CONF-910648--1

DE90 017693

A FIRST-PRINCIPLES GENERIC METHODOLOGY FOR REPRESENTING THE KNOWLEDGE BASE OF A PROCESS DIAGNOSTIC EXPERT SYSTEM

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Paper to be submitted to the 4th International Conference
on Industrial and Engineering Applications of
Artificial Intelligence and Expert Systems
June 2-5, 1991

*Work supported by the U.S. Department of Energy, Office of Technology Support Programs under Contract W-31-109-Eng-38.

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INTRODUCTION

Knowledge representation for process diagnosis expert systems has evolved from simple rule-based systems, known as shallow knowledge, to more complex model-based systems, or deep knowledge [Xiang and Srihari]. Shallow knowledge represents the domain information through a set of "if ... then" rules. These rules are generally acquired from a domain expert based on experience and judgmental knowledge with no functional representation of the underlying phenomena. The weakness of rule-based systems is one of verification and validation. Procedures can not be developed to test heuristically generated rules for correctness and completeness. Even if the diagnostic rules are generated in a systematic fashion [Reifman], diagnostic event-based rules can not guarantee functional completeness. It is simply not possible to anticipate and formulate rules to cover every conceivable plant situation. Deep knowledge represents the domain information through mathematical models of the process under consideration. This model-based system in the form of quantitative and qualitative simulation algorithms describe the underlying phenomena of the physical system.

To alleviate the limitations of rule-based systems, attempts have been made to combine both shallow and deep knowledge as the knowledge structure of a process diagnostic expert system [Yoshida et al., Venkatasubramanian and Rich]. One approach is to use shallow rules to hypothesize about the possible failures first, then follow with deep knowledge reasoning to test each one of the hypotheses. The success of this approach is highly dependent on the ability of the shallow rules, which can not in general be verified and validated [Kirk and Murray], to hypothesize correct faulty candidates. By incorporating basic physical principles into the shallow knowledge, the focus of this paper, the rules could be verified and validated. Verificatior and validation would require proving only that the knowledge is represented correctly, not that the knowledge itself is correct.

In this paper we present a methodology for identifying faulty component candidates of process malfunctions through basic physical principles of conservation, functional classification of components and information from the process schematics. The basic principles of macroscopic balance of mass, momentum and energy in thermal hydraulic control volumes are applied in a novel approach to incorporate deep knowledge into the knowledge base. Additional deep knowledge is incorporated through the functional classification of process components according to their influence in disturbing the macroscopic balance equations. Information from the process schematics is applied to identify the faulty component candidates after the type of imbalance in the control volumes is matched against the functional classification of the components. Except for the information from the process schematics, this approach is completely general and independent of the process under consideration. The use of basic first-principles, which are physically correct, and the process-independent architecture of the diagnosis procedure allow for the verification and validation of the system. A prototype process diagnosis expert system is developed and a test problem is presented to identify faulty component candidates in the presence of a single failure in a hypothetical balance of plant of a liquid metal nuclear reactor plant.

FIRST-PRINCIPLES KNOWLEDGE

The diagnostic methodology presented in this paper utilizes basic physical principles and process-based knowledge. Basic physical principles are used both for analysis of macroscopic mass, energy and momentum balances in thermal hydraulic control volumes and for the physical functional classification of the process components. Process-based knowledge is used to represent the structural arrangement of the various components and systems of the process and corresponding connectivity relations. In this section, we describe the framework for development of the balance equations, the functional classification of components and the process structural information that form a first-principles knowledge base.

The Macroscopic Balance Method

In this work, the analysis of macroscopic mass, energy and momentum imbalances in thermal-hydraulic control volumes is characterized by the effect of the variations of thermal-hydraulic and thermodynamic macroscopic properties in the equations of state. The equations of state, which describe the relations among macroscopic properties, can be used to relate the variations of properties such as fluid velocity v, pressure P and temperature T to the total mass M, energy U and momentum $\mathcal{M}$ inventories for a given control volume V

$$M = \rho(P,T)\, V, \tag{1}$$

$$U = M\, h(P,T) - P\, V, \tag{2}$$

$$\mathcal{M} = M\, v, \tag{3}$$

where ρ(P,T) is the fluid density and h(P,T) is the fluid specific enthalpy. Imbalances in the mass, energy and momentum inventories are characterized by analyzing the changes in fluid velocity, pressure and temperature in Eqs. (1) through (3). The process of evaluating these imbalances is divided into three categories: (A) Single-phase mass and energy balances, (B) Two-phase mass and energy balances, and (C) Momentum balance.

A. Single-Phase Treatment of Mass and Energy Balances

For control volumes containing single-phase fluid, pressure and temperature are two independent thermodynamic properties which are readily available and can be used to specify the state of a substance in both subcooled liquid and superheated steam conditions. Changes in pressure P and/or temperature T of a single-phase fluid would cause changes in the fluid density ρ(P,T) and specific enthalpy h(P,T), which in turn would cause variations in mass M and energy U inventories of Eqs. (1) and (2), respectively. Analysis of the variations of M and U as a function of changes in P and T can be obtained through the analysis of the differentials dM and dU of Eqs. (1) and (2), for a fixed volume V

$$dM = V\left\{\frac{\partial \rho}{\partial T}dT + \frac{\partial \rho}{\partial P}dP\right\}, and \tag{4}$$

$$dU = Vh\rho\left\{\frac{1}{\rho}\left[\frac{\partial \rho}{\partial T}dT + \frac{\partial \rho}{\partial P}dP\right] + \frac{1}{h}\left[\frac{\partial h}{\partial T}dT + \frac{\partial h}{\partial P}dP\right]\right\}, \tag{5}$$

where the term P V in Eq. (2) has been neglected.

With the use of tables that represent the equations of state, e.g., steam tables for water, the variations of ρ and h as a function of P and T can be directly obtained and used to analyze dM and dU. The analysis can be quantitative or qualitative. Quantitative analysis consists of a table lookup, where values for ρ and h are obtained from measurements of P and T and are then compared with the expected values of ρ_0 and h_0 to determine dM and dU as

$$dM = M(\rho) - M(\rho_0), \text{ and}$$

$$dU = U(\rho,h) - U(\rho_0,h_0).$$

Quantitative analysis requires the storage of the equation-of-state tables in a program routine and is performed on-line for each diagnosis operation. On the other hand, qualitative analysis requires no storage of tables, needs to be performed only once and can be incorporated in the knowledge base of a diagnosis system as a set of precompiled first-principles rules. These rules are physically correct and are completely general in that the rules are independent of the process under consideration. However, qualitative analysis may generate ambiguous results due to some loss of information [De Kleer and Brown]. For instance, the addition of quantities of opposite sign results in ambiguity, since relative magnitudes are not known. Hence, a hybrid utilization of qualitative and quantitative analysis of the balance equations is a feasible alternative. Quantitative analysis can be used when qualitative reasoning results in ambiguity.

Qualitative analysis of Eqs. (4) and (5) is performed in the equivalent equations

$$[dM] = \left[\frac{\partial \rho}{\partial T}\right].[dT] + \left[\frac{\partial \rho}{\partial P}\right].[dP], \tag{6}$$

$$[dU] = \left[\frac{1}{\rho}\right]\left\{\left[\frac{\partial \rho}{\partial T}\right].[dT] + \left[\frac{\partial \rho}{\partial P}\right].[dP]\right\} + \left[\frac{1}{h}\right]\left\{\left[\frac{\partial h}{\partial T}\right].[dT] + \left[\frac{\partial h}{\partial P}\right].[dP]\right\}, \tag{7}$$

through qualitative algebraic operations with the trends of the quantities inside the bracket [.]. Given the signs or trends (increasing, decreasing, constant) in the partial derivatives and differentials of the right-hand-side of the equations, analysis is performed by applying the operations of qualitative algebra of product (.) and addition (+) among the brackets. The trends in the differentials dT and dP are readily available from the variations in T and P, respectively. The trends in the partial derivatives, ∂ρ/∂T, ∂ρ/∂P, ∂h/∂T, ∂h/∂P, are directly obtained from the equation-of-state tables and are illustrated in Table I for the steam tables. From this point on, the steam tables are used as an example of the equation-of-state, but the presented methodology is general and is not limited to water properties. All eight partial derivatives in Table I present a monotonic behavior with the exception of $\partial h/\partial P$ for subcooled liquid after about 523 K. After 523 K $\partial h/\partial P$ becomes slightly negative. The monotonic behavior of the partial derivatives is fundamental in the qualitative analysis of the balance equations.

Table I. Trends in the Partial Derivatives.

	$\partial\rho / \partial T$	$\partial\rho / \partial P$	$\partial h / \partial T$	$\partial h / \partial P$
Subcooled Liquid	↓	↑ [a]	↑	↑ [b]
Superheated Steam	↓	↑	↑	↓

[a] negligible changes due to water incompressibility
[b] until 523K

The operations of qualitative algebra of product and addition of a change ΔX in variable X and a change ΔY in variable Y are represented in Tables II and III, respectively. The trends in ΔX and ΔY can yield either increasing (↑), decreasing (↓), constant (~) or indeterminate (?) qualitative inferences. For instance, Table II shows that the product of an increasing trend in ΔX (↑) and a decreasing trend in ΔY (↓) yields a decreasing (↓) trend. The addition of similar trends in ΔX and ΔY, illustrated in Table III, results in an indeterminate (?) or ambiguous inference.

Table II. Qualitative Product [ΔX] . [ΔY].

ΔX \ ΔY	~	↑	↓
~	~	~	~
↑	~	↑	↓
↓	~	↓	↑

Table III. Qualitative Addition [ΔX] + [ΔY].

ΔX \ ΔY	~	↑	↓
~	~	↑	↓
↑	↑	↑	?
↓	↓	?	↓

The qualitative analysis of the mass inventory of Eq. (6), for single-phase fluid, is illustrated in Table IV. The rows of Table IV correspond to the nine possible combinations in the trends of T and P, which are represented in the first and second columns of the table. The third and fourth columns correspond to the qualitative behavior of the mass inventory for subcooled liquid and superheated steam, respectively, as a function of the trends in T and P of the associated row. The qualitative behavior of the mass inventory for the first seven rows of the table are uniquely obtained by applying the information of Tables I, II and III into Eq. (6). For example, in the case of $\Delta T \uparrow$ and $\Delta P \downarrow$, represented by the sixth row of Table IV, the decreasing (↓) behavior of the mass inventory in both subcooled liquid and superheated steam conditions is obtained by substituting the trends of Table I into Eq. (6) and applying the qualitative operations of Tables II and III

$$[dM] = \left[\frac{\partial \rho}{\partial T}\right].[dT] + \left[\frac{\partial \rho}{\partial P}\right].[dP],$$

$$= \underbrace{\underbrace{[\downarrow] . [\uparrow]}_{[\downarrow]} \; + \; \underbrace{[\uparrow] . [\downarrow]}_{[\downarrow]}}_{[\downarrow]}$$

Table IV. Qualitative Analysis of Single-Phase Mass Inventory.

	Variations		Mass Inventory (ΔM)	
	Temperature (ΔT)	Pressure (ΔP)	Subcooled Liquid	Superheated Steam
1	~	~	~	~
2	↑	~	↓	↓
3	↓	~	↑	↑
4	~	↑	↑[a]	↑
5	~	↓	↓[a]	↓
6	↑	↓	↓	↓
7	↓	↑	↑	↑
8	↑	↑	↓[b]	?
9	↓	↓	↑[b]	?

[a] Negligible changes due to water incompressibility

[b] For $\left| \frac{\Delta P}{P} \right| \leq 100 \left| \frac{\Delta T}{T} \right|$

For the last two rows of Table IV, ambiguities in qualitative operations prevent a unique characterization of the behavior in the mass inventory for both subcooled liquid and superheated steam conditions. For instance, for the eighth row where $\Delta T \uparrow$ and $\Delta P \downarrow$ we obtain:

$$[dM] = \left[\frac{\partial \rho}{\partial T}\right] \cdot [dT] + \left[\frac{\partial \rho}{\partial P}\right] \cdot [dP],$$

$$= \underbrace{\underbrace{[\downarrow] \cdot [\uparrow]}_{[\downarrow]} + \underbrace{[\uparrow] \cdot [\uparrow]}_{[\uparrow]}}_{[?]}$$

The qualitative addition of a decreasing first term with an increasing second term results in the indeterminate (?) behavior of dM. Hence, the net result depends on the relative magnitude of the two terms. For subcooled liquid, parametric studies show that for reasonable changes in T and P the first term of Eq. (6) is the dominant one, due to the negligible compressibility of water, causing dM to decrease. An exception to this tendency would occur only when the relative change in P is about two orders of magnitude larger than the relative change in T. For superheated steam, a general trend cannot be obtained for the last two rows of Table IV. The net result of Eq. (6) oscillates between the two terms depending on the relative variations of T and P. In this case, quantitative analysis needs to be used to unambiguously determine the trend in dM.

A similar approach could be used to obtain the qualitative behavior of the energy inventory dU of Eq. (7). The problem with this approach is that the large number of qualitative addition operations generally results in an ambiguous inference. Instead, the analysis of the qualitative behavior of the energy inventory is obtained directly through parametric studies of T and P with the steam tables. The results of the analysis are presented in Table V, which has the same layout as that of Table IV. The table shows that a general qualitative behavior of the energy inventory can be obtained for almost all possible combinations of the variations of T and P. However, as in the analysis of the mass inventory, the last two rows of Table V for superheated steam are also indeterminate. In this case, as in Table IV, the ambiguity can be resolved only for specific changes of T and P, and quantitative analysis needs to used.

Table V. Qualitative Analysis of Single-Phase Energy Inventory.

	Variations		Energy Inventory (ΔU)	
	Temperature (ΔT)	Pressure (ΔP)	Subcooled Liquid	Superheated Steam
1	~	~	~	~
2	↑	~	↑	↓
3	↓	~	↓	↑
4	~	↑	↑	↑
5	~	↓	↓	↓
6	↑	↓	↑[a]	↓
7	↓	↑	↓[a]	↑
8	↑	↑	↑	?
9	↓	↓	↓	?

[a] For $\left|\frac{\Delta P}{P}\right| \leq 100 \left|\frac{\Delta T}{T}\right|$

B. Two-Phase Treatment of Mass and Energy Balances

The analysis of mass and energy balances for a control volume containing two-phase fluid is restricted to components in which the liquid f and the vapor g phases are separable and assumed to be at their corresponding saturation conditions. Since under saturation conditions pressure and temperature are not independent thermodynamic properties, the trend in the measurable liquid level L is used in addition to the saturation pressure P, to determine the behavior of the total mass M and energy U inventories. As an extension to Eqs. (1) and (2), P and L can be related to the total M and U inventories of a given control volume V through the equations of state

$$\begin{aligned} M &= M_f + M_g, \\ &= \rho_f(P)\, V_f(L) + \rho_g(P)\, V_g(L), \qquad (8) \\ &= A\ \{\rho_f(P)\, L + \rho_g(P)\, (H - L)\}, \end{aligned}$$

$$\begin{aligned} U &= U_f + U_g, \\ &= \rho_f(P)\, h_f(P)\, V_f(L) + \rho_g(P)\, h_g(P)\, V_g(L), \qquad (9) \\ &= A\ \{\rho_f(P)\, h_f(P)\, L + \rho_g(P)\, h_g(P)\, (H - L)\}, \end{aligned}$$

where the P V term in Eq. (2) has been neglected, and A is the cross-sectional area and H is the total height of the control volume V, ρ_f is the saturated-liquid density, ρ_g is the saturated-vapor density, h_f is the saturated-liquid enthalpy and h_g is the saturated-vapor enthalpy.

The qualitative analysis of M and U in Eqs. (8) and (9), or the differential counterparts dM and dU, requires the utilization of the steam tables for extraction of the values of ρ_f, ρ_g, h_f and h_g as functions of the variations in P and L, plus the knowledge of the component total height H. The latter requirement stipulates a geometric dependency in the analysis of both equations and prevents the precompiled construction of the physical first-principles rules. Since our approach is intended to be generic and independent of the process being diagnosed, the physical rules describing mass and energy imbalances for two-phase fluid are generated on-line, through table lookup, as the process experiences a malfunction.

C. The Momentum Balance

The analysis of momentum balance in a control volume requires more information than does that of mass and energy . In addition to the knowledge of temperature and pressure for the control volume under consideration, momentum balance also requires information about the fluid velocity. The product of the fluid velocity v and the total mass M defines momentum $\mathcal{M}$, as described in Eq. (3). Since the fluid velocity v is generally obtained through measurements of the mass flow rate W, where W = v ρ A, with A being the cross-sectional area of the control volume, Eq. (3) can be rewritten in terms of W, with the use of Eq. (1),

$$\mathcal{M} = L\,W, \tag{10}$$

where L is the length of the control volume. Since L is fixed for a given volume, the analysis of momentum balance is directly obtained through the differential

$$d\mathcal{M} = L\,dW. \tag{11}$$

Hence, momentum is added to a control volume if the associated measured flow rate W is increasing and it is subtracted from a control volume if the associated measured flow rate is decreasing.

Functional Classification of Components

The methodology for process diagnosis presented in this paper relies on the characterization of imbalances in the process components, as described in the foregoing paragraphs, along with the functional classification of the components. Each component type, e.g., pipe, pump and electric heater, is functionally classified according to the component influence in causing an imbalance in the conservation equations if and when the component fails. For example, a pump should be functionally classified as a source or sink of momentum because a pump failure causes an imbalance in the momentum conservation equation. This method differs from other approaches to functional characterization of components [Finch and Kramer] in that each component type is classified only once and that the classification is based on physical laws, as opposed to multiple and judgmental classification based on the importance of the component in a given context.

Table VI illustrates the functional classification of some of the most common components present in industrial processes. For instance, the last component in the table, a valve, functions both as a sink or source of momentum. A valve leak or unexpected closure would cause a negative balance in the momentum conservation equation, yielding a functional classification for the valve as a momentum sink. On the other hand, an unexpected valve opening would cause a positive balance in the momentum equation, yielding classification as a momentum source. The classification presented in Table VI represents the major influence of a component in one of the three (mass, energy and momentum) balance equations. Each component type can, however, be hierarchically classified according to the component capability in disturbing each one of the three balances. A hierarchical component classification would increase the comprehensiveness of the diagnosis but it would, most likely, depend on the phase of the substance, e.g., liquid or vapor, being transported through the component.

Table VI. Functional Classification of Components.

Component	Functional Classification
Pump	Momentum Source or Sink
Pipe	Momentum Source and Sink
Electric Heater	Energy Source or Sink
Valve	Momentum Source or Sink

Process Structural Representation

In addition to the functional behavior of the various systems and components of a process plant, plant operators also use their understanding of the structural arrangement of these components when faced with unexpected scenarios and being forced to diagnose the unfolding event and make corrective control actions. The operator's structural understanding of the process relates to graphical or schematic representations of the plant in the form of piping and instrumentation diagrams (P&IDs). Since the information content of a P&ID is essential for diagnosing process malfunctions and it is readily available, for a given process, it has been constantly used as part of the knowledge base of a process diagnosis expert system. In the first generation of expert systems, the information content of the P&IDs was embeded in the production rules. More recently, the P&IDs have been represented in a separate knowledge base [Hashemi] which allows for complete independence between the diagnosis methodology and the plant process. The following paragraphs describe the representation of schematic diagrams within the context of the proposed diagnosis methodology.

In this work, the structural domain knowledge of schematic diagrams of a process is represented through directed graph structures and is compiled in a separate knowledge base. The description of a schematic diagram by a graph structure is achieved through a straightforward nodalization process. Each component or component part in a schematic diagram is a node of the graph, while each connection between two components corresponds to an edge. When the edges are directed, i.e., represented by ordered pairs, the graph is a directed graph. Furthermore, a graph structure can be decomposed into loops, i.e., sub-graphs, just as one defines loops or circuits in a schematic diagram.

Figure 1 illustrates the schematic diagram of a balance of plant (BOP) for a liquid metal nuclear reactor (LMR) plant. The nodalization of the components in Figure 1 that fall inside the dashed lines is represented in Figure 2. Each component or component part surrounded by the dashed lines in Figure 1 corresponds to a node in Figure 2, while the physical connections between components, i.e., the pipings, are represented by the directed edges or arcs of the graph structure in Figure 2. The possible paths between two components and the distinction between heater tube and shell sides in the schematic diagram are characterized in the graph structure as distinct loops.

The knowledge base corresponding to the directed graph structure representation of a schematic diagram describes three kinds of information: component specific, intra-loop and inter-loop.

(i) Component specific information - describes the characteristics of each component including: component name, type, fluid phase, value and trend of four plant parameters (temperature, pressure, liquid level and flows), and behavior (source or sink of mass, momentum and energy).

(ii) Intra-loop information - describes all possible paths between any two components in a given loop.

(iii) Inter-loop - describes which components of a loop are adjacent to components of another loop and all possible paths between any two components of distinct loops.

This knowledge base is the only process-dependent data of the proposed diagnosis methodology, and it can be easily improved or modified to accommodate any changes in the process.

DIAGNOSIS PROCEDURE

After the methods for estimating macroscopic imbalances, classifying components and describing the process schematics have been developed, diagnostic rules and procedures can be applied to identify the possible faulty components. In essence, the diagnostic procedure first identifies a component malfunction with respect to violations in the conservation equations and then relates unusual changes in these factors with appropriate component functionality and location. The diagnostic procedure assumes the occurrence of single faults and availability of validated sensor measurements in the process components. In addition, knowledge of the correct state of the process at the onset of the malfunction is also assumed to be known. The single-fault assumption, and that of complete availability of sensor measurements are not constrained by the proposed methodology and may be relaxed in future developments and implementations of the algorithm.

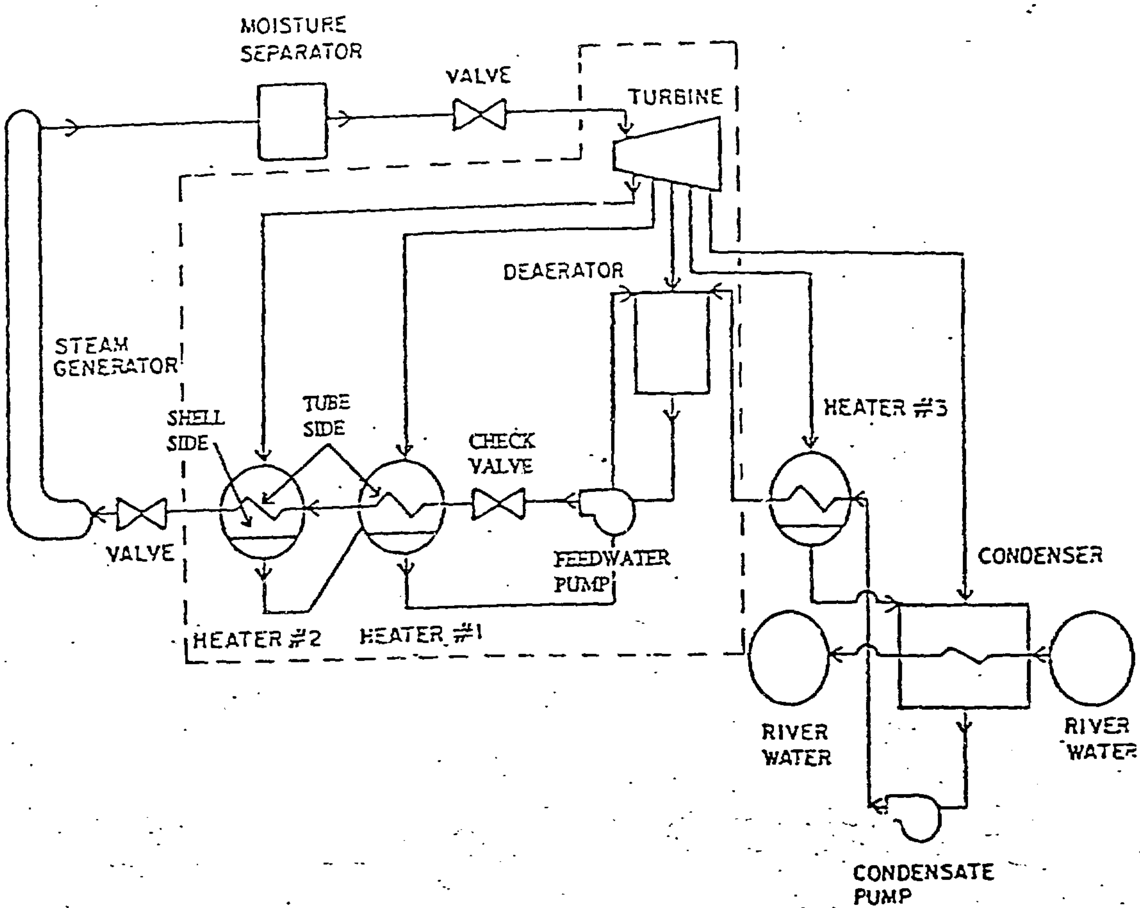

Figure 1. Schematic Diagram of a Balance of Plant for a Liquid Metal Nuclear Reactor Plant.

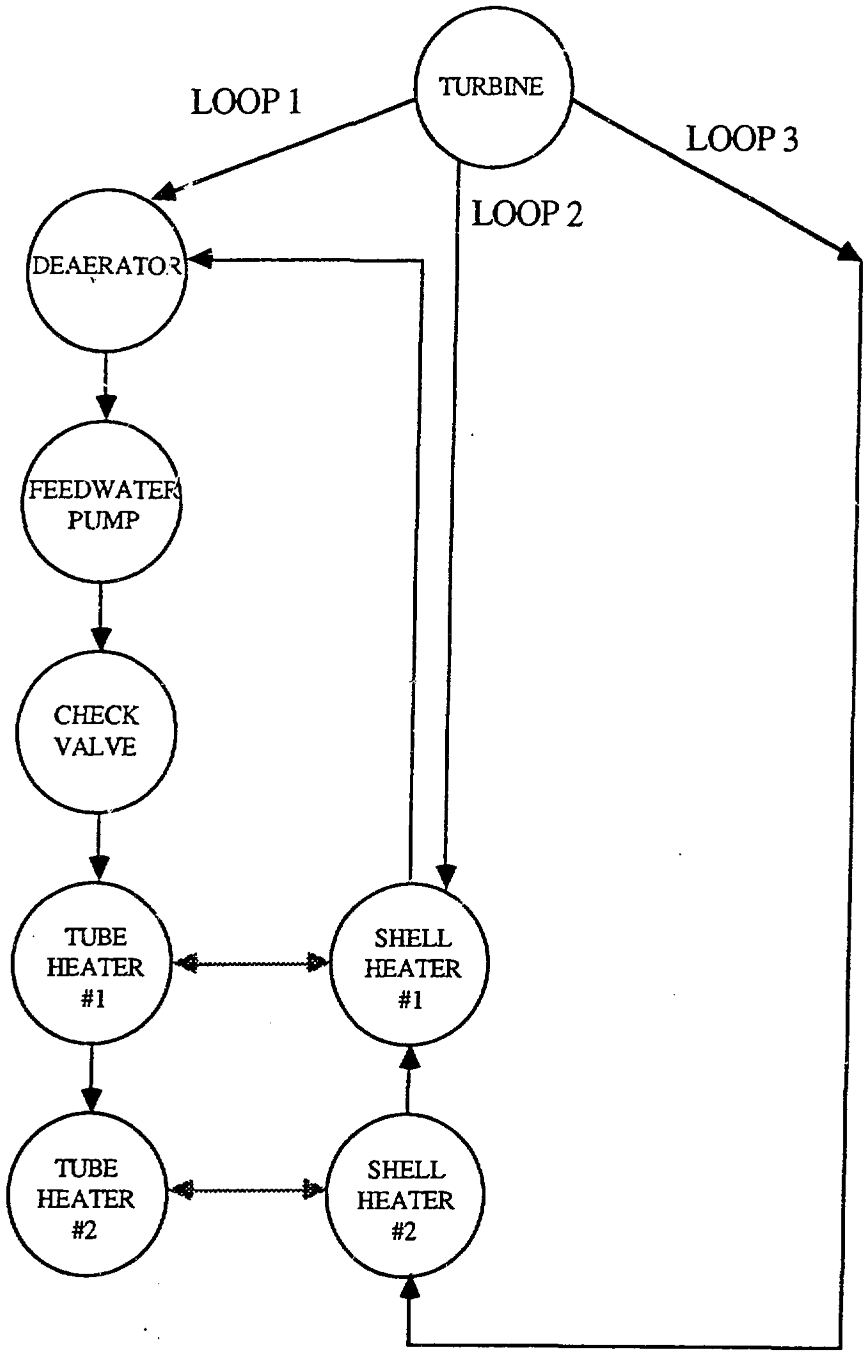

Figure 2. Directed Graph Structure Representation.

The initiating process fault will cause one or more of the four monitored sensor measurements (temperature, pressure, liquid level and flow) to deviate from the expected state in one or more components. The diagnosis procedure for these misbehaving components involves the following four steps:

1. State deviations and corresponding increasing or decreasing trends are defined by establishing threshold values [Finch and Kramer] for each one of the four sensor measurements and comparing the expected component state with associated measurements.

2. Based on the trends of the varying measurements and the condition of the components (subcooled liquid, saturated, superheated steam), the precompiled physical rules of Tables IV and V and/or table lookup through the steam tables are used to characterize mass and energy imbalances in the components. Momentum imbalances are characterized through direct measurements of mass flow rates. The increasing or decreasing imbalance directions characterize the behavior of each component as a source or sink, respectively, of mass, energy and momentum.

3. A set of possible faulty component types, e.g., pump, pipe and electric heater, is generated by matching the type (mass, momentum or energy) and direction (source or sink) of estimated imbalances against a component functional database such as the one described in Table VI.

4. Faulty component candidates are hypothesized if the type of the misbehaving components matches one of the component types generated by step 3. The matching process is implemented through the knowledge base that describes the schematic diagrams of the process.

The diagnosis procedure can be better understood through an example. An unexpected reduction of the pump motor torque of the feedwater pump in Figure 1 would cause a slight pressure increase upstream of the pump, a pressure decrease downstream and a decrease of the mass flow rate both up and downstream of the malfunctioning pump. These deviations cause the components up and downstream of the pump, which are transporting subcooled liquid, to behave as momentum sinks. The functional classification of pumps and valves as sources or sinks of momentum and the existence of these two component types in the group of misbehaving components flag the feedwater pump and check valve as possible faulty components. Detailed diagnosis, to distinguish between a pump and a valve failure, can now be applied.

TEST PROBLEM

The methodology presented in the last two sections has been incorporated in a prototype expert system for on-line process diagnosis. The diagnosis system is written in Prolog and consists of three distinct knowledge bases and an inference engine. The knowledge bases for estimating the macroscopic imbalances in mass, momentum and energy and that describing the functional classification of components are based on physical principles and so are process-independent and are constructed once for analysis of any process. The third knowledge base, describing the process schematics, is created through a query session with the user that automatically generates Prolog procedures representing the process. This knowledge base is process-specific; however, it is isolated from the rest of the system and can be easily modified or reconstructed for different processes. The inference engine is also general and process-independent and consists of the diagnosis procedures of the previous section and rules for controling the search.

To test the prototype expert system, a test case representing the BOP for a LMR plant illustrated in Figure 1 has been selected. The BOP contains subcooled water with the exception of the shell side of all heaters and in the line beyond the saturation point inside the steam generator. The entire LMR plant, from the reactor core (not shown in Figure 1) to the waterside condenser, is modeled with the SASSYS-1 system analysis code [Dunn et al., Briggs, Ku] to simulate four malfunctions:

1. Reduction of the feedwater pump motor torque by 50%,
2. Closure of the feedwater check valve area to 10% of nominal,
3. Rupture of the piping connecting the tube side of heaters #1 and #2 at a constant rate of 30 kg/s, and
4. Rupture of the piping connecting the shell side of heaters #1 and #2 at an increasing rate of 0.2 kg/s.

All four process malfunctions are correctly hypothesized by the expert system within 11s into the transient. In the first two cases, however, both feedwater check valve and pump are selected as possible faulty component candidates. This is due to the fact that the two components, valve and pump, are functionally classified as source or sink of momentum, and the failure of either one would cause the components of the tube-side loop, from the deaerator to the steam generator, to behave as a momentum sink. In this case, a more detailed diagnosis, perhaps involving quantitative simulation, is required to distinguish between the two faults. The last two events characterizing pipe ruptures in the the tube and shell sides, respectively, are uniquely hypothesized by the expert system. A tube rupture causes the upstream components to behave as momentum sources while causing the downstream components to behave as momentum sinks. Hence, by classifying a pipe as a sink and source of momentum and knowing which components are behaving as sources of momentum and which are behaving as sinks of momentum, the type and location of the malfunction is uniquely determined.

CONCLUSIONS AND FUTURE WORK

The presented methodology appears to provide a powerful and effective approach for incorporating basic first-principles into the knowledge base of a general process diagnosis system. The methodology identifies faulty component candidates which can then be singled out with deep-knowledge reasoning. The use of basic physical principles produces a small, general and comprehensive set of diagnostic rules and methods which are physically correct. The generality of this approach is achieved through the clear separation of the process-dependent schematics representation from the remaining process-independent knowledge bases and inference engine. These factors produce a robust process diagnosis methodology which can be effectively verified and validated through standard techniques.

Several different areas are currently being investigated to expand the comprehensiveness of the method and relax some assumptions. In order to increase the comprehensiveness of the method, a hierarchical functional classification of the components to each one of the three (mass, energy and momentum) balance equations is being investigated. In addition, the proposed methodology needs to handle the propagation of secondary or side effects caused by the initiating malfunction. Studies of qualitative modeling through causal reasoning are being investigated to account for the propagating effects. The assumption of complete availability of certain sensor measurements could be relaxed, in favor of a more realistic situation of limited instrumentation, through a set of physically-based rules that extrapolate data based on the existing instrumentation. The single-fault assumption can be relaxed, for the faults that cause non-masking effects on the measurements, by expanding the inference engine to represent multiple failures.

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