Fault Diagnosis Based on Qualitative/Quantitative Process Knowledge

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Recent advances in knowledge engineering have led to develop the qualitative (deep) model based diagnostic systems. As process knowledge accumulated, however, the diagnostic system remains strictly qualitative. This limits the usefulness of such systems. In this work, a framework is developed for integrating quantitative process knowledge into the qualitative model. Once quantitative process information, e.g., steady-state gains, is available, it can be incorporated into the simplest qualitative process model called the signed directed graph. The quantitative process knowledge is described in terms of membership functions of fuzzy set theory. According to the measurement pattern, the truth value of a hypothesis (e.g., a fault origin) can be calculated based on the fuzzy logic. Consequently, the diagnostic resolution can be improved significantly. Furthermore, the proposed method becomes a strictly qualitative diagnostic system, if no quantitative information is available. A chemical reactor example illustrates the design and performance of the qualitative/quantitative model-based diagnostic system. The proposed approach can also be extended to the multiple-fault situations in a straightforward manner.

Introduction

Conventionally, the process failure is diagnosed by operators. The complexity of modern chemical plants and the availability of inexpensive computer hardware prompted us to develop automated fault diagnosis (Himmeblau, 1978; Isermann, 1984; Kramer and Palowitch, 1987; Milne, 1987; Ramesh et al., 1988; Venkatasubramanian and Rich, 1988; Petti et al., 1990).

Depending on the rigorousness of the process knowledge employed, techniques for automated fault diagnosis can be classified into *quantitative* and *qualitative* approaches. Quantitative diagnostic systems utilize a rigorous process model and on-line measurements to back-calculate crucial process variables (Willsky, 1976; Isermann, 1984). A process failure is characterized by the significant deviation in the calculated process variables. Despite its ability to accurately pin down the specified process faults, this approach requires extensive quantitative process knowledge (to perform computation quantitatively). Filtering and estimation are typical examples (Isermann, 1984). Kramer (1987) relaxes the equality constraints on the governing equations (of a process model) to "approximately equal." The constraint violation is used to deduce possible faults. The non-Boolean reasoning on a quantitative model did improve the stability and sensitivity of the diagnosis in the presence of noise (Kramer, 1987). This type of approach (Kramer, 1987; Petti et al., 1990), however, has the same problem as conventional quantitative approach, which requires extensive quantitative process knowledge (e.g., numerical values of coefficients in all governing equations).

The qualitative approach, on the other hand, requires much less process knowledge (e.g., the signs of coefficients in all governing equations). Depending on the type of knowledge employed, qualitative diagnostic systems can be divided further into shallow- and deep-knowledge-based systems. As pointed out by several researchers (Kuipers, 1987, 1989; Petti et al., 1990), heuristic-knowledge (shallow-knowledge)-based systems may suffer from inconsistency in the knowledge base. Furthermore, a slight change in the process (or in the operating condition) can lead to significant modification in the knowledge base (Petti et al., 1990). Deep-knowledge-based systems provide a systematic approach for reasoning about physical

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systems (Bobrow, 1985). Generally, a *qualitative* model, e.g., an equation with variables and parameters being strictly positive, zero, or negative (+, 0, or −), is used to describe the structure of a physical system, and a reasoning technique is employed to derive the behavior, the qualitative states of system variables for a given change (de Kleer and Brown, 1984; Forbus, 1984; Kuipers, 1984; Kramer and Palowitch, Jr., 1987; Dalle Molle et al., 1988).

Qualitative reasoning mimics the human expert to derive physical phenomena. Despite its ability to systematically describe the behavior, the qualitative reasoning (or qualitative physics in general) suffers from incompleteness (Struss, 1988; Kuipers, 1988). It can offer multiple interpretations for a single event: in diagnosis, this implies that the diagnostic system provides more possible fault interpretations in addition to the true one (Kramer and Palowitch, 1987; Chang and Yu, 1990). This is an inherent limitation of the qualitative reasoning, since only *qualitative* terms are employed in the model. In process engineering, as experience accumulated, some form of quantitative process knowledge is available, e.g., the steady-state gains between process variables. Under the current framework, however, qualitative-model-based systems are not able to utilize such information to improve diagnostic resolution.

The purpose of this work is to provide a framework for qualitative/quantitative reasoning in fault diagnosis by using the simplest qualitative model, the signed directed graph (SDG). The membership function of fuzzy set theory (Zadeh, 1965) is used to integrate quantitative process knowledge into the qualitative model. A CSTR example used illustrates the design and performance of the qualitative/quantitative diagnostic system. In this article, the qualitative model (SDG) is described, as well as the derivation of the qualitative/quantitative reasoning. Procedures for the construction of a diagnostic system are presented together with a CSTR example that shows the effectiveness of the proposed method. It can be applied to multiple-fault situations as well.

Qualitative Reasoning: SDG Approach

Qualitative model

The SDG graphically describes the cause and effect relationships among process variables. The qualitative relationship between A and B can be described as the following:

$$A \xrightarrow{\operatorname{sgn}(A-B)} B \tag{1}$$

Nodes A and B represent process variables. In the qualitative sense, A and B take the values of "+", "0", or "−". The branch shows immediate influence on nodes, and $\operatorname{sgn}(A-B)$ represents the direction of influence. The term $\operatorname{sgn}(A-B)$ takes the value of "+" or "−". If $\operatorname{sgn}(A-B)=$ "+", it means, a positive (or negative) deviation in A leads to a positive (or negative) deviation in B. The SDG model provides a qualitative description of the process variables. The advantage of using the SDG is that we can visualize the structure of the system. As pointed out by Iri et al. (1979), the SDG for a physical system can be constructed according to:

1. Plant data or experienced operators
2. A mathematical model.

It should be noted that if a SDG is built from a first principle model, only qualitative information (e.g., the sign of the coefficients) is needed. For example,

Table 1. Truth Tables

		B	
A	+	0	−
		$A \xrightarrow{+} B$	
+	*T*	*F*	*F*
0	*F*	*T*	*F*
−	*F*	*F*	*T*
		$A \xrightarrow{-} B$	
+	*F*	*F*	*T*
0	*F*	*T*	*F*
−	*T*	*F*	*F*

$$\frac{dx_i}{dt}=f_i(x_1, x_2, \ldots, x_n) \tag{2}$$

the sign on the branch from x_j to x_i [$\operatorname{sgn}(x_j-x_i)$] is defined by the sign of $(\partial f_i/\partial x_j)$. Accordingly, the SDG can be constructed from a mathematical model. In this work, the SDG is built from the process model.

Qualitative simulation

Once the qualitative model is available, we will be able to derive behavior of a given disturbance. For example, in Eq. 1, the qualitative state of B can be expressed as

$$\operatorname{sgn}(B)=\operatorname{sgn}(A)\cdot\operatorname{sgn}(A-B) \tag{3}$$

A positive deviation in A [$\operatorname{sgn}(A)=$ "+"] and a positive branch between A and B [$\operatorname{sgn}(A-B)=$ "+"] result in a positive deviation in B [sgn $(B)=$ "+" from Eq. 3]. Forward simulation can be carried out easily to find the behavioral description.

Fault diagnosis

Fault diagnosis differs from forward qualitative simulation in one major way: the measurement pattern is available beforehand and thus can find the possible cause of a given behavior. Since human experts generally reason forward, the forward reasoning approach is common in many diagnostic systems (Kuipers, 1987; Kramer and Palowitch, 1987; Chang and Yu, 1990). Typically, a hypothesis is made and behavior is derived from the qualitative model, and then the prediction and observations are compared to validate or invalidate the hypothesis (Kuipers, 1987, Figure 1).

For the SDG model, the truth table constructed according to Eq. 3 (Table 1) can be used to find the *consistency* of a hypothesis for a given measurement pattern. A fault generally propagates along consistent branches (Kramer and Palowitch, 1987). Therefore, the truth table provides a convenient way of validating a hypothesis in a SDG model. In the implementation phase, logic operators such as p and m are used to represent the SDG with positive and negative branches, respectively.

$$pAB \Leftrightarrow A \xrightarrow{+} B \tag{4}$$

$$mAB \Leftrightarrow A \xrightarrow{-} B \tag{5}$$

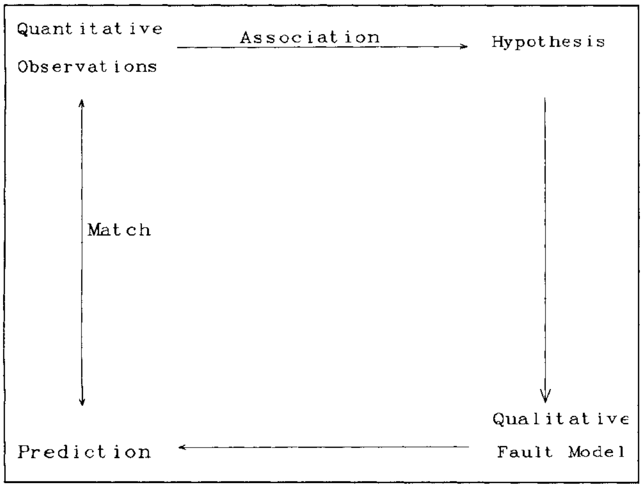

Figure 1. Concept of qualitative diagnostic system.

The truth values of the logic operators depend on the measurement pattern and the truth tables (Table 1) according to the sign on the branch. Certainly, this is a two-valued logic, since the truth value takes the value of T (.TRUE.) or F (.FALSE.).

Note that the pattern matching is performed between *qualitative* observations and *qualitative* prediction. In any realistic situation, however, *quantitative* observations (Figure 1) are available. As the restriction of the qualitative reasoning, we deliberately make quantitative observations *qualitative*. In other words, we ignore some given information because of the limitation of the model employed.

Qualitative/Quantitative Reasoning

After recognizing the limitation of a qualitative model, a method is devised to integrate quantitative knowledge into a qualitative model. In this work, the membership function of the fuzzy set theory is used to shape the quantitative information.

Fuzzy set

Zadeh (1965) proposed the fuzzy set theory to describe uncertain information. For conventional (or the crisp) set, an object either belongs to or does not belong to a set. This concept can be defined using the membership function $\mu_A(x)$.

$$\mu_A(x) = \begin{cases} 1, & x \in A \\ 0, & x \notin A \end{cases} \tag{6}$$

If x is an element of A, then its membership function is 1, or 0 otherwise. The fuzzy set theory of Zadeh provides another degree of freedom: the degree of belonging.

In fuzzy set, an object may belong partially to a set. The membership function $\mu_A(x)$ maps all elements in some universe X into [0,1]:

$$\mu_A(x): X \rightarrow [0,1] \tag{7}$$

That is, the membership function in a real number falls between 0 and 1.

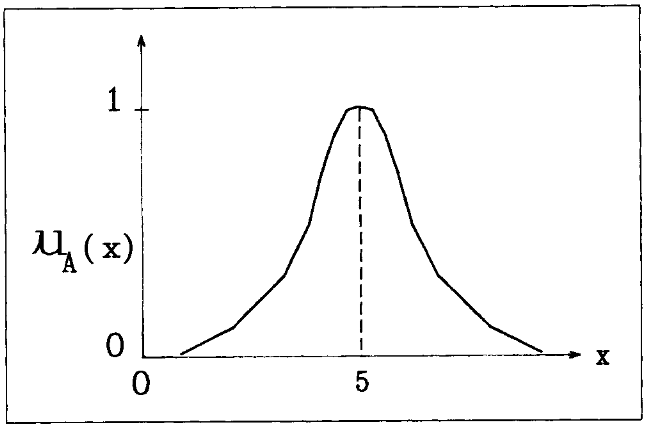

Figure 2. Membership function for the proposition "x is close to 5."

$$0 \leq \mu_A \leq 1 \tag{8}$$

where 0 means no membership and 1 means full membership in the set. The membership function provides a convenient tool to describe the degree of belonging. Furthermore, the membership function can be described graphically. For example, the proposition "x is close to 5" can be described by the membership function in Figure 2. It should be noted that this is just a description of the concept "close". Different shapes of membership functions may be constructed for the same concept, since most people see things differently. Certainly, the membership function can also be used to describe a crisp concept. For example, the proposition "x is equal to 5" is described by the membership function in Figure 3. The membership function can be used to integrate quantitative knowledge into a qualitative model.

Shaping the quantitative knowledge

Let us consider a pure qualitative model described by the SDG: $A \xrightarrow{+} B$. The binary relationship between A and B can be described by the ratio $\Delta B/\Delta A$ taking the value from 0^+ to infinity. In terms of the membership function $\mu_{BA}(\Delta B/\Delta A)$, μ_{BA} takes the value of 1 for all positive $\Delta B/\Delta A$ as shown in Figure 4A. Therefore, the qualitative relationship can be described by the fuzzy set with a membership function replacing the sign. Once some quantitative information is available, we can shape the membership function to provide a stricter constraint. For example, since the steady-state gain between A and B falls between 5 and 10, we can modify the membership function to Figure 4B. Figure 4B provides some

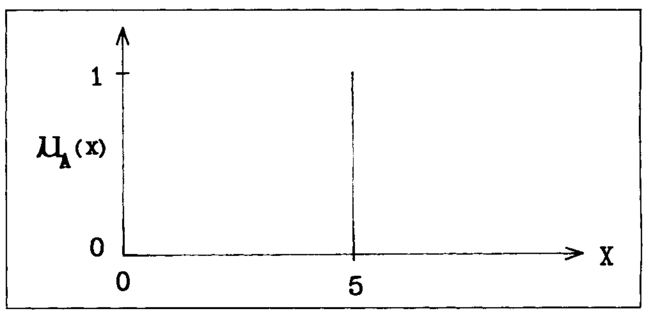

Figure 3. Membership function for "x equals 5."

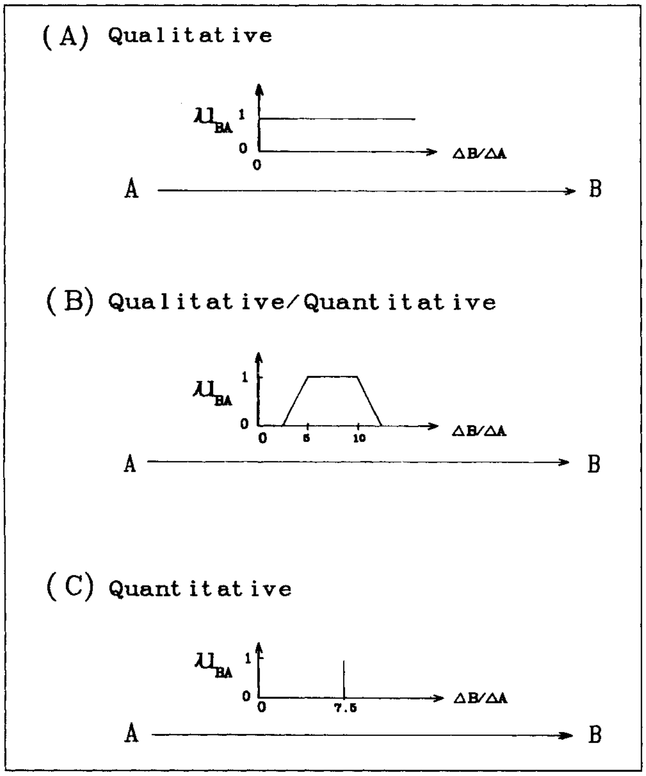

Figure 4. Membership functions for different types of models.

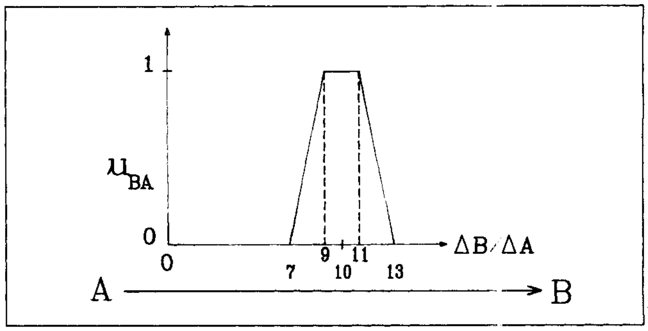

Figure 5. Membership function for the branch *A-B* when the steady-state gain *(ΔB/ΔA)* nears 10.

quantitative information into the model (Figure 4A) by tightening the range of $\Delta B/\Delta A$ having full membership (i.e., $\mu_{BA}=1$). When we exactly know the steady-state gain is 7.5, μ_{BA} can be modified further (Figure 4C). Note that Figure 4C shows a *quantitative* relationship between A and B.

The membership function of the fuzzy set theory provides a simple way to shape the quantitative knowledge. As the quantitative information becomes less ambiguous, the model changes gradually from a qualitative one to a quantitative one. The proposed qualitative/quantitative model fills the fuzzy (gray) area between conventional qualitative model and the typical quantitative model. Another advantage of using membership functions to describe quantitative knowledge is that we are able to shape the quantitative knowledge graphically. This makes it easy to transfer quantitative information into knowledge-based systems.

Scope of application

Following the approach of Chang and Yu (1990), a system response is discretized into steady-state and transient aspects, respectively.

Generally, the SDG-based qualitative model is a better tool for describing steady-state or quasisteady-state behavior. The next step is to integrate the quantitative information into the qualitative/quantitative model to describe its steady-state behavior. For simplicity and computational efficiency, a very simple membership function is used in this work. For example, the steady-state gain between A and B is approximately equal to 10. Figure 5 shows the membership function, in which μ_{BA} stays at 1 for $\pm 10\%$ deviations from the nominal value and decreases linearly to 0 for $\pm 10 \sim 30\%$ deviations. Therefore, from a given value of $\Delta B/\Delta A$, we can determine the membership from Figure 5. It should be pointed out again that this is just a way of constructing the membership function. Different shapes of membership functions can certainly be constructed for the same concept. In general, its shape depends on the preciseness of the quantitative information and the nonlinearity of the process.

For system under transient, a different set of membership functions also can be constructed. For systems with simple dynamic, quantitative knowledge also can be used to tighten the constraint between process variables. For example, if A and B are related via a first-order lag:

$$B=\frac{1}{10s+1}\cdot A \tag{9}$$

The quantitative process knowledge (Figure 6A) can be used to shape the membership function (Figure 6B). Figure 6B gives a tighter constraint in describing the relationship between A and B (then the qualitative model). The ability of the qualitative/quantitative model goes beyond the signed constraint of the SDG. For example, for a system with inverse response (Figure 7A), a membership function can be constructed to describe this transient behavior (Figure 7B). Here, the nonzero memberships cover both positive and negative $\Delta B/\Delta A$ values (Figure 7B). Note that the conditional branch (Lapp and Powers, 1977; Kramer and Palowitch, 1987) can handle sign changes on a branch under certain *conditions*. However, in this inverse response example, it is difficult to identify such conditions. Furthermore, during transient, the membership function in Figure 6B cannot distinguish the response in Figure 6A from a response going positive initially and ending at a negative value.

The qualitative/quantitative model, however, has a limitation in that the digraph has to be of the tree structure. This is understandable, since with quantitative knowledge we are describing the net effect (via different pathways) from the initial node to the terminal node. This should not pose any problem in fault diagnosis with the hypothesis-and-test approach (Figure 1), since fault interpretation is of a tree structure (Kramer and Palowitch, 1987). Therefore, at steady state the digraph is of the tree structure. However, during transient, the cyclic digraph has to be broken into a tree structure. Certainly, this can be done when such quantitative information as dominant effect (Chang and Yu, 1990) is available.

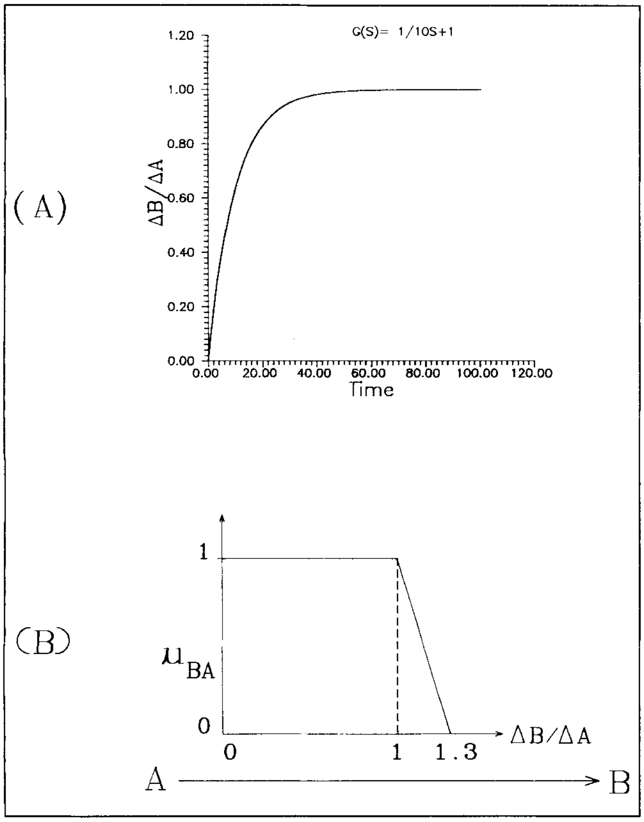

Figure 6. First-order lag system: A. ratio for a step change in *A*; B. membership function of transient response.

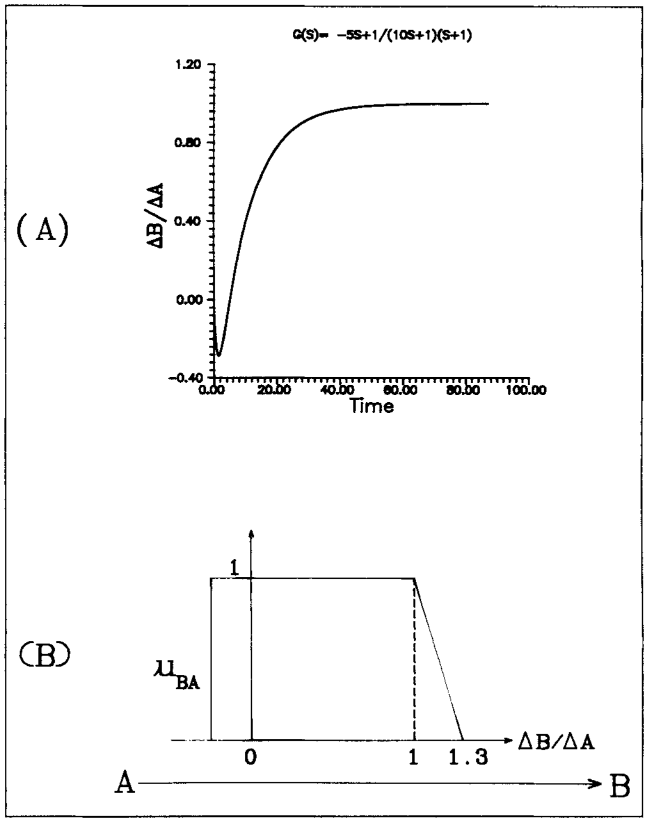

Figure 7. System with inverse response: A. ratio for a step change in *A*; B. membership function of transient response.

Qualitative/quantitative simulation

In a typical qualitative simulation, we can derive the behavior of terminal node from a given state of the initial node (Eq. 3). Here, we can also find out the qualitative/quantitative behavior of B for a given disturbance in A (e.g., Figure 5) according to:

$$\Delta B = \Delta A \odot k_{AB} \tag{10}$$

where $\odot$ is the operator for fuzzy multiplication (Dubois and Prade, 1980, p. 50), and k_{AB} is a fuzzy number defined by the membership function in Figure 5. Note that the result of the multiplication, e.g., ΔB, of a fuzzy number, e.g., k_{AB}, and a crisp (nonfuzzy) number, e.g., ΔA, is simply the rescaling of the membership function of the fuzzy number by that particular crisp number. Therefore, ΔB is also a fuzzy number (Dubois and Prade, 1980). This type of simulation is complicated and unnecessary for fault diagnosis.

As mentioned earlier, the truth table and the qualitative observations are put together to find out the *consistency* of a branch in a SDG model. From the consistency of all branches in a SDG we can further validate (or invalidate) a hypothesis. A similar technique is employed in the qualitative/quantitative model for fault diagnosis. From the quantitative observations, we can calculate the ratio ($\Delta B/\Delta A$) and the *degree of consistency* of a branch is determined by $\Delta B/\Delta A$ and the defined membership function (e.g., Figure 5). Therefore, instead of the two-valued logic (consistency or inconsistency), the multivalued logic (degree of consistency) is used to verify the fault propagation. Certainly, the fault still propagates along the consistent branch, but the truth value is defined by μ_{BA}.

Fault Diagnosis

As pointed out earlier, human experts generally reason forward. Therefore, similar to the case of qualitative reasoning, the hypothesis-and-test procedure is used in the qualitative/quantitative-model-based diagnostic system (Figure 8). For each hypothesis (fault origin), the corresponding qualitative model (SDG) is constructed, and then possible quantitative knowledge is integrated into the SDG model (Figure 8). From on-line

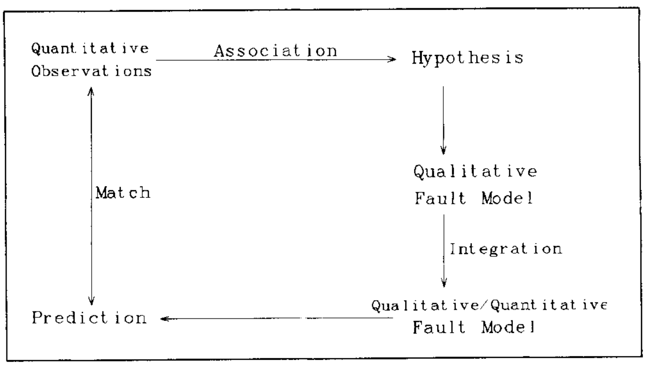

Figure 8. Concept of qualitative/quantitative diagnostic system.

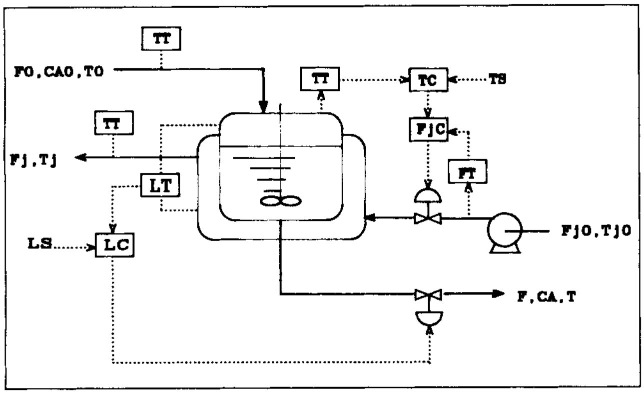

Figure 9. CSTR example.

quantitative observations, the ratios, $\Delta B/\Delta A$, are derived to determine the degree of consistency of every branch in the qualitative/quantitative model (the digraph with membership functions). The truth value of each hypothesis can be determined from membership functions on the branches.

Constructing the qualitative/quantitative model

A CSTR example (Figure 9) is used to illustrate the building of a qualitative/quantitative model. Figure 10A shows a SDG model for a CSTR with the reactant feed concentration (C_{A0}) change as a fault origin (Chang, 1988). The compensatory variable (T in Figures 10A and 10B) in the circle returns to its nominal value after an asymptotically constant change in the fault origin. To satisfy the limitation of the qualitative/quantitative model, a tree structure, the digraph is broken down into acyclic form according to the dominant effect (Chang and Yu, 1990) as shown in Figure 10B. At the ultimate steady-state, the compensatory variable disappears from the digraph (since T returns to its nominal value) and the digraph is modified slightly (Figure 10C). Up to this point, the construction of the qualitative models (for steady and transient states) is almost the same as the procedure of Chang and Yu (1990).

The next step is to integrate quantitative knowledge into the qualitative model. In this work, all quantitative information is obtained from process simulation; for example, a step change is made in the fault origin, and relative changes between variables are recorded. For example, if we know that the steady-state gains for $\Delta F_{jc}/\Delta T_c$, $\Delta F_j/\Delta F_{jc}$, and $\Delta T_j/\Delta F_j$ are around 1, -1.11, and -0.125, respectively, the membership functions on each branch can be constructed accordingly. Since F_{jc} and

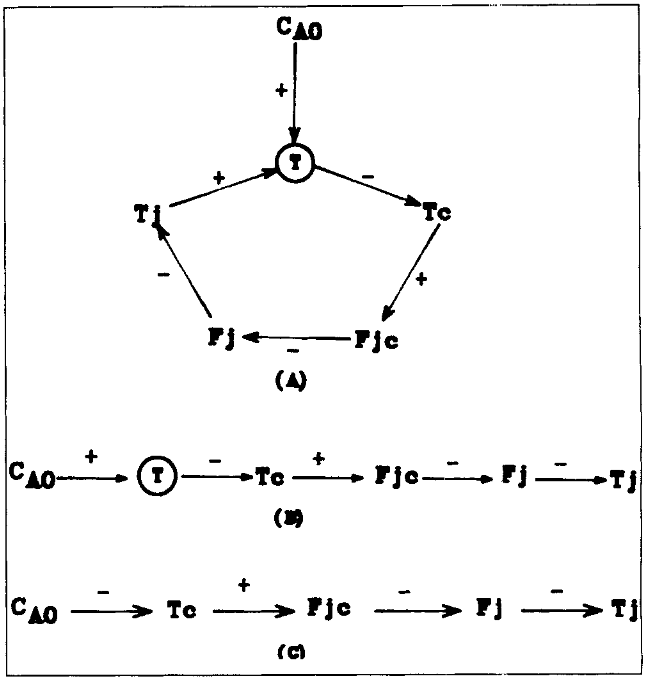

Figure 10. SDG's for the fault origin C_{A0}: A. original SDG of transient behavior; B. tree-structured SDG of transient behavior; C. SDG of steady-state behavior.

T_c are internal control signals and in the simulation these two signals are made equal, the membership function for $\Delta F_{jc}/\Delta T_c(\mu_{F_{jc}T_c})$ slightly differs from the other two (Figure 11). Since the fault origin generally is not measurable, only qualitative information is used for the branch between C_{A0} and T_c (Figure 11). Note that Figure 11 describes the qualitative/quantitative process behavior when C_{A0} goes through a positive change. For a negative change in C_{A0}, the membership function on the branch between C_{A0} and T_c should be modified (μ_{T_c} takes the value of 1 for ΔT_c between $0 \sim \infty$, Figure 11), and the rest of the membership functions remain the same. The membership function for the transient response can be constructed similarly.

If the quantitative knowledge between the root node (e.g., C_{A0}) and the subsequent node (e.g., T_c) is available, we can utilize this information to back-calculate the size of the fault. For example, the qualitative/quantitative relationship between C_{A0} and T_c is described by Figure 12 (the steady-state gain

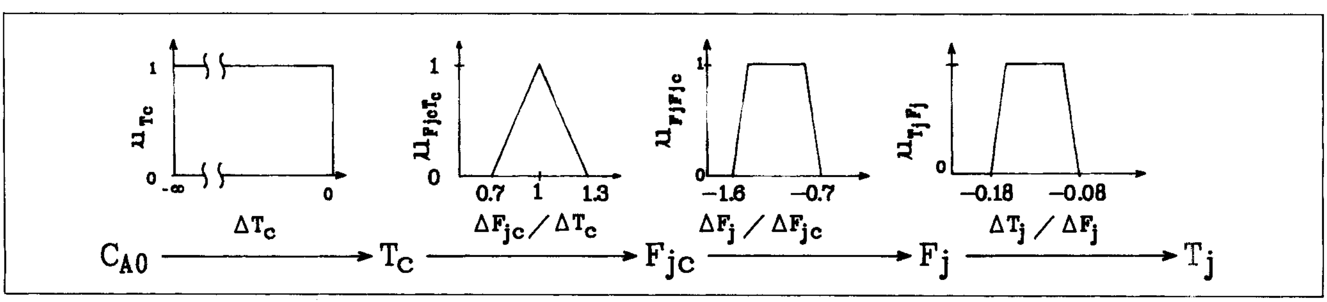

Figure 11. Qualitative/quantitative model: steady-state behavior of fault origin C_{A0} with a positive deviation.

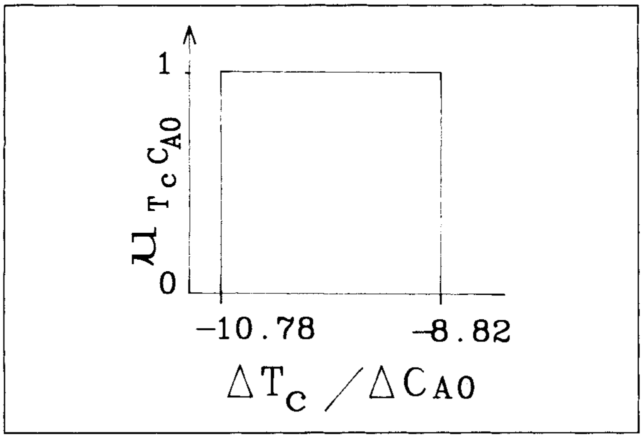

Figure 12. Membership function describing qualitative/quantitative relationship between root node C_{A0} and immediate node T_c.

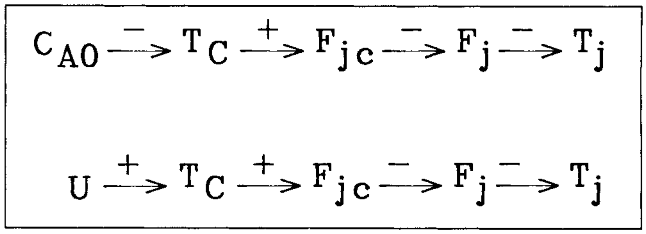

Figure 13. Qualitative (SDG) models for two fault origins: C_{A0} and U.

between $-10.78 \sim -8.82$). If ΔT_c takes the value of 4.6, then we can calculate the deviation in C_{A0} according to Figure 12.

$$\Delta C_{A0} = [-0.52, -0.42] \tag{11}$$

In other words, C_{A0} goes through a negative deviation and the magnitude of change is between $42 \sim 52\%$.

On diagnosis, we can determine the degree of consistency of each branch according to the on-line measurements (T_c, F_{jc}, F_j, and T_j) and the qualitative/quantitative model (Figure 11). The degree of consistency on each branch determines whether the fault propagates through this particular digraph.

One of the advantages of the qualitative/quantitative model is that it can eliminate some spurious solutions. In a CSTR example (Chang and Yu, 1990), the qualitative models for the fault origins C_{A0} and U are the same (Figure 13). Note that the sign difference in the immediate branch after the root node (Figure 13) does not make these two models different, since different signs just tell the opposite direction of deviations in the root variables. Therefore, the SDG-model-based diagnostic system is not able to distinguish these two faults. Once quantitative information (Figure 14) is available, these two faults can be distinguished, since the steady-state gains of F_j and T_j differ significantly for these two faults (Figure 14). In other words, the degrees of consistency on the $F_j - T_j$ branches for these two fault origins can be very different despite the fact that F_j and T_j have opposite signs.

Deriving rules

In the implementation phase, we need a set of rules for on-line diagnosis. Before deriving any rule, the number of faults to be diagnosed and possible on-line measurements should be determined *a priori*.

Each on-line measurement is expressed in the form of deviation index (Palowitch and Kramer, 1986).

$$x = \frac{\text{measured } x - \text{nominal } x}{\text{threshold for } x} \tag{12}$$

These variables represent nodes on the digraph.

For the SDG model, the rule is written for each node on the digraph with the logic operators *p*, *m*, .GT., .LT., .AND., etc. Kramer and Palowitch (1987) and Chang and Yu (1990) describe the rule writing in detail. For example, the rule for the qualitative model in Figure 10C is:

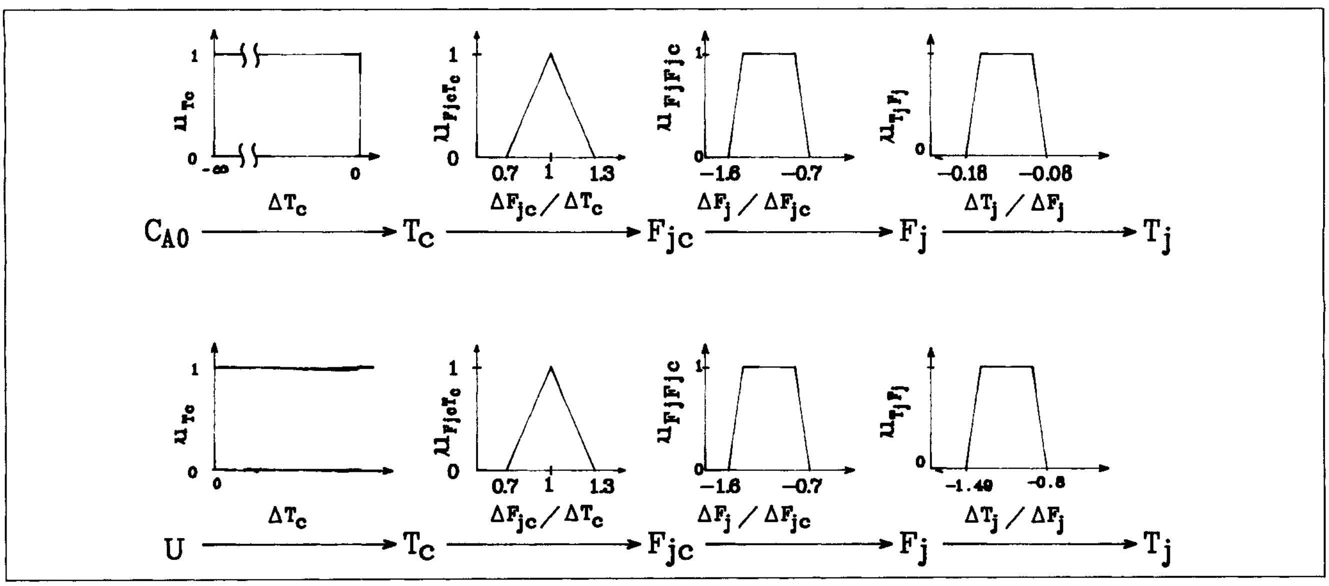

Figure 14. Qualitative/quantitative models for two fault origins: C_{A0} and U.

IF [(T_c.LT.0).AND.(pT_cF_{jc}).AND.($mF_{jc}F_j$).AND.(mF_jT_j)] THEN C_{A0} = +

This means that if the truth value of the antecedent is .TRUE., then C_{A0} is the fault origin with a positive deviation. Another rule can be used to describe a negative deviation in C_{A0}, e.g., replacing .LT. with .GT. in the first premise. Note that again this is a two-valued logic to validate the hypothesis: C_{A0} is the fault origin with a positive deviation.

Rule writing principle for the qualitative/quantitative model is similar to the SDG model. We would like to find the truth value of a hypothesis, i.e., to find the degree of consistency in a digraph. Since membership functions are used here, the logic operator .AND. is replaced by the fuzzy logic operator "min" (Dubois and Prade, 1980, p. 161). For the same fault origin with a qualitative/quantitative model (Figure 11), the rule becomes:

$$\mu_{C_{A0}+} = \min[\mu_{T_c}(T_c),\ \mu_{F_{jc}T_c}(F_{jc}/T_c),\ \mu_{F_jF_{jc}}(F_j/F_{jc}),\ \mu_{T_jF_j}(T_j/F_j)] \quad (13)$$

where $\mu_{C_{A0}+}$ is the truth value for C_{A0} going through a positive change, the min operator taking the smallest value in the bracket. Here, μ_{T_c} is the degree of consistency for the first branch (Figure 11), $\mu_{F_{jc}T_c}$ is the degree of consistency for the second branch, $\mu_{F_jF_{jc}}$ is the degree of consistency for the third branch and so on. Unlike the two-valued logic, the truth value of a hypothesis takes a value between $0 \sim 1$, and the strength (truth value) of a digraph is equivalent to the weakest link (the branch with the smallest μ) between branches. Rules for a negative deviation in C_{A0} is the same except that the membership function for T_c differs from the positive one.

Procedure

The present analyses used the following procedure:

- Enumerate all the fault origins and available measurements for the process.
- Construct the signed directed graph (SDG) for each fault origin.
- Remove unmeasured nodes and reduce each SDG to a *tree structure*.
- Simulate or induce each fault and record measured variables. Compute the gains of the branches of each reduced SDG for the transient and steady state, respectively. Then, construct the membership functions of fuzzy set for each of these gains.
- Construct the rules (e.g., Eq. 13) for each fault with corresponding branches and membership functions.

When a real fault occurs, the real gains from process measurements are compared with the membership functions on each digraph. For each comparison, the consistency of the branch is computed. The overall consistency of a fault is the minimum branch consistency on its digraph, e.g., Eq. 13. Using this we can rank the possible faults in the order of likelihood.

Application

A CSTR example is used to illustrate the design and performance of the qualitative/quantitative-model-based diagnostic system. The proposed approach is compared with that of Chang and Yu (1990).

Table 2. Fault Origins

Symbol	Fault Origin
F_0	changes in the feed flow rate
C_{A0}	changes in the feed concentration
T_0	changes in the feed temperature
T_{j0}	changes in the cooling water inlet temperature
k_0	changes in the pre-exponential factor of rate constant
U	changes in the overall heat transfer coefficient
LS	bias in the level controller set point
TS	bias in the temperature controller set point
L_c	malfunction in the level controller
T_c	malfunction in the temperature controller
F_{jc}	malfunction in cooling water flow controller
VL	failure in the control valve in the level loop
VT	failure in the control valve in the temperature loop
F_{max}	blockage in the reactor outlet line
F_{jmax}	blockage in the cooling water line

Process diagnosed

An irreversible, exothermic reaction is carried out in a perfectly mixed CSTR as shown in Figure 9 (Chang and Yu, 1990). Parameter values are taken from the data of Luyben (1973, p. 144). Reactor temperature (T) is controlled by changing the set point of a cooling water flow controller (F_{jc}). Perfect cooling water flow control is assumed. Reactor level (L) is controlled by changing outlet flow rate (F). PI controllers are used in all control loops. Tuning constants are: $K_c = 32$ and $\tau_i = 0.9$ (1/h) for the temperature loop and $K_c = 10$ and $\tau_i = 0.6$ (1/h) for the level loop, respectively. In addition to the necessary measurements for the control loops (T, F_j, and L from the transmitter), reactor feed temperature (T_0) and cooling water outlet temperature (T_j) are also measured for diagnosis. All control signals (T_c, TS, F_{jc}, L_c, and LS) are also utilized for diagnosis.

Diagnostic system

Fifteen fault origins are to be diagnosed, including external disturbances, equipment failure, and performance degradation, Table 2. The qualitative (SDG) model is derived from the differential equations describing the reactor (Luyben, 1973). The SDG for each fault origin is also constructed according to the simplification procedure of Chang and Yu (1990).

For the qualitative/quantitative model, the digraph for each fault origin has to be of tree structure. The tree-structured digraph describing transient behavior can be constructed easily once the tree-structured digraph describing steady-state behavior is available. The next step is to integrate the quantitative information into the model. The quantitative process knowledge is obtained from a step change in the root variable and, the membership function is constructed according to the procedure in Figure 11. This step is repeated for all fault origins. Therefore, a relatively large database is needed for the qualitative/quantitative-model-based diagnostic system. A pair of rules are written for each fault origin, and the corresponding membership functions are recalled from the database when the rule is fired. Rules for the steady and transient states are programmed with corresponding membership functions. The steady state is verified by checking the incremental changes of measured variables (Chang and Yu, 1990). On-line measurements are expressed in the dimensionless form (deviation index) and the ratios are calculated. To avoid overflow in the computation, when too small a denominator and/or too large a

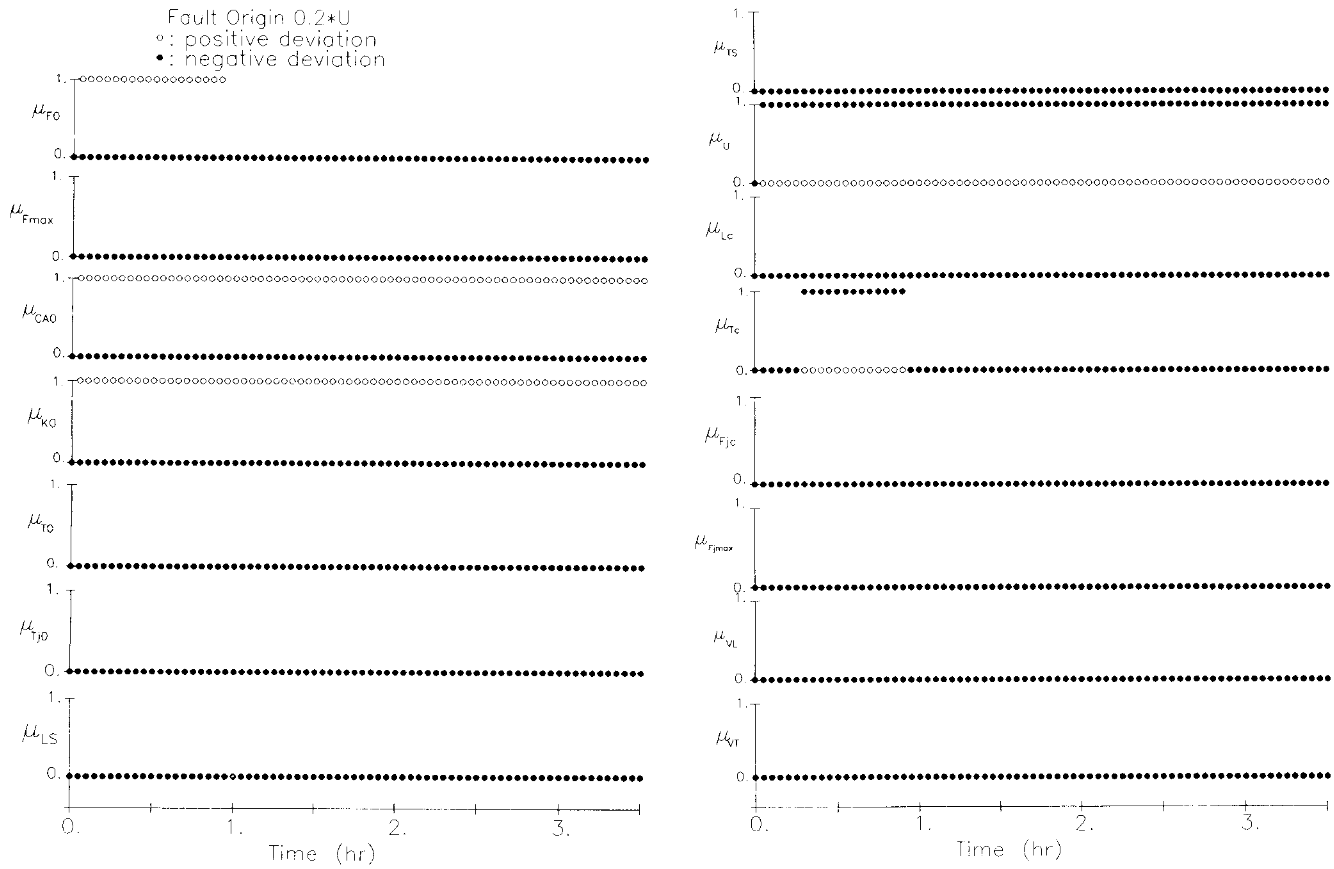

Figure 15. Diagnosed results for qualitative-model-based approach (fault origin: *U*).

numerator are encountered, the ratio is set to a value of 999 (or −999). The qualitative/quantitative-model-based diagnostic system is programmed in FORTRAN and the sampling time is 3 min (the system is executed every 3 min).

Results

Two diagnostic systems, the qualitative approach of Chang and Yu (1990) and the proposed qualitative/quantitative approach, are compared. The proposed approach can eliminate some spurious interpretations which are indistinguishable in the qualitative sense (e.g., U and C_{A0} in Figure 13). For example, a decrease in the overall heat transfer coefficient (U) leads to spurious solution in the approach of Chang and Yu (1990) as shown in Figure 15. Figure 15 shows that toward the steady state the qualitative diagnostic system interprets C_{A0} (increase), k_0 (increase), and U (decrease) as possible fault origins. Note that, during transient, T_c and F_0 are ranked as possible fault origins. These two faults are dismissed as steady-state rules become active. Here, the open circle represents a positive deviation, the filled circle a negative deviation, and μ_x is the truth value (1 represents .TRUE. and 0 .FALSE.) of the hypothesis when x is the fault origin. Obviously, these three fault origins offer the same *qualitative* behavior. This situation cannot be improved *unless* quantitative information is available. The proposed qualitative/quantitative approach does eliminate the spurious interpretations as shown in Figure 16. This result is within expectation, since steady-state gains achieved by F_j and T_j differ significantly for the fault origin U and the other two as mentioned earlier. Furthermore, the qualitative/quantitative diagnostic system based on the fuzzy set theory provides the truth values between 0 and 1 (degree of truth). Lee (1990) presents the results of diagnoses for all 15 faults.

Discussions

Multiple-fault situations

The single-fault assumption (the faults with only one cause) has been made for the development of the qualitative/quantitative diagnostic system. In practice, however, the multiple fault can still occur. The proposed approach can be extended to multiple-fault situations in the following two ways.

In some cases, the fault with multiple causes can be treated as a single-fault. Take the control loop with an external disturbance L (Figure 17A) as an example. Assume that the load disturbance comes into the system *and* the control loop is not functioning. This is a fault with multiple causes. The reduced digraph (Figure 17B), however, shows that this fault situation can be treated as a single-fault problem. The resulting digraph (Figure 17B) can be used for the fault diagnosis. In our approach, the consistency of the branch C-D indicates the likelihood of the fault "load change *and* inactive control." The single-fault approach works here, because the controller has two distinct states: active or inactive. An inactive controller gives the zero gain on the M-C branch. Therefore, the feedback pathway disappears and the digraph is reduced to a tree struc-

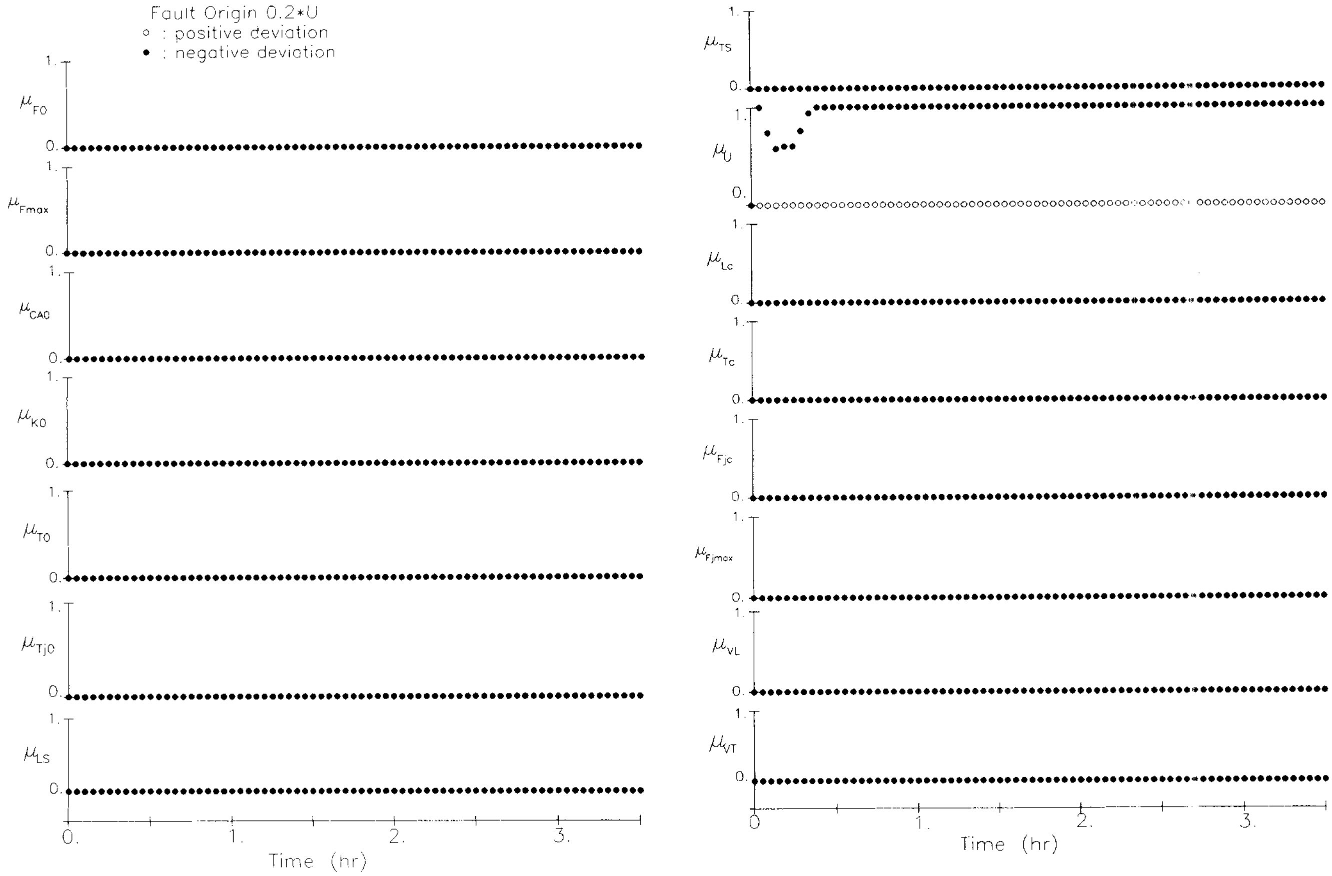

Figure 16. Diagnosed results for the qualitative/quantitative-model-based approach (fault origin: *U*).

ture for this multiple-fault problem. This simple solution can handle the limited cases of faults with multiple causes.

A general solution to the multiple-fault problem should be able to handle the cases of a combined inputs leading to a node: it can discern that the measurement pattern is the result of the combination of inputs from two branches. Consider the benchmark digraph:

$$A_0 \longrightarrow A \xrightarrow{k_{ac}} C \xleftarrow{k_{bc}} B \longleftarrow B_0$$

where A_0 and B_0 are the root nodes, and A, B, and C are process measurements. k_{ac} and k_{bc} are fuzzy set membership functions (fuzzy numbers) that describe steady-state gains of A-C and B-C (Figure 18A). The likelihood of the multiple fault (A_0 and B_0 as the root causes) can be found by checking the consistency of the digraph with available measurements. This problem differs from the single-fault situation, since k_{ac} and k_{bc} describe the binary relation between A and C and B and C, respectively; however, the measurement C is the result of the combined effects of A and C. Therefore, some modification has to be made for the multiple-fault situations. In an algebraic form, the digraph is equivalent to:

$$C = k_{ac}A \oplus k_{bc}B \tag{14}$$

where $\oplus$ is the fuzzy addition. Note that the addition of two fuzzy numbers with trapezoid membership functions is, again, a trapezoid membership function with corners being the summation of the corners of each individual membership function (Dubois and Prade, 1988, p. 50). Equation 14 divided by A becomes:

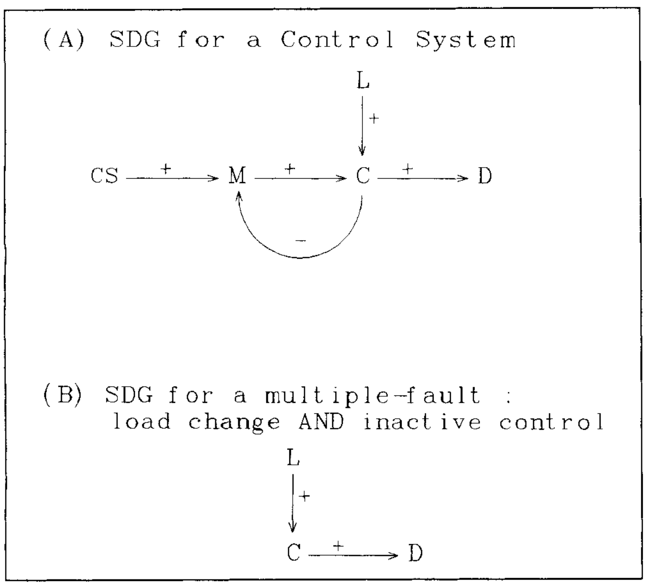

Figure 17. SDG for a control loop.

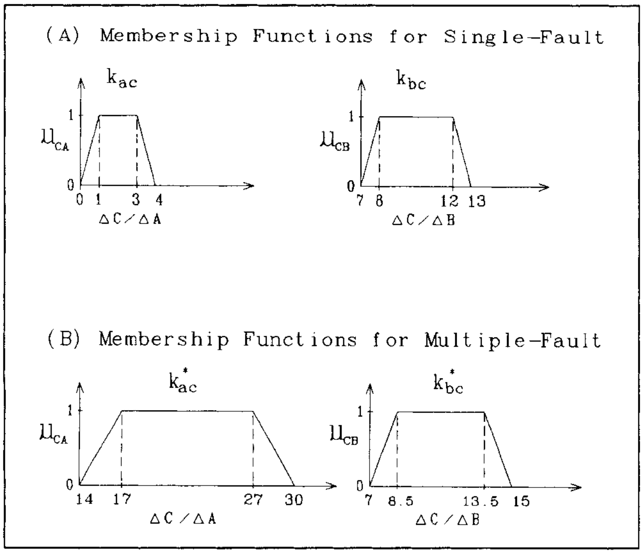

Figure 18. Membership functions with $A=1$, $B=2$, and $C=22$.

$$\frac{C}{A}=k_{ac}\oplus\frac{B}{A}k_{bc}=k^*_{ac} \tag{15}$$

where k^*_{ac} is the modified membership function of the combined inputs A and B. Equation 15 also shows that k^*_{ac} depends on k_{ac} as well as the measurements A and B. Similarly, k^*_{bc} can be expressed as:

$$\frac{C}{B}=k_{ac}\frac{A}{B}\oplus k_{bc}=k^*_{bc} \tag{16}$$

Consider the following numerical example,

$$A=1,\ B=2,\ \text{and}\ C=22$$

Since both A and B deviate from the nominal values, it can bring about a possible multiple-fault situation. With A and B available, the membership functions can be modified according to Eqs. 15 and 16 as shown in Figure 18B. Note that k^*_{ac} and k^*_{bc} in Figure 18B are constructed explicitly for the multiple-fault situation. The consistency of the digraph can be checked using the following rule:

$$\mu_{A0\&B0}=\min[\mu_{CA}(C/A),\mu_{CB}(C/B)] \tag{17}$$

According to k^*_{ac} and k^*_{bc} (Figure 18B), the truth value is:

$$\mu_{A0\&B0}=\min[\mu_{CA}(22),\mu_{CB}(11)]=1$$

This example shows how the proposed method can be extended to handle the multiple-fault situations.

It is well known that it is difficult for a digraph to handle the cases of combined inputs since the digraph cannot perform such basic mathematical operations as addition (Lapp and Powers, 1977). The qualitative/quantitative model based on the fuzzy set does perform the mathematical operation by implicitly manipulating the membership functions.

Robustness vs. performance

While, in the design of a diagnostic system, quantitative information is needed for good performance (less spurious solution), exact quantitative information (e.g., crisp number in Figure 4C) is not desirable in view of the robustness consideration. For example, when diagnosing a nonlinear system, if a membership function with a narrow width is chosen, the diagnostic results can be erroneous (missing the true solution) as the process deviates from the nominal operating point. Therefore, the engineering judgment is critical in the success of a diagnostic system: the width of a membership function depends not only on the quantitative information available but also on the process uncertainties and measurement noise. Unlike the quantitative or qualitative diagnostic systems, the proposed method offers this degree of freedom in the design.

Conclusion

Even though it is a unanimously held view that quantitative and qualitative knowledge should be integrated into any realistic knowledge-based systems, the approaches of achieving this goal vary. One approach, starting with quantitative governing equations, attempts to make the constraints qualitative by relaxing the equality constraints (Kramer, 1987; Petti et al., 1990). The proposed method takes a different approach which starts from the qualitative model and becomes quite quantitative as additional process information is available. A framework is proposed to integrate quantitative process knowledge into a qualitative model. The quantitative information can be shaped via the membership function of fuzzy set theory. This architecture has the following advantages:

- Changes in the operating condition of the diagnosed process require only the reshaping of the membership functions, since the model consists of a qualitative structure (SDG) and the quantitative knowledge (the membership function).
- Graphical representations (of the qualitative structure and the quantitative knowledge) make the model transparent to the designers as well as the users. Furthermore, in the absence of quantitative information, the proposed model is reduced to a qualitative model.

A design procedure for the qualitative/quantitative-model-based diagnostic systems is also proposed. A CSTR example is used to demonstrate the design and performance of the diagnostic system. Simulation results show that the qualitative/quantitative-model-based system improves the diagnostic resolution by eliminating some spurious solutions which are indistinguishable from a qualitative point of view. Extensions to multiple-fault situations are also given, and tradeoff between robustness and performance in the design is also discussed.

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Notation

C_A = concentration of reactant A
C_{A0} = feed concentration of reactant A

F = .FALSE.
F = reactor outlet flow rate
F_0 = reactor inlet flow rate
F_j = cooling water flow rate in the jacket
F_{jc} = cooling water flow controller output
F_{jmax} = maximum cooling water flow rate
F_{max} = maximum reactor outlet flow rate
k = fuzzy set membership function for the steady-state gain
k^* = modified membership function for multiple faults
k_0 = preexponential factor of the rate constant
K_c = controller gain
L = reactor level
L_c = reactor level controller output
LS = reactor level set point
m = logical function for negative branches
$\min(\cdot)$ = minimum of $(\cdot)$
p = logical function for positive branches
$\operatorname{sgn}(\cdot)$ = sign of $(\cdot)$ with the value of $+$, 0 or $-$
T = .TRUE.
T = reactor temperature
T_0 = reactor inlet temperature
T_c = temperature controller output
T_j = cooling water outlet temperature
T_{j0} = cooling water inlet temperature
TS = temperature controller set point
U = overall heat transfer coefficient
VL = control valve in the level loop
VT = control valve in the temperature loop

Greek letters

μ_A = membership function of fuzzy set A
τ_i = reset time

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