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A diagnostic expert system for helping the operation of hazardous waste incinerators

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Abstract

This paper presents a diagnostic expert system for detecting sensor failures of the incinerator control system. The domain knowledge of the system is based on system models, causal relationships among failure events, and the heuristic operator knowledge for handling off-normal situations. The inference functions of the diagnostic system are jointly provided by rule-based backward/forwarding chaining, causal relationship-based Bayesian network inference, and system model-based Kalman filtering inference. As examples of applying the proposed framework, failure diagnosis of the steam temperature regulator and the detection of thermocouple drifts are presented.

1. Introduction

The regulation of emissions from hazardous waste incinerators is defined in terms of steady state operations within a defined operating range. However, emissions may vary markedly from those at steady state during transients or due to operational failures. Furthermore, unnoticed drifts from defined operating conditions may lead to a marked increase in one type of emission, say, submicron metal aerosols, even though the destruction efficiency of the principal organic waste stays in the required range. Due to diversity of waste composition, system malfunction, lack of operator experience and operator error, off-normal situations may occur during the operation of incinerators. Particulate, metal products of incomplete combustion (PICs) and hydrogen chloride (HCl) emissions may go beyond the regulation limits.

Under off-normal situations, operators use sensor information or alarm signals to do fault diagnosis based on their training and operating experience. When a system alarm is activated, the operator determines the seriousness of the situation and initiates appropriate action. The diagnostic decision is based on the type of alarm, the value of related process variables, and the operator's background, training, and mental model of the system. This human decision process has certain disadvantages. First, the availability of process experts may

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depend on work shift, vacations, and the like. Second, operators may be well-trained in standard procedures but ill-equipped to handle unusual events such as spurious signals, and wrong controller set-values due to human error, etc, and stress associated with emergency situations can compound the difficulty of decision making. Third, the operator's logic model of the process may be incorrect. Therefore, when systems are very complex and as the information available to operators increases, it becomes more difficult to rely on human operators for diagnosis.

In recent years, research in the field of Artificial Intelligence (AI) has had many important successes. Among the most significant of these has been the development of powerful computer systems known as "expert" or "knowledge-based" systems. These computer systems are designed to represent and apply factual knowledge of specific areas of expertise to solve problems. The potential usefulness of expert systems has led to worldwide efforts to apply them to various technologies [1]. Expert systems that perform diagnosis use situation descriptions, monitoring data, behavior characteristics, and some other knowledge about the system to infer probable causes of system malfunctions. These systematic and automatic diagnosis functions should allow a more rapid and detailed analysis of the problem in a timely fashion and reduce errors in human judgement.

The problem of diagnosis has been addressed by many authors and is the subject of books by Himmelblau [2] and Pau [3]. Qualitative approaches involving fault trees and related diagrams have been reviewed by Lees [4]. Quantitative approaches involving filtering and estimation have been reviewed by Isermann [5]. An extensive survey of diagnostic expert systems was provided by Pau [6] and Gilmore and Gingher [7].

The automation of fault diagnosis was primarily handicapped in the past by the lack of appropriate techniques to represent the knowledge-based, symbolic reasoning of an expert diagnostician. Many of the past approaches in applying expert system methodology to fault diagnosis have focused on designing systems that reason with deterministic knowledge that is system or process specific. Such systems often lead to erroneous conclusions when confronted with unanticipated faults.

Although expert systems have been put into practical use in other applications, such as medical diagnosis [8], expert system development for hazardous waste incinerators is still in its infancy. Very few papers have been published [9,10]. This paper is on the application of the developed methodology for real-time expert systems [11–14] to a hazardous waste incineration system. This expert system is developed to perform diagnosis of sensor or system component failures during operation of an incinerator. The diagnosis system infers the most probable causes of control system malfunctions from the observed evidence.

The domain knowledge representation of the diagnostic expert system for a liquid injection incinerator is based on system models, the physical interconnections of the instrument elements, and the causal relationships among failure events as well as heuristic operator knowledge for handling off-normal situations. The system models consists of a set of discrete stochastic state equations which represent the relationships between the system state variables and the control variables, and a set of discrete stochastic measurement equations which describe the relationships between the real-time monitored state variable and the unmeasurable state variables. The causal-consequence relationships among failure events are represented by Bayesian networks [15] which are directed acyclic graphs in which the nodes represent failure events, the arcs signify the existence of direct causal influence between the linked failure events, and the strengths of these influences are quantified by conditional probabilities. The rules and facts are collected based on system design and operating experience with incinerators. Based on the created knowledge base, Kalman filter theory [16] and Bayesian inference theory [15] are used to perform diagnosis of the most probable sensor or control system failures under off-normal situations.

2. Inference engines for diagnosis

Expert systems that perform diagnosis use situation descriptions, behavior characteristics, or knowledge about the system to infer probable causes of system malfunctions. Examples are determining the causes of diseases from symptoms observed in patients, locating faults in electrical circuits, detecting spurious sensor signals in a process control system, finding defective components in a chemical treatment plant, and inferring the proper causes of inflation in an economical system, etc. Diagnosis systems are often consultants that not only diagnose the problem but also predict possible hidden failures. They may interact with the user to help find the faults and then suggest courses of action to correct them.

2.1 Diagnosis by a rule-based system

Rule-based diagnosis approaches systematize the thought process that human experts use to perform diagnosis. Rule-based expert systems can capture engineering design and operating experience and make it available at all times. By using empirical knowledge, diagnosis can be very efficient as the length of the reasoning process required to reach a conclusion tends to be quite small.

Many cases of diagnosis (especially medical diagnosis) have been successfully demonstrated through the development of first generation expert systems which use only the so-called shallow or heuristic knowledge of human experts in the form of production rules [8]. Shallow knowledge in this form constitutes a heuristic association between observed data and either an intermediate or final diagnostic conclusion. These associations are based on the empirically derived knowledge of human experts and represent the compilation of a deeper

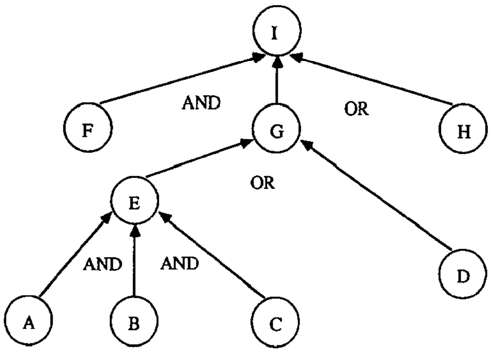


Fig. 1. A typical inference tree.

understanding of the problem domain. This reasoning process constructs a logical inference chain which begins with the given data and ends with a diagnostic conclusion produced by inferring the strongest association of the given symptoms.

In order to discuss diagnosis by rule-based systems, we present the inference tree conception. As is well known, each rule consists of a premise (or a condition, or a cause) part and a conclusion (or an action, or a consequence) part. We can construct a tree whose nodes are the clauses used in the rule and whose branches are arrows connecting the clauses. When clauses are joined by an AND connective, we have an "AND node", whenever clauses are joined with the OR connective, we have an "OR node". Sometimes nodes may consist of both an AND connective and an OR connective; then we call them "AND/OR nodes". The branching in such trees reflects the structure of a set of rules. Such trees are called inference trees.

These trees often provide a good intuition about the structure of the rules. By using these trees, we can visualize the process of inference as a movement along the branches of the tree. This is called tree traversal. To traverse an AND node, we must traverse all of the nodes below it, i.e., we have to prove every clause in the AND node. To traverse an OR node, it is sufficient to traverse just one of the nodes below, i.e., to prove just one of the OR conditions. A typical inference tree is shown in Fig. 1. The corresponding rules are

RULE 001
  IF A and B and C
  THEN E
RULE 002
  IF E or D
  THEN G
RULE 003
  IF F and G or H
  THEN I

In order to perform diagnosis, we start at the root of the tree and follow the branches toward the leaves until we find causes of the observed consequences.

2.2 Diagnosis by using Bayesian networks

Many cases of diagnosis have been demonstrated through the development of first generation expert systems which mainly use the shallow or heuristic knowledge of human experts in the form of production rules. Expert systems based only upon heuristics (rule-based knowledge) lack a detailed model framework to analyze process operation and control. This limits their completeness, their ability to perform diagnosis beyond current operating experience, and their usefulness in tracing and explaining the diagnosis.

Diagnosis expert systems based on rule-based knowledge alone can prove to be inadequate in terms of completeness, performance, flexibility, and explanation capabilities. To overcome these difficulties, different sources of knowledge about the diagnosis have to be modeled in the expert systems. In particular, deep knowledge of the domain should be used in the diagnostic expert systems. Deep knowledge allows the expert to consider theorems and axioms of the application area to reach a solution. Deep knowledge provides the lower level (causal, functional, and physical) information involved in a diagnostic environment and permits a more accurate modeling of the problem domain.

In this section, we present a diagnosis approach based on probabilistic causal knowledge: Bayesian networks [15]. Diagnosis is performed using Bayesian inference. Multiple faults can be diagnosed by propagating each new piece of evidence (consequences) through the network via local communication among neighboring nodes, with minimum external supervision. At equilibrium, each variable in the whole network has a specified probabilistic value which, together with all other value assignments, is the optimal global probabilistic interpretation of the observed faults.

Let E stand for all the observed faults (evidence) and W stand for the set of all variables in the Bayesian network, including those in E. Any assignment of values to the variables in W that is consistent with E will be called a diagnostic interpretation of E. Our diagnostic problem is to find a W^* that maximizes the conditional probability $P(W/E)$. In other words, W^* is the most-probable-explanation (MPE) of the observed faults E if

$$P(W^*/E) = \underset{W}{\mathrm{MAX}}\, P(W/E) \tag{1}$$

The task of finding W^* will be performed locally, by letting each variable X compute the function

$$\mathrm{BEL}^*(X) = \underset{W_x}{\mathrm{MAX}}\, P(X, W_x/E) \tag{2}$$

where $W_x = W - X$. Thus, $\text{BEL}^*(X)$ stands for the probability of the most probable explanation of E that also is consistent with the hypothetical assignment $X = x$.

The diagnosis inference engine presented here is based on the following decomposition principle: For every value x of a singleton variable X, there is a best assignment of the complementary variables W_x^* which are the best explanation of the observed faults and are consistent with the hypothetical assignment $X = x$. Because there are so many independence relationships embedded in the network, the problem of finding the best explanation $X = x$ and E can be decomposed into finding the best complementary explanation for each of the neighboring nodes, then using this information to choose the best value of X. This process of decomposition, which resembles the *principle of optimality* in dynamic programming, can be applied recursively until, at the network's periphery, we meet evidence variables whose fault values were observed, and the process halts. Detailed description of the Bayesian diagnosis inference engine can be found in reference [11]. We summarize the algorithm as follows.

For a given Bayesian network, if node X has n parents, $U = \{U_1, U_2, \ldots U_n\}$, and m children, $Y_1, Y_2, \ldots, Y_m$, and node X receives the messages $\Pi^*_{U_i \to X}(U_i)$ $(i = 1, 2, \ldots, n)$ from its parents and $\lambda^*_{X \leftarrow Y_j}(X)$ $(j = 1, 2, \ldots, m)$ from its children.

Using these $n + m$ messages together with the fixed conditional probability matrix $P(X/U_1, U_2, \ldots, U_n)$, X can identify its best value and further propagate these messages using the following three steps:

*Step 1 - updating BEL**

When node X is activated to update its parameters, it simultaneously inspects the $\Pi^*_{U_i \to X}(U_i)$ and $\lambda^*_{X \leftarrow Y_j}(X)$ messages communicated by each of its parents and children and forms the product

$$F(X,U) = \prod_{j=1}^{m} \lambda^*_{X \leftarrow Y_j}(X) P(X/U) \prod_{i=1}^{n} \Pi^*_{U_i \to X}(U_i) \tag{3}$$

This F function enables X to compute its $\text{BEL}^*(X)$ function and simultaneously identify the best value of X^* from the domain of X:

$$x^* = \underset{X}{\text{MAX}^{-1}}\ \text{BEL}^*(X) \tag{4}$$

where

$$\text{BEL}^*(X) = \beta \underset{U}{\text{MAX}}\ F(X,U) \tag{5}$$

and β is a constant that is independent of X and need not be computed in practice.

Step 2 – Updating λ^* messages

Using the F function computed in Step 1, node X computes the messages to its parents by performing n vector maximizations, one for each parent:

$$\lambda^*_{U_i \leftarrow X}(U_i) = \underset{X,U_k:k\neq i}{\text{MAX}} [F(X,U) \mid \Pi^*_{U_i \rightarrow X}(U_i) = (1, 1, ..., 1)]$$

$$(i=1, 2, ..., n) \tag{6}$$

Step 3 – Updating Π^* messages

Using the BEL* (X) function computed in Step 1, node X computes the messages to its children by

$$\Pi^*_{X \rightarrow Y_j}(X) = \text{BEL}^*\ (X) / \lambda^*_{X \leftarrow Y_j}(X) \tag{7}$$

The boundary conditions are summarized below for the sake of completeness:
1. Anticipatory node: representing an uninstantiated variable with no successors. For such a node X, we set $\lambda^*_{X \leftarrow Y_j}(X) = (1, 1, ..., 1)$.
2. Observed fault node: representing instantiated leaf nodes. If variable $X = \mathrm{x}_i$, we introduce a dummy child Z with $\lambda^*_{X \leftarrow Z}(X) = (0, 0, ..., 1, ..., 0)$ (with 1 in the x_i position)
3. Root node: representing a variable with no parents. For each root variable X, $\Pi^*(X)$ is equal to the prior probability of node X.

These boundary conditions ensure that the messages defined in eqns. (6) and (7) retain their correct semantics on peripheral nodes.

2.3 Structure of the diagnosis system

Of primary importance in determing the performance of a diagnostic expert system is understanding actually what knowledge is to be used and how that knowledge should be formalized, represented, and integrated. In previous sections, we discussed the diagnosis inference engine by rule-based and causal deep knowledge networks. In this section, we present an integrated diagnostic inference engine based on heuristics, causal knowledge, and the system model-based deep knowledge.

Figure 2 shows a block diagram for fault diagnosis. If a system fault appears, it has to be detected as early as possible. This can be done by checking if particular measurable or unmeasurable estimated state variables are within a certain tolerance of the normal value. If this check is not passed, this leads to a fault message. The functions up to this point are generally called monitoring or, as indicated in the first block of Fig. 2 (feedback loop), as fault detection. Once the fault messages are received, the integrated diagnosis system is activated to find out the causes of the faults, the size of the faults, and the time

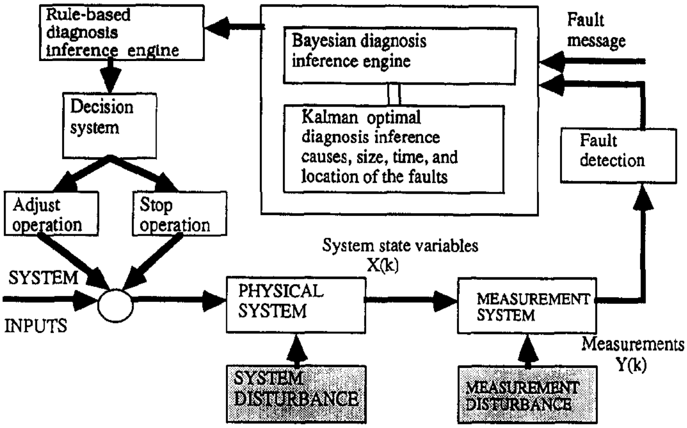


Fig. 2. Structure of the integrated diagnosis system.

when the faults occur. The next step is the fault evaluation, that means an assessment is made of how the fault will affect the system.

After the effect of the fault is known, a decision on the action to be taken can be made. If the fault is evaluated to be tolerable, the operation of the system may continue and if it conditionally tolerable, an adjustment has to be performed. However, if the fault is intolerable, the operation must be stopped immediately and the faults must be eliminated.

How to use the observed fault messages to find out the probable causes and size of the fault is the essential task of the diagnosis inference engine. If we use the discrete linear stochastic system model, this diagnosis problem can be stated as follows:

Consider a dynamic system S whose state variables as a function of time are a discrete-time stochastic process $\{X(k), k \in T\}$. Suppose that we are interested in knowing the value of $X(k)$ for some fixed k, but that $X(k)$ is not directly accessible to us for observation. Suppose further, then, that we have made a sequence of measurements $Y(1)$, $Y(2)$, ..., $Y(N)$ $(N>k)$ which are causally related to $X(k)$ by means of some measurement system as shown in Fig. 2 and that we wish to utilize these observed data to infer the value of $X(k)$, which we call as $\hat{X}(k/N)$.

For the diagnosis problem, we have N observations: $Y(1)$, $Y(2)$, ..., $Y(N)$. We want to know what is the actual system state status $\hat{X}(k/N)$ $(k=0, 1, 2, ..., N-1)$ which leads to such a set of observations.

Basically, this corresponds to the following practical situation. With the information observed, we have monitoring data over the fixed interval $[0, N]$. For each time point k within the interval, we wish to obtain the optimal inference $\hat{X}(k/N)$ of the state $X(k)$ which is based on all the available measurement data $Y(j)$ $(j=1, 2, ..., N)$.

Our primary interest here is to have a relationship between $\hat{X}(k/N)$ and the observed information $Y(1)$, $Y(2)$, ..., $Y(N)$. In particular, we wish to have an inference engine which is recursive in time, thereby permitting us to perform diagnosis efficiently with a computer. The algorithms can be derived by using Kalman filtering theory [16] and the results can be found in reference [11].

As is shown in Fig. 2, the integrated diagnosis system consists of rule-based heuristic inference, Bayesian network inference, and Kalman filtering inference. These inference functions are jointly provided by rule-based backward/forward chaining, cause-consequence relationship-based Bayesian inference theory and system model-based Kalman filtering inference theory. When the reasoning is based on rule-based knowledge, backward chaining is used to perform diagnosis. If the domain knowledge is represented by Bayesian networks, the reasoning conclusions are obtained by propagating the observed evidence through the whole network. When the knowledge base for the target problem is system model-based, Kalman filtering theory is used to perform inference. The inference is to determine an approximation to the time history of the system's response variables from the erroneous measurements. The approximation is to be chosen so that the estimate error is minimized. Therefore, the obtained approximation of the observed data is optimal in the sense of best estimate of the real situation.

3. Detecting failures of incinerator control system

The diagnosis inference engines presented in Section 2 are system or process independent. In other words, they can be applied to any diagnosis problems as long as the diagnosis problem can be well defined by using heuristic rules, probabilistic causal networks and functional system models. As examples of how to apply the proposed diagnosis method, failure diagnosis of steam temperature regulator and the detection of thermocouple drifts are presented in this section.

3.1 Combustion boiler control system

Figure 3 shows the combustion-boiler instrumentation system of a liquid injection incinerator. There are three control functions provided by the instrumentation system. They are control of the waste organic flow rate and the amount of excess air (V-12–V-13), the three-element feedwater control system (LT-FE-FIC-V-03), and the steam temperature regulator (TE-408–TIC-408–V-09). These three controllers are designed to control the following nine state variables: X_1 (enthalpy of water in mud drum), X_2 (amount of water in drum), X_3 (the mean density of steam–water mixture in risers), X_4 (density of the steam), X_5 (primary superheater tube temperature), X_6 (secondary superheater tube temperature), X_7 (desuperheater tube temperature), X_8 (economizer tube temperature), and X_9 (air preheater tube temperature). The system state

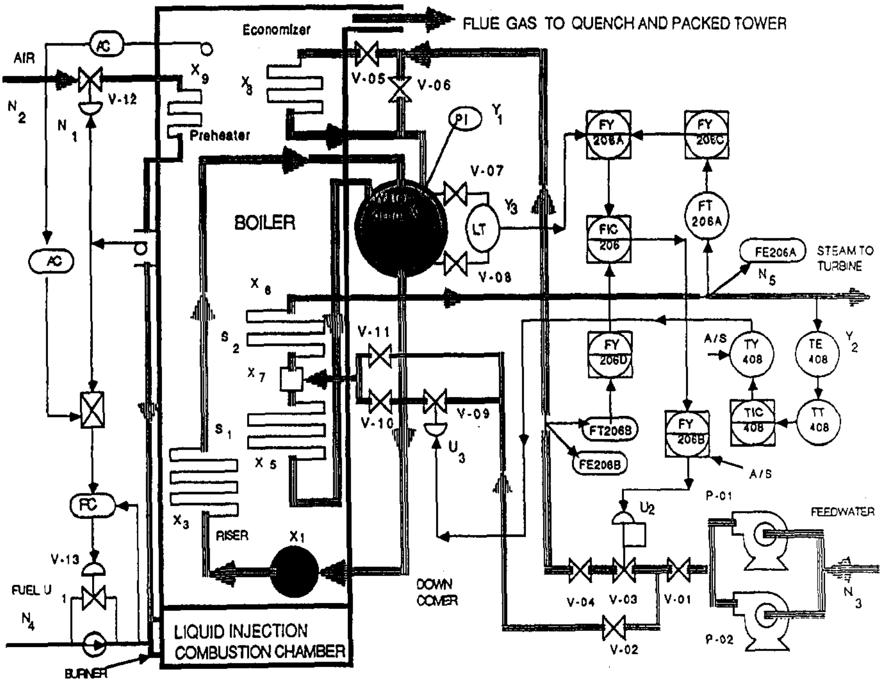


Fig. 3. The incinerator-boiler system.

variables are controlled by three control variables: U_1 (fuel and organic waste flow rate), U_2 (feedwater flow rate), and U_3 (desuperheater bypass valve position); they are affected by five input variables: N_1 (excess air), N_2 (air temperature), N_3 (feedwater temperature), N_4 (fuel temperature), and N_5 (steam flow rate).

3.2 Diagnosis of steam temperature regulator malfunctions

As shown in Fig. 3, thermocouple TE-408 measures the temperature of high pressure steam to the turbine and temperature transmitter (TT-408) transmits a signal to remote temperature indicating controller (TIC-408) in console display screen. TIC-408 sends a control signal to local I/P converter (TY-408). TY-408 converts the electric signal to a pneumatic signal which modulates the temperature control valve V-09.

As shown in the figure, many valves, pumps, sensors, transmitters, indicators, recorders, relays, and regulators are served as part of the operation system to control the steam temperature. Any of these instrument components may fail for a variety of reasons during the operation period. Thermocouple TE-408 may fail to measure the steam temperature correctly; or the temperature transmitter TT-408 may fail to transmit the signal to the relay TY-408, which leads to the failure of the steam temperature control system. It is not difficult to understand that the failure rate of different components should be different. In addition, the failure probability of the same component should be different for different periods of operation.

The Bayesian network for the steam temperature control system has been constructed causally and is shown in Fig. 4. $X1$ through $X11$ are used to represent the failure of the individual instrument components in the steam temperature control system (as described in Table 1). Parameters $Y1$ through $Y5$ are explained as follows:

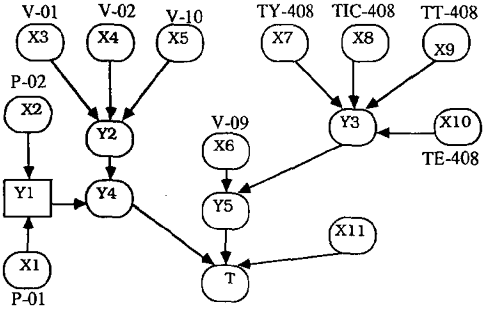
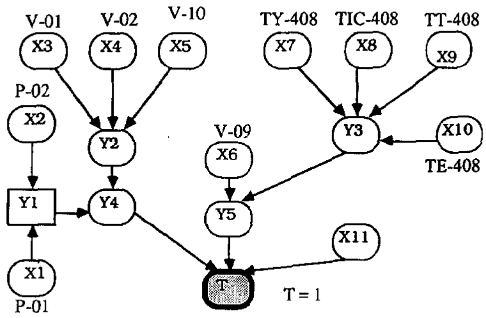


Fig. 4. Bayesian network for the failure of the steam temperature regulator.

TABLE 1

Quantification of the Bayesian network for the steam temperature regulator

Root nodes	Description of the components	Failure rate (std-500-1984) failures/10+6h	Prior failure probability (2 years) (A)	Prior failure probability (5 years) (B)	Prior failure probability (5 years) (C)
$X1$	Centrifugal pump (P-01)	543.0 (p.1001)	0.907 (0.5 y)	0.907 (0.5 y)	0.907 (0.5 y)
$X2$	Standby centrifugal pump (P-02)	20.00 (p.918)	0.084 (0.5 y)	0.084 (0.5 y)	0.084 (0.5 y)
$X3$	Gate (>3″) (V-01)	1.60 (p.1110)	0.028	0.068	0.068
$X4$	Gate (>3″) (V-02)	1.60 (p.1110)	0.028	0.068	0.068
$X5$	Gate (>3″) (V-10)	1.60 (p.1110)	0.028	0.068	0.068
$X6$	Pneumatic diaphrag m (V-09)	3.49 (p.1126)	0.059	0.142	0.142
$X7$	Temperature relay (TY-408)	3.02 (p.529)	0.052	0.124	0.124
$X8$	Temperature indicator (TIC-408)	9.0 (p.544)	0.039 (0.5 y)	0.039 (0.5 y)	0.326
$X9$	Temperature transmitter (TT-408)	2.39 (p.530)	0.041	0.099	0.099
$X10$	Thermocouple (TE-408)	9.19 (p.546)	0.040 (0.5 y)	0.040 (0.5 y)	0.331
$X11$	Desuperheater	2.70 (p.1356)	0.046	0.112	0.112



$\pi^*(X1) = (0.907, 0.093)$ $\pi^*(X2) = (0.084, 0.916)$ $\pi^*(X3) = (0.068, 0.932)$
$\lambda^*(X1) = (1.000, 1.000)$ $\lambda^*(X2) = (1.000, 1.000)$ $\lambda^*(X3) = (0.196, 0.096)$

$\pi^*(X4) = (0.068, 0.932)$ $\pi^*(X5) = (0.068, 0.932)$ $\pi^*(X6) = (0.142, 0.858)$
$\lambda^*(X4) = (0.196, 0.096)$ $\lambda^*(X5) = (0.196, 0.096)$ $\lambda^*(X6) = (0.213, 0.105)$

$\pi^*(X7) = (0.124, 0.876)$ $\pi^*(X8) = (0.326, 0.674)$ $\pi^*(X9) = (0.099, 0.901)$
$\lambda^*(X7) = (0.208, 0.035)$ $\lambda^*(X8) = (0.271, 0.045)$ $\lambda^*(X9) = (0.204, 0.034)$

$\pi^*(X10) = (0.331, 0.669)$ $\pi^*(X11) = (0.112, 0.888)$ $\pi^*(Y1) = (0.076, 0.831)$
$\lambda^*(X10) = (0.274, 0.045)$ $\lambda^*(X11) = (0.206, 0.102)$ $\lambda^*(Y1) = (0.220, 0.109)$

$\pi^*(Y2) = (0.059, 0.810)$ $\pi^*(Y3) = (0.176, 0.356)$ $\pi^*(Y4) = (0.062, 0.673)$
$\lambda^*(Y2) = (0.226, 0.111)$ $\lambda^*(Y3) = (0.513, 0.085)$ $\lambda^*(Y4) = (0.272, 0.134)$

$\pi^*(Y5) = (0.151, 0.306)$ $\pi^*(T) = (0.090, 0.183)$
$\lambda^*(Y5) = (0.598, 0.075)$ $\lambda^*(T) = (1.000, 0.000)$

Fig. 5. Bayesian network for fault diagnosis of the steam temperature regulator.

*Y*1 is the failure of the feedwater pump system.
*Y*2 is the failure of all the valves.
*Y*3 is the failure of all the temperature measurement elements.
*Y*4 is the failure of both pump system and all the valves.
*Y*5 is the failure of the temperature regulator.

The quantification of this Bayesian network is based on the IEEE Std-500-1984 failure rate handbook. For convienence, we assume that all the nodes in the network can take either failure status (1) or success status (0). The internal elliptical nodes are OR gate and the internal rectangular nodes are AND gate. Based on the IEEE Std-500-1984 failure rate handbook, prior failure probabilities of the individual instrument elements are estimated and given in Table 1. Here, we assume the failure is exponential. In other words, the relationship between failure probability and failure rate is given by following equation.

$$P(t) = 1 - e^{pt},$$

where p is the element failure rate.

$P(t)$ is the failure probability of the corresponding element at time t. The quantification of the Bayesian network corresponds to the following system operation conditions:

Operation condition A

1. The system has been operated for 2 years.
2. The feedwater pumps (P-01 & P-02) have been on service for 0.5 years.
3. Thermocouple (TE-408) had been replaced for 0.5 years.

4. The temperature indicating controller (TIC-408) had been replaced for 0.5 years.

Operation condition B.

1. The system has been operated for 5 years.
2. The feedwater pumps (P-01 & P-02) have been on service for 0.5 years.
3. Thermocouple (TE-408) had been replaced for 0.5 years.
4. The temperature indicating controller (TIC-408) had been replaced for 0.5 years.

Operation condition C.

1. The system has been operated for 5 years.
2. The feedwater pumps (P-01 & P-02) have been on service for 0.5 years.
3. There is no replacement or maintenance.

As an example of applying the proposed diagnosis algorithm, Fig. 5 shows the Bayesian network for the steam temperature regulator. Assume we observed evidence $T=1$, i.e., the failure of the steam temperature regulator has occurred. What we need to do is to find out the most probable causes of the observed consequence $T=1$.

The boundary conditions for this diagnosis problem are:

1. T is the evidence node, i.e., $\lambda^*(T)=(1.000, 0.000)$
2. Root nodes: Xi $(i=1, 2, ..., 11)$

$\Pi^*(X1)=(0.907, 0.093)$ $\Pi^*(X2)=(0.084, 0.916)$
$\Pi^*(X3)=(0.068, 0932)$ $\Pi^*(X4)=(0.068, 0.932)$
$\Pi^*(X5)=(0.068, 0.932)$ $\Pi^*(X6)=(0.142, 0.858)$
$\Pi^*(X7)=(0.124, 0.876)$ $\Pi^*(X8)=(0.326, 0.674)$
$\Pi^*(X9)=(0.099. 0.901)$ $\Pi^*(X10)=(0.331, 0.669)$
$\Pi^*(X11)=(0.112, 0.888)$

Following the three-step inference algorithm, we can determine all other Π^* messages and λ^* messages through the network.

Π^* Message passing

Because all parent node Xi have only one child Yj, we have

$$\Pi^*_{Xi\rightarrow Yj}(Xi)=\Pi^*(Xi)$$

From eqn. (7), we have

$$\Pi^*(Y1)=\max_{X1, X2} P(Y1/X1, X2)\,\Pi^*(X1)\,\Pi^*(X2)$$

$$\Pi^*(Y1=1)=\max_{X1, X2} P(Y1,=1/X1, X2)\,\Pi^*(X1)\,\Pi^*(X2)$$

$$=\text{MAX}[P(Y1=1/X1=0, X2=0)\,\Pi^*(X1=0)\,\Pi^*(X2=0),$$

$$P(Y1=1/X1=0, X2=1)\,\Pi^*(X1=0)\,\Pi^*(X2=1),$$

$P(Y1=1/X1=1,X2=0)\Pi^*(X1=1,)\ \Pi^*(X2=0),$

$P(Y1=1/X1=1,X2=1)\Pi^*(X1=1)\ \Pi^*(X2=1)]$

$=P(Y1=1/X1=1,X2=1)\ \Pi^*(X1=1)\ \Pi^*(X2=1)$

$=\Pi^*(X1=1)\ \Pi^*(X2=1)=0.076$

$$\Pi^*(Y1=0)=\max_{X1,X2} P(Y1=0/X1,X2)\ \Pi^*(X1)\ \Pi^*(X2)$$

$=\text{MAX}\ [P(Y1=0/X1=0,X2=0)\ \Pi^*(X1=0)\ \Pi^*(X2=0),$

$P(Y1=0/X1=0,X2=1)\ \Pi^*(X1=0)\ \Pi^*(X2=1),$

$P(Y1=0/X1=1,X2=0)\ \Pi^*(X1=1)\ \Pi^*(X2=0),$

$P(Y1=0/X1=1,X2=1)\Pi^*(X1=1)\ \Pi^*(X2=1)]$

$=\text{MAX}\ [0.093\times 0.916, 0.093\times 0.084, 0.907\times 0.916]=0.831$

Therefore, we have

$\Pi^*(Y1)=(0.076, 0.831)$

Similarly, we have

$\Pi^*(Y2)=(0.059, 0.810)$
$\Pi^*(Y3)=(0.176, 0.356)$
$\Pi^*(Y4)=(0.062, 0.673)$
$\Pi^*(Y5)=(0.151, 0.306)$
$\Pi^*(T)=(0.090, 0.183)$

λ^* Message passing with evidence $T=1$

Because T is an evidence node, we have $\lambda^*(T)=(1.000, 0.000)$. From eqn. (6), we have

$$\lambda^*_{Y4\leftarrow T}(Y4)=\max_{T,Y5,X11} \lambda^*(T)\ P(T/Y4,Y5,X11)\ \Pi(Y5)\ \Pi^*(X11)$$

$$=\max_{Y5,X11} P(T=1/Y4,Y5,X11)\ \Pi^*(Y5)\ \Pi^*(X11)$$

$$\lambda^*_{Y4\leftarrow T}(Y4=1)=\max_{Y5,X11} P(T=1/Y4=1,Y5,X11)\ \Pi^*(Y5)\ \Pi^*(X11)$$

$$=\Pi^*(Y5=0)\ \Pi^*(X11=0)=0.272$$

$$\lambda^*_{Y4\leftarrow T}(Y4=0)=\underset{Y5,\,X11}{\text{MAX}}\ P(T=1/Y4=0,\,Y5,X11)\ \Pi^*(Y5)\ \Pi^*(X11)$$

$$=\underset{Y5,\,X11}{\text{MAX}}[P(T=1/Y4=0,\,Y5,X11)\ \Pi^*(Y5)\ \Pi^*(X11)]$$

$$=\text{MAX}\ [\Pi^*(Y5=1)\ \Pi^*(X11=0),\Pi^*(Y5=0)\ \Pi^*(X11=1)]$$

$$=\text{MAX}\ [0.151\times 0.888, 0.306\times 0.112]=0.134$$

Therefore, we have

$\lambda^*_{Y_4\leftarrow T}(Y_4)=0.272, 0.134)$
$\lambda^*(Y4)=\lambda^*_{Y4\leftarrow T}(Y4)=(0.272, 0.134)$

Similarly, we can determine all the λ messages in the network.

$\lambda^*(X1)=\lambda^*_{X1\leftarrow Y1}(X1)=(1.000, 1.000)$
$\lambda^*(X2)=\lambda^*_{X2\leftarrow Y1}(X2)=(1.000, 1.000)$
$\lambda^*(X3)=\lambda^*_{X3\leftarrow Y2}(X3)=(0.196, 0.096)$
$\lambda^*(X4)=\lambda^*_{X4\leftarrow Y2}(X4)=(0.196, 0.096)$
$\lambda^*(X5)=\lambda^*_{X5\leftarrow Y2}(X5)=(0.196, 0.096)$
$\lambda^*(X6)=\lambda^*_{X6\leftarrow Y5}(X6)=(0.213, 0.105)$
$\lambda^*(X7)=\lambda^*_{X7\leftarrow Y3}(X7)=(0.208, 0.035)$
$\lambda^*(X8)=\lambda^*_{X8\leftarrow Y3}(X8)=(0.271, 0.045)$
$\lambda^*(X9)=\lambda^*_{X9\leftarrow Y3}(X9)=(0.204, 0.034)$
$\lambda^*(X10)=\lambda^*_{X10\leftarrow Y3}(X10)=(0.274, 0.045)$
$\lambda^*(X11)=\lambda^*_{X11\leftarrow T}(X11)=(0.206, 0.102)$
$\lambda^*(Y1)=\lambda^*_{Y1\leftarrow Y4}(Y1)=(0.220, 0.109)$
$\lambda^*(Y2)=\lambda^*_{Y2\leftarrow Y4}(Y2)=(0.226, 0.111)$
$\lambda^*(Y3)=\lambda^*_{Y3\leftarrow Y5}(Y3)=(0.513, 0.085)$
$\lambda^*(Y5)=\lambda^*_{Y4\leftarrow T}(Y4)=(0.272, 0.134)$
$\lambda^*(Y5)=\lambda^*_{Y5\leftarrow T}(Y5)=(0.598, 0.075)$

The corresponding belief functions are determined as follows:

$\text{BEL}^*(X1)=\lambda^*(X1)\ \Pi^*(X1)=(0.907, 0.093)$
$\text{BEL}^*(X2)=\lambda^*(X2)\ \Pi^*(X2)=(0.084, 0.916)$
$\text{BEL}^*(X3)=\lambda^*(X3)\ \Pi^*(X3)=(0.013, 0.089)$
$\text{BEL}^*(X4)=\lambda^*(X_4)\ \Pi^*(X_4)=(0.013, 0.089)$
$\text{BEL}^*(X5)=\lambda^*(X5)\ \Pi^*(X5)=(0.013, 0.089)$
$\text{BEL}^*(X6)=\lambda^*(X6)\ \Pi^*(X6)=(0.030, 0.090)$
$\text{BEL}^*(X7)=\lambda^*(X7)\ \Pi^*(X7)=(0.026, 0.031)$
$\text{BEL}^*(X8)=\lambda^*(X8)\ \Pi^*(X8)=(0.088, 0.030)$
$\text{BEL}^*(X9)=\lambda^*(X9)\ \Pi^*(X9)=(0.020, 0.031)$
$\text{BEL}^*(X10)=\lambda^*(X8)\ \Pi^*(X10)=(0.091, 0.030)$
$\text{BEL}^*(X11)=\lambda^*(X9)\ \Pi^*(X_{11})=(0.023, 0.091)$
$\text{BEL}^*(Y1)=\lambda^*(Y1)\ \Pi^*(Y1)=(0.017, 0.091)$

$BEL^* (Y2) = \lambda^* (Y2)\, \Pi^* (Y2) = (0.013, 0.090)$
$BEL^* (Y3) = \lambda^* (Y3)\, \Pi^* (Y3) = (0.090, 0.030)$
$BEL^* (Y4) = \lambda^* (Y4)\, \Pi^* (Y4) = (0.017, 0.090)$
$BEL^* (Y5) = \lambda^* (Y5)\, \Pi^* (Y5) = (0.090, 0.023)$
$BEL^* (T) = \lambda^* (T)\, \Pi^* (T) = (0.090, 0.000)$

The diagnosis results are:

$X1^* = MAX^{-1}\, BEL^* (X) = 1$ (pump P-01 has failed)
$X2^* = MAX^{-1}\, BEL^* (X2) = 0$ (the standby pump P-01 is working)
$X3^* = MAX^{-1}\, BEL^* (X3) = 0$ (the valve V-01 is working)
$X4^* = MAX^{-1}\, BEL^* (X4) = 0$ (the valve V-02 is working)
$X5^* = MAX^{-1}\, BEL^* (X5) = 0$ (the valve V-10 is working)
$X6^* = MAX^{-1}\, BEL^* (X6) = 0$ (the valve V-09 is working)
$X7^* = MAX^{-1}\, BEL^* (X7) = 0$ (the temperature relay TY-408 is working)
$X8^* = MAX^{-1}\, BEL^* (X8) = 1$ (the temperature indicator TIC-408 has failed)
$X9^* = MAX^{-1}\, BEL^* (X9) = 0$ (the temperature transmitter TT-408 is working)
$X10^* = MAX^{-1}\, BEL^* (X10) = 1$ (the thermocouple TE-408 has failed)
$X11^* = MAX^{-1}\, BEL^* (X11) = 0$ (the desuperheater is working)
$Y1^* = MAX^{-1}\, BEL^* (Y1) = 0$ (the pump system is working)
$Y2^* = MAX^{-1}\, BEL^* (Y2) = 0$ (all the valves are working)
$Y3^* = MAX^{-1}\, BEL^* (Y3) = 1$ (some of the temperature instruments has failed)
$Y4^* = MAX^{-1}\, BEL^* (Y4) = 0$ (both pump system and valve line are working)
$Y5^* = MAX^{-1}\, BEL^* (Y5) = 1$ (the temperature regulator has failed)
$T^* = MAX^{-1}\, BEL^* (T) = 1$ (the steam temperature control system has failed)

Therefore, we conclude that the most probable causes of the failure of steam temperature control system are: 1. the failure of thermocouple TE-408, and 2. the failure of temperature indicating controller TIC-408.

3.3 Detection of thermocouple drifts

Thermocouples, properly used under favorable conditions, can measure temperature within an acceptable tolerance. However, when improperly applied or exposed to hostile mechanical, chemical, thermal environments such as hazardous waste incinerators, they often fail without the error being evident in the temperature record. Thermocouple drift, the thermal electromotive force (emf) change at constant temperature, is an important thermocouple failure mode that may seriously affect the operation of the whole incineration system. Thermocouples may drift either low or high up to 100°C, and thermocouple drift may be caused by many factors such as insulator and sheath materials, assembly geometry, fabrication method, gas environment, rate of thermal cycling, etc. Therefore, it is very difficult to determine if there is a thermocouple drift.

When this kind of hidden failure occurs during measurement, deliberate recording and use of supplementary information is necessary to distinguish valid from faulty monitoring data. Here, we will show how to use the proposed methodology in Section 2 to diagnose spurious temperature monitoring data by using supplementary information, such as system model-based Kalman filtering information, causal relationship-based Bayesian inference information, and the real-time monitoring information.

Based on the real-time monitoring data, the system model-based Kalman filtering information ($X_i(k)$, $i=1, 2, ..., 10$; $k=0, 1, 2, ...$) and the Bayesian inference information (failure probabilities of the feedwater system and the steam temperature regulator), we formulate the following heuristic rules to detect steam temperature thermocouple drift (STTD).

RULE STTD-001
IF
1) $|U_2(k)-U_2(k-1)|+|U_2(k-1)-U_2(k-2)|\leq\delta U_2$
(the real-time monitoring information)
and 2) $|U_2(k)-U_2(\text{design})|\leq\delta U_2$
and 3) Prob (T) (feedwater system) $\leq$ safety margin
(Bayesian inference information)
THEN
the feedwater supply system is normal

RULE STTD-002
IF
1) $|U_1(k)-U_1(k-1)|+|U_1(k-1)-U_1(k-2)|\leq\delta U_1$
(the real-time monitoring information)
and 2) $|N_1(k)-N_1(k-1)|+|N_1(k-1)-N_1(k-2)|\leq\delta N_1$
(the real-time monitoring information)
THEN
the heating rate is constant

RULE STTD-003
IF
1) $|X_7(k+2)-X_7(k+1)|+|X_7(k+1)-X_7(k)|+|X_7(k)-X_7(k-1)|+|X_7(k-1)-X_7(k-2)|\leq\delta X_7$
(provided by Kalman filtering inference)
and 2) $|X_1(k)-X_7(\text{design})|\leq\delta X_7$
and 3) Prob (T) (the steam temperature control) $\leq P_s$
(Bayesian inference information)
THEN
the desuperheater system is normal

RULE STTD-004

IF
1) $|X_6(k+2)-X_6(k+1)|+|X_6(k+1)-X_6(k)|+|X_6(k)-X_6(k-1)|+|X_6(k-1)-X_6(k-2)|\leq\delta X_6$
(provided by Kalman filtering inference)
and 2) $|X_6(k)-X_6(\text{design})|\leq\delta X_6$
and 3) $|N_5(k)-N_5(k-1)|+|N_5(k-1)-N_5(k-2)|\leq\delta N_5$
(provided by monitoring information)
and 4) $|N_5(k)-N_5(\text{design})|\leq\delta N_5$
THEN
the steam line is normal
RULE STTD-005
IF
Prob(TIC-408) $\leq P_s$ (provided by the Bayesian network)
THEN
the temperature indicating is normal
RULE STTD-006
IF
1) $|Y_2(k)-Y_2(\text{design})|\geq$ drift margin
(provided by monitoring information)
and 2) the temperature indicating is normal
and 3) the steam line is normal
and 4) the desuperheater system is normal
and 5) the feedwater supply system is normal
and 6) the heating rate is constant
THEN
the thermocouple TE-408 is drifting rapidly
RULE STTD-007
IF
1) the thermocouple TETE-408 is drifting rapidly
and 2) $Y_2(k)-Y_2(\text{design})\geq$ drift margin
THEN
the thermocouple TE-408 drifts high
RULE STTD-008
IF
1) the thermocouple TE-408 is drifting rapidly
and 2) $Y_2(k)-Y_2(\text{design})\leq-$drift margin
THEN
The thermocouple TE-408 drifts low
RULE STTD-009
IF
1) the heating rate is constant
and 2) the feedwater supply system is normal
and 3) Prob $(T)\leq P_s$ (provided by the steam temperature control network)

and 4) $U_3(k)-U_3(k-1)\geq\delta U_3$, $U_3(k-1)-U_3(k-2)\geq\delta U_3$, ..., $U_3(k-i)-U_3(k-i-1)\geq\delta U_3$ (real-time monitoring data)
and 5) $X_6(k)-X_6(k-1)\leq-\delta X_6$, $X_6(k-1)-X_6(k-2)\leq-\delta X_6$, ..., $X_6(k-i)-X_6(k-i-1)\leq-\delta X_6$ (provided by Kalman filtering)
and 6) $Y_2(k)-Y_2(k-1)\geq\delta Y_2$, $Y_2(k-1)-Y_2(k-2)\geq\delta Y_2$, ..., $Y_2(k-i)-Y_2(k-i-1)\geq\delta Y_2$ (real-time monitoring data)
THEN
the thermocouple TE-408 is drifting high slowly

RULE STTD-010
IF
1) the heating rate is constant
and 2) the feedwater supply system is normal
and 3) Prob (Y_3) $\leq P_s$ (provided by the steam temperature control network)
and 4) $U_3(k)-U_3(k-1)\leq-\delta U_3$, $U_3(k-1)-U_3(k-2)\leq-\delta U_3$, ..., $U_3(k-i)-U_3(k-i-1)\leq-\delta U_3$ (real-time monitoring data)
and 5) $X_6(k)-X_6(k-1)\geq\delta X_6$, $X_6(k-1)-X_6(k-2)\geq\delta X_6$, ..., $X_6(k-i)-X_6(k-i-1)\geq\delta X_6$ (provided by Kalman filtering)
and 6) $Y_2(k)-Y_2(k-1)\leq-\delta Y_2$, $Y_2(k-1)-Y_2(k-2)\leq-\delta Y_2$, ..., $Y_2(k-i)-Y_2(k-i-1)\leq-\delta Y_2$ (real-time monitoring data)
THEN
the thermocouple TE-408 is drifting low slowly.

4. Conclusions

The automation of fault diagnosis was primarily handicapped in the past by the lack of appropriate techniques to represent the knowledge-based reasoning of an expert diagnostician. Many of the past approaches in applying expert system methodology to fault diagnosis are system or process specific. The diagnosis inference engines presented in this paper are system or process independent. In other words, the proposed diagnosis framework can be applied to many other diagnosis problems as long as the problem can be well defined by using heuristic rules, probabilistic causal networks, and functional system models. The problem domain independence is guaranteed by a generic inference engine which is jointly performed by rule-based backward/forward chaining, causal knowledge-based Bayesian network inference, and system model-based Kalman filtering inference.

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