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Development of On-Line Diagnostic Expert System : Heuristics and Influence Diagrams

현장진단 전문가 시스템의 개발 : 휴리스틱과 인플루언스 다이아그램

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Abstract

This paper outlines a framework for a diagnosis of a complex system with uncertain information. Sensor validation plays a vital role in the ability of the overall system to correctly determine the state of a system monitored by imperfect sensors. Here, emphases are put on the heuristic technology and post-processor for reasoning. Heuristic Sensor Validation (HSV) exploits deeper knowledge about parameter interaction within the plant to cull sensor faults from the data stream. Finally the modified probability distributions and validated data are used as input to the reasoning scheme which is the run-time version of the influence diagram. The output of the influence diagram is a diagnostic mapping from the symptoms or sensor readings to a determination of likely failure modes. Once likely failure modes are identified, a detailed diagnostic knowledge base suggests corrective actions to improve performance. This framework for a diagnostic expert system with sensor validation and reasoning under uncertainty applies in HEATXPRT™ a data-driven on-line expert system for diagnosing heat rate degradation problems in fossil power plants [1].

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1. Introduction

Sensor validation is an important preprocessor of any reasoning scheme since it provides necessary information for a system [3][10][11]. Here, we are concerned with two area that we have developed so far. First is the Heuristic Sensor Validation (HSV), which provides the information regarding the system level. Second is the Influence Diagram based Knowledge Base (InDiaKB), which is the backbone of the reasoning scheme. Schematic of information flow is shown in Figure 1.

Heuristic Sensor Validation is a component of the overall sensor validation system which combines evidence from multiple sources to separate sensor faults out of the process data used by the heat rate diagnostic expert system. Various methods of obtaining statistical features from a set of sensor data take place

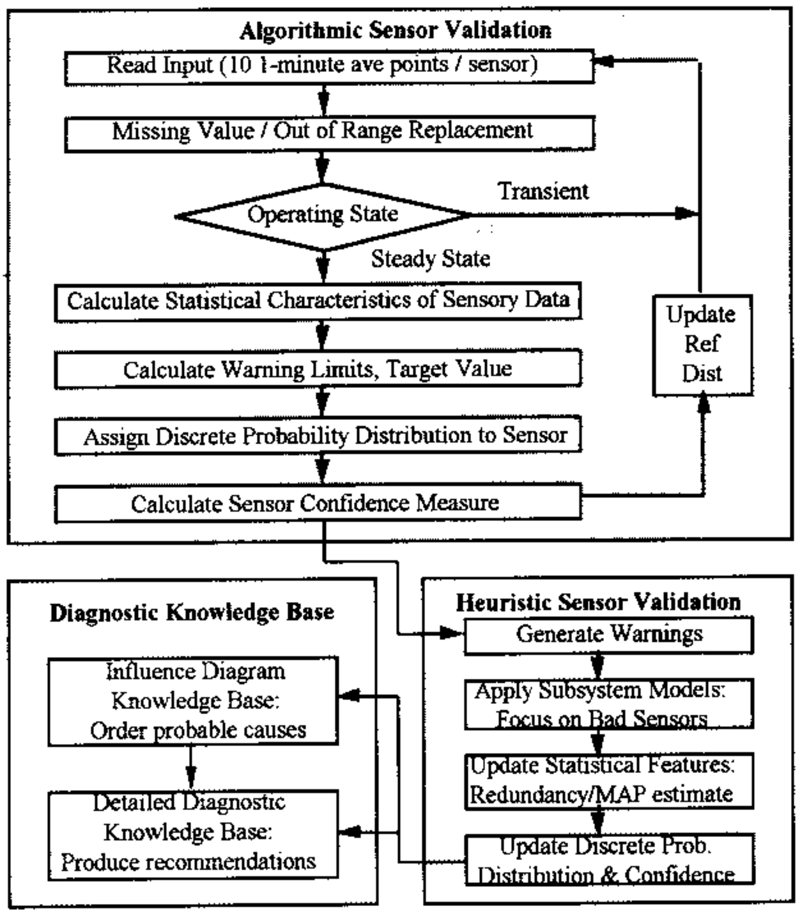

Figure 1. Schematic Diagram of Main Functional Blocks of HEATXPRT™ [10]

in Algorithmic Sensor Validation (ASV) [10]. These same features are used by HSV, coupled to knowledge of plant connectivity and operation. While an ASV analysis on an individual sensor provides important insight regarding validity, synthesizing individual parameter and overall system information is a vital part of sensor validation. HSV does this by analyzing groups of related sensors to determine whether observed deviations are process based or are misrepresentations due to sensor faults [11].

The following techniques are used as theoretical schemes in HSV in order to identify sensor faults:

1. Redundancy of sensor readings
2. Connectivity of parameters and subsystems
3. Expected behavior of subsystems
4. First principles in a subsystem
5. Heuristic knowledge by experts

HSV's role is to eliminate faulty contributions to the influence diagram knowledge base which are caused by sensor failure.

The depicted framework ends with validated data and updated probability distributions being input into the Influence Diagram Knowledge Base (InDiaKB) [2][5][6]. Sets of discrete marginal and conditional probability distributions define the parametric form of the influence diagram which can be tailored to the operating history of the target utility. Quantification of the probabilistic relationships is based on statistical data where available, e.g. maintenance data, and on the experts experiential knowledge, including the experts assessment of the conditional probabilities of failures given ranges of sensor readings [4][7][12]. This InDiaKB has been reduced to a run-time matrix version by transforming influence diagrams constructed from a causal point of view into equivalent sensor driven form. It is followed by a secondary detailed knowledge base developed entirely by Sargent & Lundy Engineers which contains more specific knowledge and recommendations. Since the knowledge and the information within the influence diagrams are usually plant specific, the InDiaKB should be different from plant to plant. Here, we introduce the InDiaKB of HEATXPRT™ and provides an example influence diagram of heat rate failure in a feedwater heater [1].

2. Heuristic Sensor Validation

2.1 Overview of the Database and Basic Reasoning Process in Heuristic Sensor Validation

All sensors, parameters, and subsystems in HSV are encoded objects in an internal data validation database. These objects are created from templates called classes and are stored as lists of class instances. Assignment of sensors to parameters and parameters to subsystems is specified in the configuration file. Also given by the configuration database are connective relationships among parameters and subsystems. Necessary properties of the sensor object are as follows:

1. Sensor readings in one-minute average
2. Sample period average and statistical features
3. Calculated parameter values from the sensor readings (target values)
4. Manual input values
5. Actual values
6. Replacement and warning limits
7. Probability associated with sensor readings (High, Normal, Low)
8. Sensor confidence measure assigned in ASV
9. Trend analysis
10. Redundant sensors

Probability and sensor confidence values are compared to thresholds stored for each parameter. These comparisons generate warnings that are used to focus analysis in HSV; each warning directs the system to assemble and assess the subsystem model containing the warning. For warnings of parameters which have associated upstream and/or downstream neighbors, analysis is carried out on the adjoining subsystems as well. Sensor redundancy is exploited for neighboring parameters and cases where several sensors are used to measure a single parameter.

2.2 Subsystem Models

The output of ASV is a set of statistical features along with probability distributions and confidence estimates for each sensor. Each sensor is associated with a parameter. Several sensors may be associated with the same parameter. Each parameter is, in turn, associated with a subsystem. As a result, the set of statistical features can be expanded to cover a subsystem and model parameter interactions within it.

As discussed in the earlier paper, unit gross generation is used to predict the readings of sensors measuring a parameter [10]. ASV compares actual statistical features of sample data to expert-set thresholds (functions of gross generation) to determine a probability distribution for the sensor. Additionally ASV uses parameter reference distributions to measure the confidence behind each sensor sample set. These techniques are meant to provide a quick means of eliminating gross sensor failures and to help focus deeper, more costly analysis to be performed in HSV. It is the role of HSV to 'know' how parameters and the sensors measuring them should be grouped and to 'know' the valid interactions within these groupings.

In addition, there did not exist the wealth of knowledge about operations that had been assumed. This opened to door for a different approach to subsystem models, one that is generic, applying to groupings of any size within the plant. The basis of the model is the Gaussian probability distribution used to model individual parameters expanded to handle vectors of parameter values:

$$P(x) = \frac{e^{-\frac{1}{2}[x^T R^{-1} x]}}{(2\pi)^{\frac{N}{2}} \| R \|^{\frac{1}{2}}} \quad (1)$$

where:

p = the probability density function

x = the vector of subsystem parameter values (normalized)

R = the covariance matrix

An argument was made in the earlier paper that a Gaussian (or normal) distribution represents the normalized system performance with acceptably low error [10]. In HSV, this argument is the basis of the subsystem model; normalized parameter values for a subsystem create a single, multivariate Gaussian distribution with the covariance encoding the interactions. The properties of this distribution are very desirable: using a single probability density function to represent a subsystem provides a means of analyzing the effects of changing any single parameter with respect to others. The following sections serve to illustrate the use of the multivariate Gaussian probability distribution throughout the HSV module.

2.2.1 Establishing the Distribution

The first step in the development of heuristics within the HSV module is analysis of actual plant data. Simply selecting a model like Eq. (1) and assuming that it models the data would not yield a good result. As discussed in the paper, individual sensors tend to follow a Gaussian distribution about their expected operating points [10]. This led to the development of the ASV methodology for statistically characterizing the performance of each sensor as a distribution and the application of this distribution to the tasks of producing a discrete probability distribution and sensor confidence. In HSV, we strive to do the same sorts of analyses except that now several sensors must be considered at once. To start, we again establish the dependence of parameter values on gross generation (load). Figures 2 and 3 show that a quadratic polynomial curve fit can be used to predict parameter values given load.

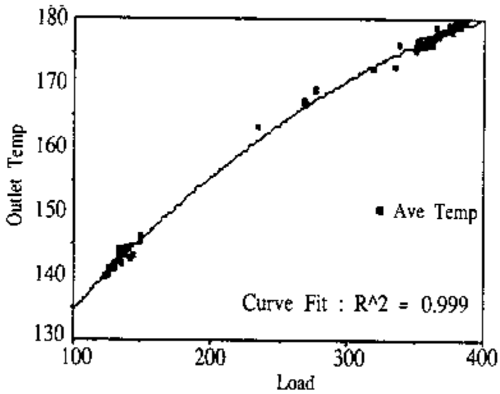

Figure 2. FW Heater Outlet Temp vs. Gross Generation

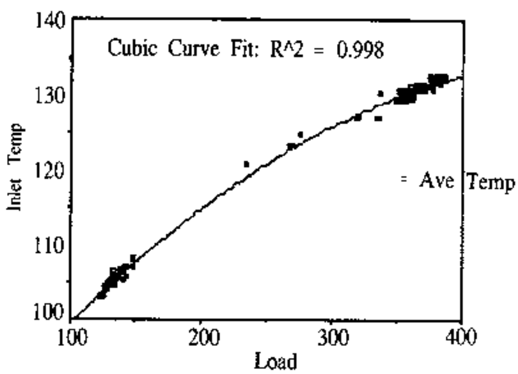

Figure 3. FW Heater Inlet Temp vs. Gross Generation

The performance of the plant can be analyzed with respect to its predicted behavior described by a cubic curve fit for each operating parameter. Is the difference between observed and predicted values systematic or is it random? If it is random, there is not much that can be done beyond ASV; HSV becomes just a set of specialized rules instead of a flexible approach to data validation. In order to decide whether performance deviation is systematic, we can look at an example from the feedwater heater prototype system. Figures 4 through 6 plot three temperatures in the feedwater heater normalized for predicted behavior (simply subtracting the curve fits out of the data stream). They show that there is a clear systematic deviation from the predicted performance curves. The set of probability distributions used to approximate the behavior of individual sensors can be extended to sets of sensors such as these through modeling this systematic behavior.

Of note in Figures 4 through 6 is the nice clustering of the data. This shows that there is high covariance of each parameter with respect to the others. This is an important aspect of the data that can be exploited through the above mentioned multivariate Gaussian probability distribution.

The data from Figures 4 through 6 can be summarized nicely by a mean vector of length three and a covariance matrix of dimension three by three. These are:

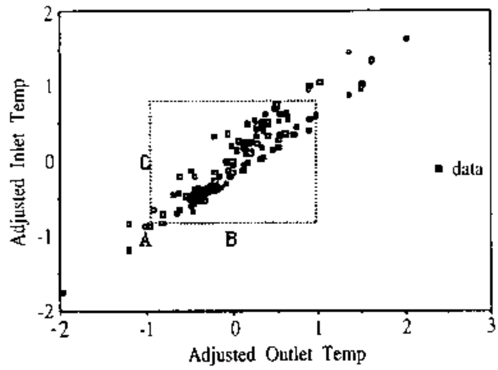

Figure 4. Adjusted Inlet temp vs. Adjusted Outlet Temp

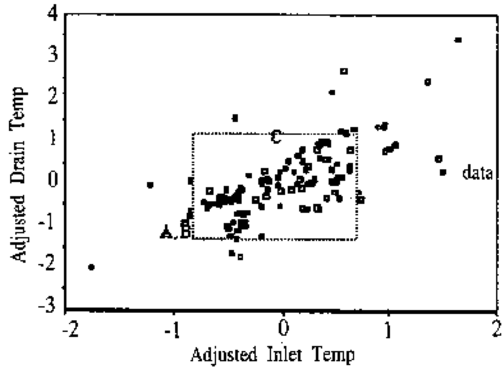

Figure 5. Adjusted Drain Temp vs. Adjusted Inlet Temp

$$\mu^T = \begin{bmatrix} 0.0035 \\ 0.0068 \\ -0.0037 \end{bmatrix}, \quad R = \begin{bmatrix} 0.621 & 0.331 & 0.189 \\ 0.331 & 0.569 & 0.339 \\ 0.189 & 0.339 & 0.849 \end{bmatrix} \quad (2)$$

Thus, a model for a subsystem can be encoded using only a covariance matrix whose dimension is that of the number of parameters in the model (the mean vector is zero for values that have been adjusted for expected (target) value). This encoding scheme is not handicapped by its simplicity: it handles errors

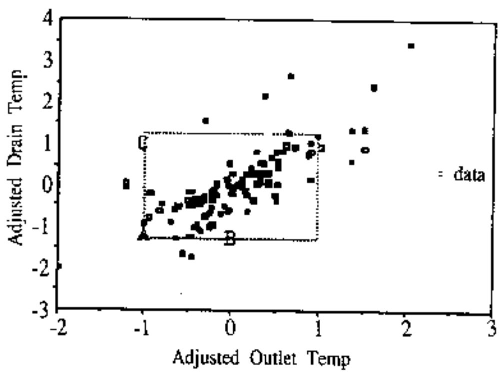

Figure 6. Adjusted Drain Temp vs. Adjusted Outlet Temp

in the curve fits, seasonal operating changes, and missing data with aplomb. In cases where data does not cluster as well as seen in Figure 4 through 6, sums of multivariate Gaussian distributions can be used. Thus, we have provided a robust and flexible means of handling expertise about subsystem operation within a power plant.

2.2.2 The *Maximum A Posteriori* (MAP) Parameter Value Estimate

The multivariate Gaussian probability distribution that captures systematic interactions of parameters within a subsystem can be used in many ways. Sensor faults propagated through ASV to HSV are those which are independent from sensor to sensor (e.g. calibration drift or isolation tube leakage). Gross errors will be detected and corrected in ASV. The covariance matrix of Eq. (2) shows no entry in which the covariance is near zero (relative to the variance values on the diagonal); any two of the three values can be used to predict the other. Looking at the plots gives one an idea of how to predict a missing outlet temp value given inlet temp and/or drain temp. However, when more than three or four parameters are present in the distribution the task is not so simple. The computer must have a way of determining which parameter values are valid and which ones are faulty. This is done by taking each of the parameters one at a time and using all of the other parameters and the subsystem model as predictive information. The goal of the prediction is to maximize the probability (the density function of Eq. (1)) by assigning the best value for the parameter without changing any other parameters values. This is done by using the *Maximum A Posteriori* Estimate. Starting with Eq. (1), its partial derivative with respect to the parameter being predicted (x_i) is taken and set equal to zero:

$$0 = \frac{\partial}{\partial x_i} P(x) = \frac{\partial}{\partial x_i}\left[\frac{e^{-\frac{1}{2}[x^T R^{-1} x]}}{(2\pi)^{\frac{N}{2}} \| R \|^{\frac{1}{2}}}\right] \qquad (3)$$

Taking all other parameter values as input constants, this becomes:

$$0 = \frac{\partial}{\partial x_i}\left[\frac{e^{-\frac{1}{2}[a_i x_i^2 + b_i x_i + c]}}{(2\pi)^{\frac{N}{2}} \| R \|^{\frac{1}{2}}}\right] \qquad (4)$$

where:

$a_i = R_{ii}^{-1}$

$b_i = \sum_{\substack{i=0 \\ j \neq i}}^{N} R_{ij}^{-1} x_j^2$

Taking the derivative:

$$0 = -(2a_i x_i + b_i) \left\{ \frac{e^{-\frac{1}{2}[a_i x_i^2 + b_i x_i + c]}}{(2\pi)^{\frac{N}{2}} \| R \|^{\frac{1}{2}}} \right\} \qquad (5)$$

Solving for the value which maximizes probability:

$$MAP(x_i) = -\frac{b_i}{2a_i} \qquad (6)$$

A MAP estimate is made for each x_i in the parameter vector x. The estimate is then substituted in the probability density function to provide a normalization factor for the probability of the observed parameter value:

$$goodness_i = \frac{p(x_1, \ldots, x_i, \ldots, x_N)}{p(x_1, \ldots, MAP(x_i), \ldots, x_N)} \qquad (7)$$

This new *goodness* vector represents a set of measures of consistency of the parameter values with respect to the most probable substitution that can be made for each. Eq. (7) can be used to focus attention on parameters where a change in value would greatly increase the overall probability of the operation of the subsystem being studied. The analysis is directed toward single parameters because sensor failures are assumed to occur independent of other sensor failures within a subsystem. Process deviations, on the other hand, produce effects in several interacting parameters. Thus, process deviations would produce high goodness values where adjustments to single parameter values would not appreciably increase the probability of the operation of the subsystem. These point bears reiteration as they are the backbone of HSV:

1) system models contain information about parameter interactions within a piece of equipment.
2) Many of these interactions hold in the presence of a process deviation.
3) In *detectable* sensor faults at least one of these interactions will be violated. (A sensor fault is not detectable if it mimics closely a valid process deviation.)
4) A *goodness* measure consisting of a ratio of the probability of the operating point as measured to the probability of the operating point substituting a MAP estimate for a parameter provides a means of assessing the value of changing a single parameter.

2.3 Redundancy

Section 2.2.2 demonstrates the use of the MAP estimate in HSV but does not give any indication of how it can be used in cases where redundant sensor information exists. We must go back to the *goodness* measure of Eq. (7) to understand the application of sensor redundancy to the problem. This measure is a vector of numbers between 0 (low normalized probability) and 1 (point coinciding with the MAP) that is used to focus attention on parameters lying furthest from their expected values. The problem is: How do we apply knowledge of sensor redundancy to improve information about a parameter?

One method available in HSV maintains a tie to actual sensors, a preference expressed by experts in plant operations. In most instances, there will exist a sensor measuring each parameter that is preferred (for operational reasons) over other sensors. This sensor is the default and is used unless it appears to have failed. If a redundant sensor supports the value given by the primary sensor, analysis is performed on other sensors with low *goodness* measures. If the redundant sensor is significantly closer to the MAP estimate produced by the data from other sensors in the model, it is substituted for the faulty sensor. This redundant sensor then becomes the primary sensor for the parameter it measures. The rationale for this method of redundancy handling is:

1) The subsystem model contains information about each parameter that is independent of process faults.
2) Sensor faults of the type diagnosed during HSV are independent (i.e. there are no common causes for sets of sensors to drift from calibration).
3) Sensor faults of the type diagnosed during HSV are relatively infrequent.
4) The above conditions indicate a low probability of concurrent multiple sensor failure.

This is a Maximum Likelihood (ML) estimate that assumes that one of the available sensors is measuring the actual value. Other available sources of information are ignored in this case, leading to a potential loss of integrity.

A second methodology used for the application of redundant sensor information involves Bayes' rule for updating continuous probability distributions. One component of this method is a continuous probability distribution is formed which represents the probability density of sensor readings given an actual value [8]. This would include such factors as instrument accuracy (including calibration drift), failure mode types, and failure mode probabilities. An example of such a distribution based on Gaussian distributions is:

$$p(x|y) = (1-p_f)\frac{e^{-\frac{(x-y)^2}{2\sigma_{acc}^2}}}{(2\pi)^{\frac{1}{2}}\sigma_{acc}} + p_f\frac{e^{-\frac{(x-x_f)^2}{2\sigma_f^2}}}{(2\pi)^{\frac{1}{2}}\sigma_f} \quad (8)$$

where:

x = Sensor value

y = Parameter actual value

p_r = Probability of failure

σ_{acc} = Standard deviation due to instrument accuracy

x_f = Sensor value for failure mode
σ_f = Standard deviation of failure mode values

Figure 7 demonstrates a situation where there is a relatively inaccurate sensor with a failure mode that results in a constant reading much lower than expected. This might be the case for a temperature probe or an electronic fault. Some other cases would be represented as a probable offset from the actual reading. In all cases the offset is relatively large, usually far outside the normal process swings of the plant. A Gaussian distribution is chosen for this case, but any parameterized distribution can be used.

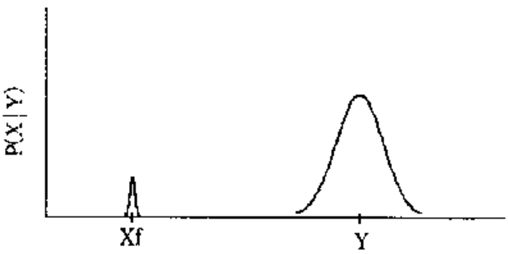

Figure 7. Probability distribution of sensor readings given the correct value, Y

Just as in the MAP estimate, the subsystem model is used to form a probability density function for the parameter being analyzed using the values of other parameters within the model as evidence. In this case, however, a probability distribution over x_i is the result of applying subsystem knowledge. The probability density function becomes:

$$p(x_i) = \frac{e^{-\frac{1}{2}[a_i x_i^2 + b_i x_i + c]}}{(2\pi)^{\frac{N}{2}} \left| |R| \right|^{\frac{1}{2}}} \quad (9)$$

where:

$a_i = R_{ii}^{-1}$

$b_i = \sum_{\substack{j=0 \\ j \neq i}}^{N} R_{ij}^{-1} x_j^2$

Unlike the case of a MAP estimate where a single maximum value of the distribution is used, other characteristics of the distribution are captured. Figure 8 shows sets of system model-generated distributions for situations where there is a varying degree of covariance. Note that the three curves shown have then same MAP estimate point but differ greatly in quality. It seems that predictive quality of the subsystem model should be used in determining the best sensor value. The ML estimate that requires an actual sensor to read the parameter value cannot exploit this information.

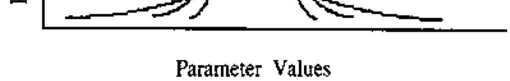

Figure 8. Probability distribution of process variable, Y, given the subsystem model and other parameter values.

Bayes' rule is applied to the above distributions to create a new probability density function given all sensor values recorded for the parameter under investigation and its subsystem model. The general form of Bayes rule for this case is given:

$$p(Y|X)=\frac{p(X|Y)p(Y)}{p(X)} \qquad (10)$$

where:

$p(X) = \int_{-\infty}^{\infty} p(X|Y)p(Y)dY$

$p(X|Y)$ = The probability density function of X given Y

$p(x)$ = The probability distribution of X

Y = The actual value of the parameter

X = The value of the sensor reading

Sensor readings can be independent of each given the value of the parameter being sensed (i.e. a sensor's measured value depends only on the actual value, not other sensors' measurements), so Eq. (10) can be applied to multiple redundant sensors:

$$p(Y|X_1X_2)=\frac{p(X_1|X_2Y)p(X_2|Y)p(Y)}{p(X_1X_2)}$$

$$=\frac{p(X_1|Y)p(X_2|Y)p(Y)}{p(X_1X_2)} \qquad (11)$$

Eq. (11) is used to combine the probability density function for N redundant sensors Eq. (8) and the probability density function for the actual value generated by the subsystem model Eq. (9). Eq. (12) is the resulting probability density function for the actual parameter value. For simplicity, the second term of Eq. (8) has been excluded. This term represents the probability of sensor failure and can reasonably be eliminated from consideration after the ASV analysis that has already taken place (absolute failures are weeded out by ASV). In addition,, all scaling constants have been grouped together:

$$p(Y|X_1 \ldots X_N)=Ke^{-\frac{1}{2}\left[aY^2+bY+c+\sum_{i=1}^{N}\frac{(Y-X_i)^2}{\sigma_{acc}^2}\right]} \qquad (12)$$

In order to determine the most probable value for the parameter and use this as a virtual sensor value, we need only set the derivative to zero and solve:

$$0=Y_{max}\left(a+\frac{N}{\sigma_{acc}^2}\right)+\left(\frac{b}{2}-\sum_{i=1}^{N}\frac{X_i}{\sigma_{acc}^2}\right) \qquad (13)$$

$$Y_{max}=-\frac{\left(\frac{b}{2}-\sum_{i=1}^{N}\frac{X_i}{\sigma_{acc}^2}\right)}{\left(a+\frac{N}{\sigma_{acc}^2}\right)}$$

Note that this result becomes the MAP estimate given in Eq. (10) for the case of zero sensors. Note also that in the parameters a and b, the characteristics of the subsystem model are included in the estimate. Additionally, a large number of accurate sensors will completely overwhelm the MAP estimate. Cases in between these extremes will produce an optimal fusion of sensor and subsystem model. The Bayesian combination of evidence for parameter value provides a means of using all redundant sensors rather than just picking one of them. The only drawback is a semantic one: an operator would prefer to be told which of several sensors is most accurate rather than be given a value that accounts for all sensor readings but does not represent a single sensor. For this reason the prototype HSV contains both the simple ML algorithm along with the more accurate Bayesian scheme presented here. In another section, a method for combining sensor uncertainties based on sensor confidence measures is also proposed.

2.4 Connectivity

Another form of knowledge available to the HSV module is the arrangement of equipment within the power plant. This knowledge adds a second form of redundancy to the system. Each parameter in the system contains information about any direct upstream or downstream neighbors. In the event that the goodness measure falls below the acceptable threshold, these neighbors are consulted in combination with redundant sensors. Because the normalized values for each parameter-neighbor pair will reflect the expected offset in actual value and the parameters measure the same variable type, an upstream or downstream neighbor can be ' plugged' directly into the subsystem model of a suspect sensor. The methods described in Section 2.3 can then be applied using a close neighbor as a redundant sensor.

Connectivity within the plant can be exploited to yield an even higher level of redundancy because each neighboring parameter is also contained within a separate subsystem model. This model is used to compare MAP estimates of parameters along equipment interfaces to gauge agreement. By moving from one subsystem to the next, HSV can operate on symptoms of sensor faults and trace them to a root cause somewhere else. This is a an important aspect of HSV; initial analysis can be localized to only those parameters that show heat rate warnings because the source of a false positive warning can be identified wherever it might be. HSV techniques are not initially used in subsystems that do not show warning states but will propagate throughout subsystem connections until each warning is validated or explained by a sensor fault.

2.5 Heuristics

Heuristics can be defined as the specific experiential knowledge one might have after a long engagement with the operation of a specific domain. This knowledge is differentiated from statistical features, first principle relationships, or connectivity of specific parameters as we have explained so far. Since this knowledge is acquired through an operators experience rather than a certain calculation, it is difficult to translate into a quantified metric. One approach in representing heuristics is through hybrid knowledge bases of rules and objects. For our application where much of the knowledge is about plant connectivity and instrument location the object oriented database provides most of the encoding.

In Artificial Intelligence, the representation of knowledge is a combination of data structures and interpretive procedures that leads to an inference of behavior. To structure a problem-solving procedure, one usually uses a multi-dimensional approach. This is composed of interaction, deduction, and induction components. Interaction signifies the participation of some other knowledge representation in the same problem-solving task. Deduction is the rule that we use during problem-solving. Induction is the data-driven discovery needed in the process. We specify their representation as interaction, deduction, and induction *rules*. If a system uses these declarative rules in reasoning a behavior, we call this a rule-based system. Since a rule-based system has an IF~, THEN~ structure, it is best suited to representing deterministic, goal-oriented knowledge such as a logic tree or a fault tree containing no uncertain parameters.

A data structure organizes parameter and state information about the system into a form that is easily accessed and modified. We specify the basic core of information as an *object*. If we use these objects in representing a data structure, we call it an object-oriented system. An object-oriented system is more appropriate for understanding a hierarchical relationship of parameters. It usually classifies the parameters with the same properties as a class, which then makes it possible for the knowledge process to maneuver through several knowledge islands. A certain class shares a series of inheritance of properties among objects to give a systematic knowledge representation.

We introduce here a *hybrid* knowledge base that manipulates the merits of rule-based and object-oriented systems. We transform the parameters into objects and a set of parameters with common properties into a class. A set of rules is applied to the specific problem domain to identify the designated goal. By doing so, it becomes possible to accelerate the knowledge processing time and to identify the previously unnoticed hierarchical relationships of parameters. The following sections will illustrate how we define the objects and classes in the power plant domain and how we apply these concepts to sub-domains such as a feedwater heater and a boiler.

3. Influence diagram knowledge base

Diagnosis is the process of determining the state of a system based on system observable. It is sometimes viewed as an inverse mapping of the causal behaviors of the system; this mapping rarely enjoying a one to one correspondence. The correspondence between observable and failures becomes even more difficult in situations where there is some uncertainty in both the mappings and in the observable themselves. In HEATXPRT™ an influence diagram knowledge base is used to represent and process this uncertainty.

Influence diagrams have proven successful in complex decision making problems with uncertainty, by graphically representing the diagnostic problem domain through simple topological symbols and arcs between them. Knowledge engineering schemes allow them to exploit both first principle knowledge of a system along with subjective assessments based on experiential knowledge. Bayes Theorem is the backbone of the influence diagram inference procedure. The role of influence diagrams in diagnostic expert systems is to identify the necessary relationships between parameters in the domain and represent and exploit conditional independence where possible. Thus the operators expertise, the first principles, and the sensory data are integrated into the three representational levels of the diagram: the topological, numerical, and functional levels. The topological level of the influence diagram is a simple representation of the problem using a combination of nodes and arcs, where nodes represents critical parameters and decisions, and arcs representing the functional relationships among parameters. The lack of an arc is the most important information at the topological level, signifying a statement of conditional independence. The nature of the influences is determined at the functional level and further quantified at the numerical level. Bayesian probabilities are the mathematical functional measure used in HEATXPRT™.

There are many approaches to solving influence diagrams and Bayes belief networks (influence diagrams without decision nodes). The IDES (Influence Diagram Based Expert System) developed at UC Berkeley, was used as a preprocessor to create the run-time version of the influence diagram knowledge base in HEATXPRT™ [5][6][7][9]. This is stored as a matrix of numerical solutions for every combination of qualitative ranges on the input sensor values.

3.1 Generating a Generic Influence Diagram Knowledge Base

The UC Berkeley team, Sargent & Lundy Engineers, and experts from collaborating utilities have developed an influence diagram knowledge base of a generic feedwater heater. Although the goal of the diagnostic procedure is to infer heat rate degradation in the system from the measured sensory values, the influence diagram model was constructed in a causal direction. There are four major reasons for this: 1) numerous studies have shown that humans are poor Bayesians and that the integrity of subjective probabilities assessed for this kind of diagnostic mapping is questionable, 2) the causal mapping allows the use of first principle information in constructing the model, 3) a causal model allows for parametrizing the prior probabilities of failures to take into account individual utility an power plant maintenance, reliability and heat rate performance histories, and thus 4) the causal mapping enables easier updating of the underlying prior and conditional probabilities as more operating experience is gained. Much of the influence diagram knowledge base was derived from previously developed logic trees and first principle relationships between measured parameters (sensors) and calculated parameters. Utility experts and consulting engineers identified the critical variables and the relationships between measured parameters and heat rate degradation failure modes. Seven major failure modes were identified as knowledge islands for further diagnostic and remediation analysis in the rest of the knowledge base: 1) non-condensable gases, 2) tube leaks, 3) tube blockage, 4) tubes fouled internally, 5) excessive venting/steam leaks, 6) baffle of bypass valve leak, and 7) feedwater heater out of service. The major knowledge acquisition tasks were:

Identifying major failure modes for heat rate degradation

Identifying critical parameters indicating heat rate failures

Discretizing the state nodes representing continuous variables

Constructing arcs denoting dependencies among nodes

Assessing arc directions and conditional independence

Deriving the meaning of the diagram for explanation and use in the rest of the HEATXPRT™ knowledge base

An example influence diagram is shown in Figure 9. The model is causal in the sense that the likelihood of achieving certain sensor value ranges is conditioned on the failure state of the system. In this example, the failure mode is internal fouling of the tubes in the feedwater heater. Major influences between measured parameters and the failure are identified by the arcs and conditional independence are implied by the missing arcs in the diagram. Conditional and prior probabilities were assessed from

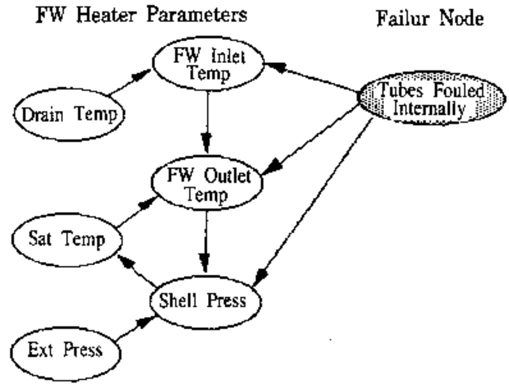

Figure 9. Influence Diagram for Tubes Fouled Internally Failure

experts and from statistical data supplied by EPRI.

The names of the nodes are meant to relate to an 'alarm' condition, in respect to heat rate degradation, of the variable represented by each node. A discretization of the values of measured or calculated parameters into high, normal, and low states, again in regards to heat rate degradation, was determined to be adequate and could be efficiently generated in the ASV module. Faults are represented as either being TRUE or FALSE.

3.2 Testing of Uncertainty Propagation in Influence Diagrams

Verification of an influence diagram should include comparison of its results with the actual diagnosis of experts over various sets of conditions. The only verification of influence diagram so far, however, is to test for two desirable characteristics with appropriate sensitivity to critical and non-critical parameters.

When there is more than one failure with similar symptoms, the ability to distinguish which parameter is critical to the actual inference is indicative of one of the desirable characteristics of an influence diagram. Using this criterion, influence diagrams are evaluated for two failures: Tube Fouled Internally (Figure 9) and Tube Blockages (Figure 10). Later, the resulting probabilities of each failure in the feedwater heater are calculated over a different set of parameter states.

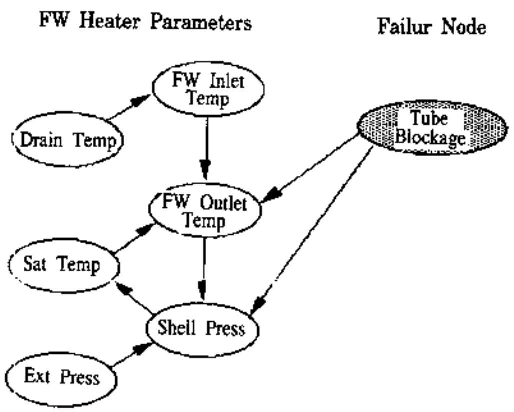

Figure 10. Influence Diagram for Tube Blockage

Two failures, Tube Fouled Internally and Tube Blockage, display similar symptoms according to the heat rate logic tree used by experts. They are:

1. Increased tube bundle pressure drop.
2. Decreased feedwater flow.
3. Decreased extraction pressure drop.
4. Decreased feedwater outlet temperature.

Variations in critical parameter states for Tube Fouled Internally failure, as shown in Table 1, demonstrate the sensitivity trends of the corresponding influence diagram. For this example, the states of feedwater heater shell pressure and feedwater heater drain temperature are set differently. One of the major symptoms common to both failures, decreased feedwater heater outlet temperature is set to low. Referring to Table 1, the resulting probabilities for each failure are calculated for four different scenarios.

If set to high, the feedwater heater shell pressure (Case 1) and drain temperature (Case 2) play important roles in diagnosing the Tube Fouled Internally failure. These may be compared with Case 3 where the two parameters are set to normal. As expected, the resulting probability for TRUE is greater for Cases 1 and 2 than for Case 3. As shown in Case 4, the resulting probability of the failure TRUE is further increased as we change the state to high for both parameters. This illustrates the sensitivity of the influence diagram to changes in the states of these critical parameters.

The variation of the feedwater heater drain temperature demonstrates that the results from the influence diagram are insensitive to variations in non-critical parameters, as variations have little impact on the resulting probability of Tube Blockage, as shown in Table 1 by comparing Cases 1 and 3. This outcome is verified by experts who have concluded that the heater drain temperature is not strongly correlated with the Tube Blockage failure. Rather, the feedwater heater shell pressure is the key parameter in diagnosing this failure as

Table 1. Calculation of Resulting Probabilities for Two Failures with Similar Symptoms

Parameters	Case 1	case 2	case 3	case 4
Turbine Extraction Pres.	Normal	Normal	Normal	Normal
FW Heater Shell Pres.	Normal	High	Normal	High
FW Heater Drain Temp.	High	Normal	Normal	High
FW Inlet Temp.	Normal	Normal	Normal	Normal
FW Outlet Temp.	Low	Low	Low	Low
Sat. Stm. Temp.	Normal	Normal	Normal	Normal
Failures[TRUE, FALSE]				
Tubes Fouled Internally	[0.35, 0.65]	[0.35, 0.65]	[0.01, 0.99]	[0.97, 0.03]
Tube Blockage	[0.01, 0.99]	[0.24, 0.76]	[0.01, 0.99]	[0.24, 0.76]

shown by comparing Cases 2 and 3 in Table 1.

4. Conclusion

Heuristic Sensor Validation has been presented as a means of applying plant knowledge to the task of eliminating errors in the InDiaKB data stream due to faulty sensors. The framework for HSV is a unified one in which objects representing plant subsystems, operating parameters, and sensors are combined in a generic fashion. This provides a portable platform in which HSV can adapt to a changing application environment.

Several strategies have been posed as valuable parts of the HSV module. Probabilistic subsystem models form the basis of applying sensor redundancy and plant connectivity knowledge to sensor validation. Again, a unified theory has been presented which is flexible, robust, and includes the bonus of automated adaptation to changing plant operating characteristics.

Additionally, a means of applying location specific rules and first principles has been provided for future development. Examples of situations where both of these techniques might be useful has been given. However, if the system is applied to a plant where the instrumentation has been properly calibrated, these rules will be implicitly coded within subsystem models. In plants where instrumentation contains typical calibration errors and equipment operates under less than ideal circumstances, the probabilistic framework maintains effectiveness. This would not be the case for the more cumbersome rules involved with first principle analysis or expert heuristics. These will prove to be much more useful in subsystems where instrumentation is sparse or subsystem models weak. This has not been the case with the subsystems targeted for the prototype system, so these aspects have be de-emphasized.

Robustness and sensitivity on the developed influence diagrams have been tested using the on-line data. From the knowledge acquisition by the experts, prior and conditional probabilities representing the relationships among the parameters were retrieved and fine-tuned. Influence diagram methodology has been proved to be a reliable technique in implementing probabilistic reasoning and uncertainty propagation. However, a continuous effort should be done in improving these probabilities to guarantee a successful reasoning.

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