + \frac{UA}{\rho_j c_{pj}}(T - T_j) = 0 \tag{55}$$

Obviously, one can utilize eqs 53–55 to generate residuals once the tolerances (eq 5) are available, as mentioned in section 2. For the sake of clarity, in this work, eqs 53–55 are linearized and formulated as a set of linear algebraic equations.

4.2.2. Linearization. The set of nonlinear parity equations are linearized with respect to the fault origins and the known process variables. Appendix B gives the derivation. The resultant *linear* parity equations are

$$e_1 = F_0 - F \tag{56}$$

$$e_2 = 729.68F_0 + 40T_0 - 871.62T - 699.58F + 1000T_j - 35.70U + 16000C_{A_0} - 5.57 \times 10^{-8} k_0 + 166.67V - 108578 \tag{57}$$

$$e_3 = 49.90T_{j0} + 21.50U + 601.87T - 64.63F_j - 651.78T_j \tag{58}$$

4.2.3. Normalization. It can be seen that the coefficients in the parity equations differ by several orders of magnitude. This can lead to problems in online computing. Therefore, a simple way to overcome this is to normalize the fault origins and process measurements such that deviations in these variables are expressed in terms of percent deviation. In other words, the variable a_i is normalized with respect to its nominal steady-state values:

$$\check{a}_i = \frac{a_i}{a_i^s} \tag{59}$$

Therefore, the linear parity equations become

$$e_1 = 40\check{F}_0 - 40\check{F} \tag{60}$$

$$e_2 = 29187.25\check{F}_0 + 21182.9\check{T}_0 - 523002.4\check{T} - 27979.5\check{F} + 594600\check{T}_j + 8000.3\check{V} - 5355.93\check{U} + 8000.3\check{C}_{A_0} + 3946.9\check{k}_0 - 108578 \tag{61}$$

$$e_3 = -3225\check{F}_j + 26445\check{T}_{j0} + 3225\check{U} + 361122\check{T} - 387548\check{T}_j \tag{62}$$

To simplify these equations, a further normalization with respect to the smallest coefficient of each parity equation is carried out.

$$e_1 = \check{F}_0 - \check{F} \tag{63}$$

$$e_2 = 7.395\check{F}_0 + 5.367\check{T}_0 - 132.51\check{T} - 7.089\check{F} + 150.65\check{T}_j + 2.027\check{V} - 1.357\check{U} + 2.027\check{C}_{A_0} + \check{k}_0 - 27.51 \tag{64}$$

$$e_3 = -\check{F}_j + 8.20\check{T}_{j0} + \check{U} + 111.97\check{T} - 120.17\check{T}_j \tag{65}$$

where the caron (ˇ) indicates the normalized variables. In

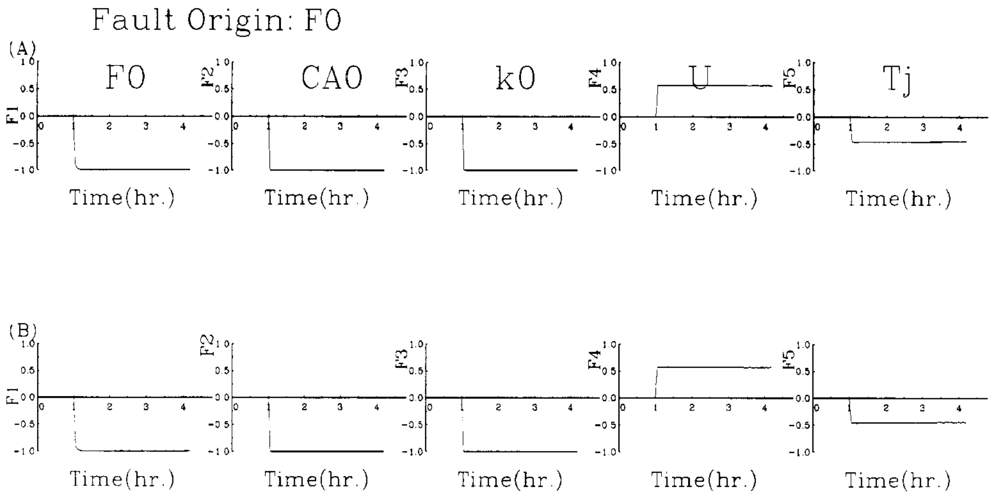

Figure 11. Diagnostic results of DMP with (A) perfect measurements and (B) measurement corrupted with noises.

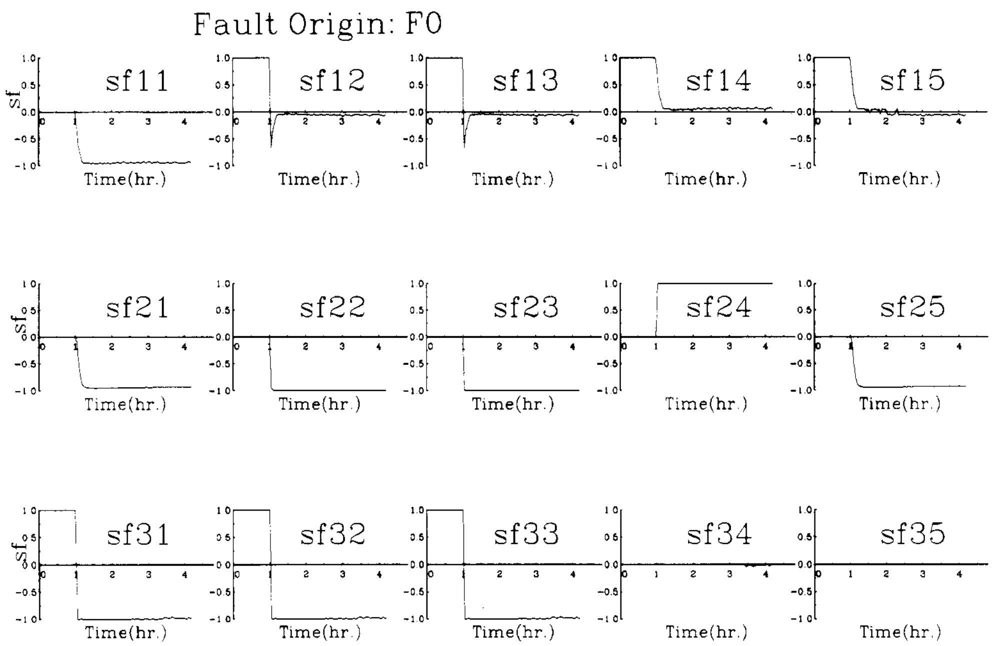

Figure 12. Satisfaction factors (sf_{ji}'s) of CSTR example for fault in F_0 failure with measurement noises.

a matrix form, the parity equations become

$$\begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 7.395 & 2.03 & 1.0 & -1.357 & 150.65 \\ 0 & 0 & 0 & 1.0 & -120.17 \end{bmatrix} \begin{matrix} \check{F}_0 \\ \check{C}_{A_0} \\ \check{k}_0 \\ \check{U} \\ \check{T}_j \end{matrix} + \begin{bmatrix} -\check{F} \\ -132.51\check{T} + 5.367\check{T}_0 - 7.089\check{F} + 2.03\check{V} - 27.51 \\ 111.97\check{T} - \check{F}_j + 8.20\check{T}_{j0} \end{bmatrix} \quad (66)$$

4.3. Diagnosis Procedure. Following the methodology of DMA, discussed in section 3, the procedure is outlined as follows.

S1. Define the Tolerances for Each Fault Origin with Respect to Each Parity Equation. In the CSTR example, the tolerances are defined as ±10% deviations from nominal steady-state.

$$\begin{bmatrix} \tau_{11} & \tau_{12} & \tau_{13} & \tau_{14} & \tau_{15} \\ \tau_{21} & \tau_{22} & \tau_{23} & \tau_{24} & \tau_{25} \\ \tau_{31} & \tau_{32} & \tau_{33} & \tau_{34} & \tau_{35} \end{bmatrix} = \begin{bmatrix} 0.1 & \tau_{1,\min} & \tau_{1,\min} & \tau_{1,\min} & \tau_{1,\min} \\ 0.739 & 0.2 & 0.1 & -0.135 & 15.06 \\ \tau_{3,\min} & \tau_{3,\min} & \tau_{3,\min} & 0.1 & -12.02 \end{bmatrix} \quad (67)$$

Here $\tau_{j,\min}$'s are used for the tolerances with zero coefficients.

S2. Generate Residuals. The residuals (e_j's) can be generated in a straightforward manner using eq 66 once process measurements ($\check{F}, \check{T}, \check{T}_0, \check{T}_j, \check{F}_j$, and $\check{V}$) are available. Notice that the fault origins, $\check{F}_0$, $\check{C}_{A_0}$, $\check{k}_0$, $\check{U}$, and $\check{T}_j$, take the values of unity in generating residuals.

S3. Calculate the Satisfaction Factors, sf_{ji}'s. Once the residuals (e_1, e_2, and e_3) are available, the sf_{ji}'s can be found. Since the zero exists in the parity equations (eq 66), $\tau_{j,\min}$'s are used to find the sf's according to eq 36. The values of $\tau_{j,\min}$'s are defined as the smallest τ_{ji} (in an absolute sense). Therefore, we have $\tau_{1,\min} = 0.1$ and $\tau_{3,\min} = 0.1$. Notice that $\tau_{j,\min}$ is employed for the calculation of sf_{ji} by using eqs 33 and 34 for the non-zero/zero configuration.

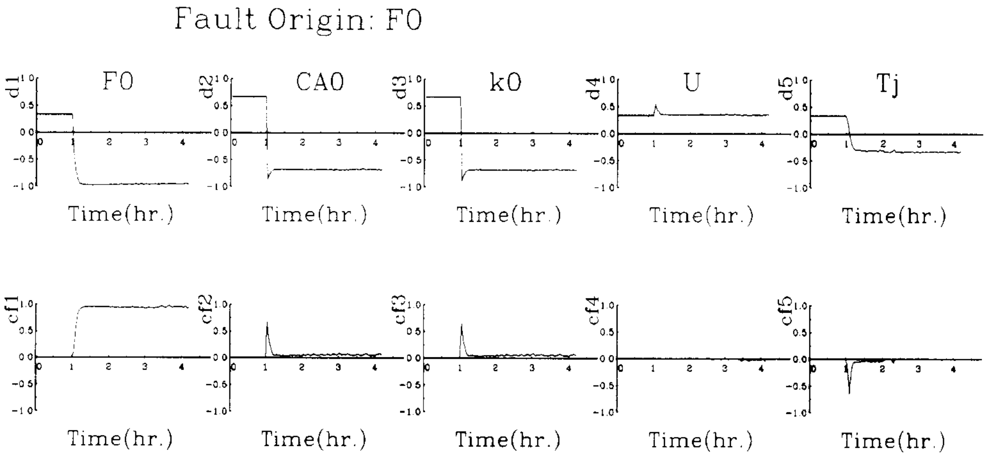

Figure 13. Diagnostic results of CSTR example for fault in F_0 failure with measurement noises.

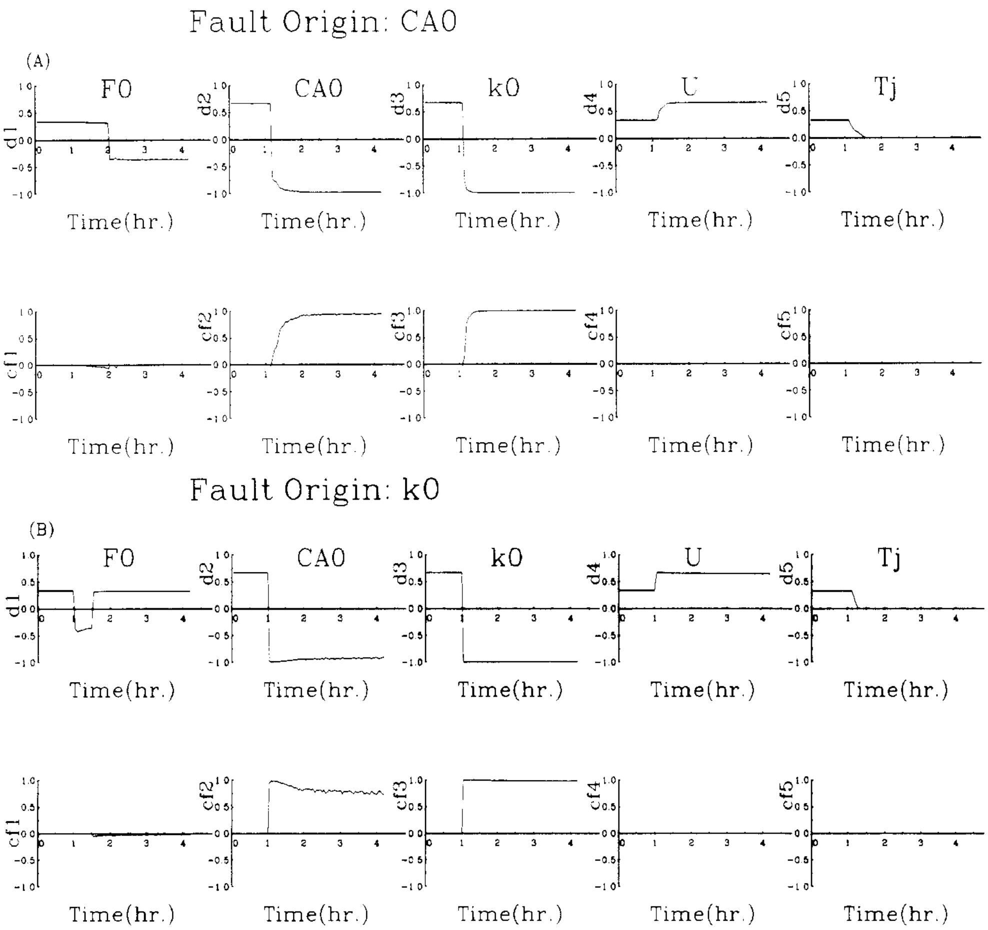

Figure 14. Diagnostic resolutions of DMA for (A) C_{A_0} failure and (B) k_0 failure.

S4. Calculate Degree of Fault (d_i) and Consistency Factor (cf_i). Once sf_{ji}'s are available, d_i and cf_i can be computed according to eqs 40 and 42. The diagnostic results can be interpreted by using the index $(d_i)_{cf_i}$ that d_i indicates the fault degree and cf_i supports the certainty.

4.4. Results and Discussion. Two diagnostic systems, the DMP of Petti *et al.* (1990) (e.g., the likelihoods $\mathcal{F}_i$'s of eq 13) and the proposed DMA (e.g., fault degrees and consistency factors $(d_i)_{cf_i}$ of eqs 40 and 42) are tested on the CSTR studied by Hsu and Yu (1992). The diagnosis is performed online with a sampling period of 3 min.

Consider the case of a fault being introduced at $t = 1$ h for a -20% decrease in F_0. The sf_{ji}'s of DMA are shown in Figure 8, and d_i and cf_i of $(d_i)_{cf_i}$ are given in Figure 9. The results show that DMA can correctly identify the fault origin F_0 using $(d_i)_{cf_i}$. Figure 9 reveals that despite the fact that some of the d_i's are non-zero (even before for the occurrence of fault, $t < 1$ h), the combination of d_i and cf_i serves as a useful measure for the fault diagnosis. The DMP, on the other hand, produces spurious solutions as shown in Figures 10A and 11A. It finds F_0, C_{A_0}, and k_0 are possible fault origins. Notice that, from the SDG-based analyses (Hsu and Yu, 1992), this fault is qualitatively isolable. Unfortunately, the DMP fails to isolate the fault origin. In an operating environment, the measurements are often corrupted with noise. Therefore, the diagnostic systems are tested against process with measurement noises. The temperature (T) and level (L) measurements are corrupted with white measurement noises with variances of 1 °C and 1%, respectively. Again, for the fault in F_0, DMA can find the fault origin correctly (Figures 12 and 13) and DMP fails to isolate F_0 (Figures 10B and 11B).

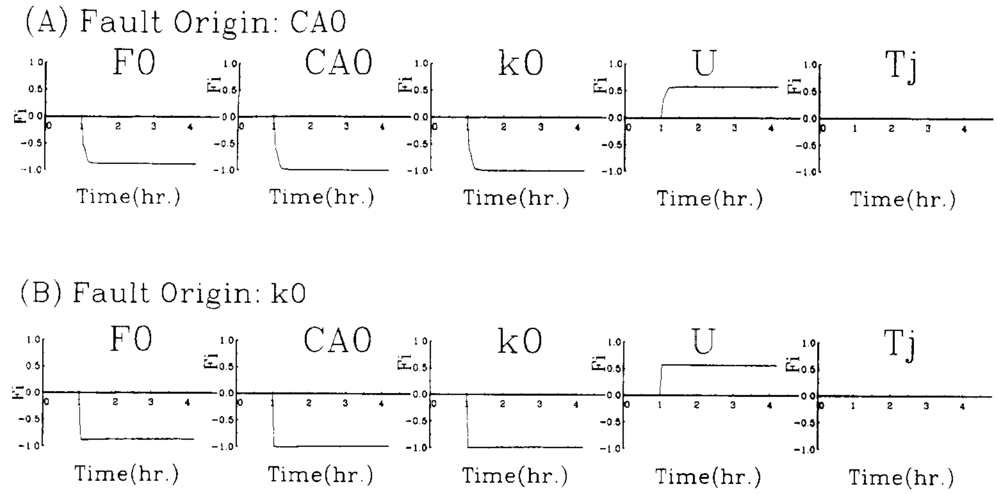

Figure 15. Diagnostic resolutions of DMP for (A) C_{A_0} failure and (B) k_0 failure.

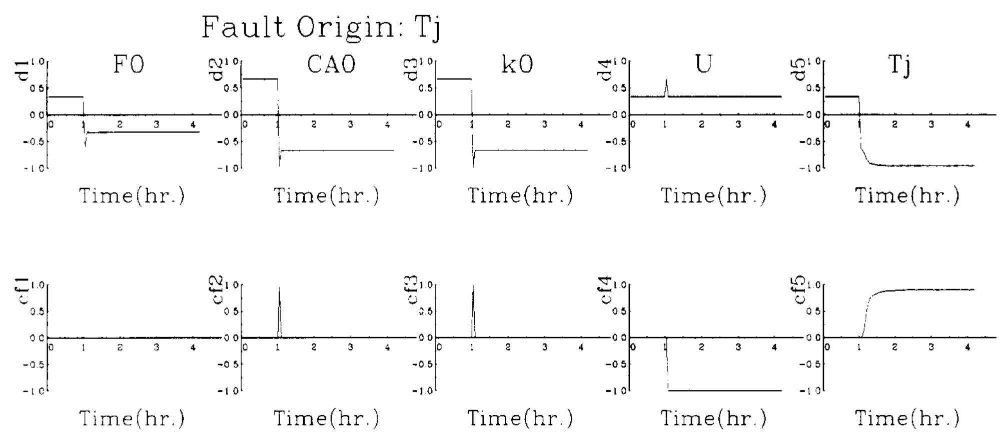

Figure 16. Diagnostic resolutions of DMA for sensor T_j failure.

Next, consider a fault in C_{A_0} (−20% decrease in C_{A_0}). Notice that the SDG-based analyses (Yu and Lee, 1991; Hsu and Yu, 1992) show that the patterns from the fault in C_{A_0}, k_0, and U are not qualitatively distinguishable. However, the equation-based approach (eq 66) shows that C_{A_0} and k_0 are not qualitatively isolable (the zero-nonzero configuration and the coefficient are nearly the same for these two faults). Simulation results show that DMA produces spurious solution for this fault. It finds C_{A_0} and k_0 as possible faults (Figure 14). Obviously, this result is expected from the analyses of the parity equations (eq 66). The DMP also gives spurious solutions (faults in F_0, C_{A_0}, and k_0, as shown in Figure 15). Similarly, for the situation of sensor T_j failure, the proposed method can correctly find the fault origin, as shown in Figure 16.

Simulation results show that the proposed DMA gives better resolution in fault diagnosis than the DMP. As expected, the resolution of DMA is up to the qualitative isolable level. However, for a given system, the qualitative behaviors from the quantitative parity equations and from the SDG-based model are obviously not the same. The qualitatively indistinguishable faults C_{A_0}, k_0, and U from the SDG model are now reduced to C_{A_0} and k_0 from the parity equations. This can be understood since the quantitative process model is employed in the parity equations and its qualitative behavior depends on the structure of the parity equations.

5. Conclusion

Equation-oriented process models are often used for fault diagnosis. However, the resolution of equation-oriented diagnosis systems is often limited to, at most, the qualitative level. That is, the extent of quantitative process model is utilized only up to its qualitative level. In order to improve diagnostic resolution, the deep model algorithm (DMA) is proposed for process fault diagnosis using parity equations. The framework of DMA includes a renewed definition of satisfaction factors and the use of d_i (degree of fault) and cf_i (consistency factor) in isolating the fault origin. A procedure is also given for the construction of DMA. A CSTR example is used to illustrate the resolution of DMA. Results show that the proposed DMA is effective in isolating fault origins.

Nomenclature

A = heat transfer area of CSTR, ft^2
$\mathbf{a}$ = vector of fault assumption
a_i = ith fault
$c_j(.)$ = jth confluence of system model
c_p = heat capacity of process liquid, BTU/lb$_m$ °R
c_{pj} = heat capacity of cooling water, BTU/lb$_m$ °C
C_A = concentration of reactant A, mol/ft^3
C_{A_0} = feed concentration of reactant A, mol/ft^3
cf_i = consistency factor for ith fault
d_i = fault degree of ith fault
E = activation energy, BTU/mol
e = residual vector
e_j = residual value of jth parity equation
F = reactor outlet flow rate, ft^3/h
F_j = cooling water flow rate, ft^3/h
F_0 = reactor inlet flow rate, ft^3/h
$\mathcal{F}$ = failure likelihood vector
$\mathcal{F}_i$ = failure likelihood of ith fault
$\mathbf{k}$ = constant vector term of parity equations
k_j = constant term of jth parity equation

k_0 = Arrhenius constant, h^{-1}
$\mathbf{m}$ = vector of process measurements
m = number of parity equations
n = number of fault origins
$\mathbf{P}$ = matrix of p_{ji}
p_{ji} = coefficient for ith fault on jth parity equation
q_i = fault supportability of ith fault
r = number of equations with non-zero coefficient in parity equations
sgn* = sign of sf_{ji}, defined by eq 36
sf_j = satisfaction factor of jth confluence, defined by DMP method
sf_{ji} = satisfaction factor for ith fault of jth parity equation
T = reactor temperature, °R
T_j = cooling water temperature, °R
T_{j0} = cooling water inlet temperature, °R
T_0 = reactor inlet temperature, °R
U = overall heat transfer coefficient, BTU/h ft^3 °R
V = reactor volume, ft^3
V_j = heat transfer area of jacket, ft^2

Greek letters

α_i = percent of deviation in a_i
ΔH = heat of reaction, BTU/mol
τ_{Ii} = reset time for ith loop of PI controller
τ_{ij} = tolerance for ith fault of jth parity equation
τ_j = tolerance for jth confluence of DMP method
ρ = density of process liquid, lb$_\mathrm{m}$/ft^3
ρ_j = density of cooling water, lb$_\mathrm{m}$/ft^3

Subscripts

$-$ = lower bound
meas = measured data
max = maximum value
min = minimum value

Superscripts

$\bar{}$ = upper bound
$\check{}$ = normalized fault with respect to steady-state value
s = steady-state value
set = set point

Appendix

Appendix A. Derivation of Consistency Factor, cf_i. In a decision-making process, most heuristic methods have sought to justify exhausting information by some quasiprobabilistic interpretations. The certainty factor CF is the most common representation of heuristic weights that indicates the certainty with which each evidence is believed (Shortliffe, 1976). The value of CF falls between -1 and $+1$ for the indications of disbelief and belief, respectively. The concept of CF is extended to find the consistency of sf_{ji}'s for fault isolation.

For a system with m parity equations and a given fault a_i, the satisfaction factors $\mathrm{sf}_{1i}, \mathrm{sf}_{2i}, ..., \mathrm{sf}_{mi}$ are randomly distributed between the bounds of $\mathrm{sf}_{i,\min}$ and $\mathrm{sf}_{i,\max}$. From the definition of sf_{ji} (eqs 33 and 34), it is clear that sf_{ji} is the indication of the direction as well as *degree* of fault. Therefore, sf_{ji}'s have to be normalized before it can be processed further. A simple way to do this is to make the largest $|\mathrm{sf}_{ji}|$ (j = 1, 2, ..., m) equal to 1. Therefore, the normalized sf_{ji} becomes (Figure 17)

$$\check{\mathrm{sf}}_{ji} = \frac{\mathrm{sf}_{ji}}{\max(|\mathrm{sf}_{1i}|, |\mathrm{sf}_{i2}|, ..., |\mathrm{sf}_{mi}|)} \tag{A1}$$

Since we have m evidences ($\check{\mathrm{sf}}_{1i}, \check{\mathrm{sf}}_{2i}, ..., \check{\mathrm{sf}}_{mi}$) supporting the fault a_i, the consistency between these evidences is a measure of belief or disbelief. For example, if $\check{\mathrm{sf}}_{ji}$'s are all positive and distributed over a small range, then these evidences are consistent (Figure 17A). On the other hand,

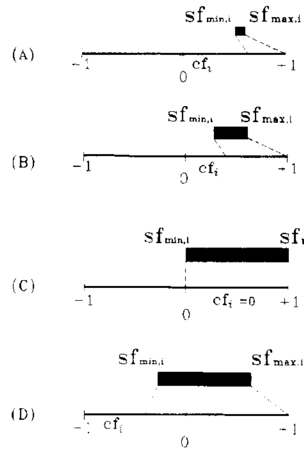

Figure 17. Conceptual diagram of consistency factor with decreasing consistency (from A to D).

if $\check{\mathrm{sf}}_{ji}$ ranges from positive to negative, then these parity equations give conflicting evidence (Figure 17C and D). Therefore, the width between the largest and smallest $\check{\mathrm{sf}}_{ji}$ is an indication of consistency. The consistency factor for the ith fault cf_i can be defined as

$$\begin{aligned}\mathrm{cf}_i &= 1 - (\check{\mathrm{sf}}_{\max,i} - \check{\mathrm{sf}}_{\min,i}) \\ &= 1 - \left(\frac{\mathrm{sf}_{\max,i} - \mathrm{sf}_{\min,i}}{\max(|\mathrm{sf}_{1i}|, |\mathrm{sf}_{2i}|, ..., |\mathrm{sf}_{mi}|)}\right)\end{aligned} \tag{A2}$$

Figure 17 shows four cases with decreasing consistency.

Appendix B. Linearized Parity Equations for CSTR. The steady-state equations for the CSTR (eqs 53–55) can be linearized with respect to fault origins and process measurements as

$$0 = F_0 - F \tag{B1}$$

$$\begin{aligned}0 = {} & \left(T_0^\mathrm{s} - \frac{\Delta H}{\rho c_\mathrm{p}} \frac{C_{\mathrm{A0}}^{\mathrm{s}} k^\mathrm{s}}{F^\mathrm{s} + k^\mathrm{s} V^\mathrm{s}} V^\mathrm{s}\right) F_0 + F_0^\mathrm{s} T_0 + \left(-F^\mathrm{s} - \frac{U^\mathrm{s} A}{\rho c_\mathrm{p}} - \right. \\ & \left. \frac{\Delta H}{\rho c_\mathrm{p}} \frac{F_0^\mathrm{s} F^\mathrm{s} C_{\mathrm{A0}}^{\mathrm{s}} V^\mathrm{s}}{(F^\mathrm{s} + k^\mathrm{s} V^\mathrm{s})^2} \frac{E k^\mathrm{s}}{R T^{\mathrm{s}^2}}\right) T - \left(T^\mathrm{s} - \frac{\Delta H}{\rho c_\mathrm{p}} \frac{F_0^\mathrm{s} k^\mathrm{s} C_{\mathrm{A0}}^{\mathrm{s}} V^\mathrm{s}}{(F^\mathrm{s} + k^\mathrm{s} V^\mathrm{s})^2}\right) F + \\ & \left(\frac{U^\mathrm{s} A}{\rho c_\mathrm{p}}\right) T_j + \left(-\frac{A}{\rho c_\mathrm{p}} T^\mathrm{s} + \frac{A}{\rho c_\mathrm{p}} T_j^\mathrm{s}\right) U + \\ & \left(-\frac{\Delta H}{\rho c_\mathrm{p}} \frac{F_0^\mathrm{s} C_{\mathrm{A0}}^{\mathrm{s}} V^\mathrm{s}}{(F^\mathrm{s} + k^\mathrm{s} V^\mathrm{s})^2} \mathrm{e}^{-E/RT^\mathrm{s}}\right) k_0 + \left(-\frac{\Delta H}{\rho c_\mathrm{p}} \frac{F_0^\mathrm{s} k^\mathrm{s} V^\mathrm{s}}{F^\mathrm{s} + k^\mathrm{s} V^\mathrm{s}}\right) C_{\mathrm{A}_0} + \\ & \left(-\frac{\Delta H}{\rho c_\mathrm{p}} \frac{C_{\mathrm{A0}}^{\mathrm{s}} k^\mathrm{s} F_0^\mathrm{s}}{F^\mathrm{s} + k^\mathrm{s} V^\mathrm{s}}\right) V + \left(\frac{\Delta H}{\rho c_\mathrm{p}} \frac{F_0^\mathrm{s} F^\mathrm{s} C_{\mathrm{A0}}^{\mathrm{s}} V^\mathrm{s}}{(F^\mathrm{s} + k^\mathrm{s} V^\mathrm{s})^2} \frac{E k^\mathrm{s}}{R T^\mathrm{s}} + \right. \\ & \left. \frac{\Delta H}{\rho c_\mathrm{p}} \frac{F_0^\mathrm{s} V^\mathrm{s} C_{\mathrm{A0}}^{\mathrm{s}} k^\mathrm{s}}{(F^\mathrm{s} + k^\mathrm{s} V^\mathrm{s})}\right)\end{aligned} \tag{B2}$$

$$\begin{aligned}0 = F_j^\mathrm{s} T_{j0} = {} & \frac{A}{\rho_j c_{\mathrm{p}j}} (T^\mathrm{s} - T_j^\mathrm{s}) U + \frac{A}{\rho_j c_{\mathrm{p}j}} U^\mathrm{s} T - (T_j^\mathrm{s} - T_{j0}^\mathrm{s}) F_j - \\ & \left(F_j^\mathrm{s} + \frac{A U^\mathrm{s}}{\rho_j c_{\mathrm{p}j}}\right) T_j\end{aligned} \tag{B3}$$

Substituting the steady-state values (Table 2) into eqs B1–B3, we have

$$0 = F_0 - F \tag{B4}$$

$$\begin{aligned}0 = {} & 729.68 F_0 + 40 T_0 - 871.62 T - 699.58 F + 1000 T_j - \\ & 35.70 U + 16000 C_{\mathrm{A}_0} - 5.57 \times 10^{-8} k_0 + 166.67 V - 108578\end{aligned} \tag{B5}$$

$$0 = 49.90T_{j0} + 21.50U + 601.87T - 64.63F_j - 651.78T_j \tag{B6}$$

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