A Framework for an On-Line Diagnostic Expert Systemwith with Intelligent Sensor Validation

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(*Received December 23, 1995*)

This paper outlines a framework for performing two different but inter-related functions in diagnosis, i. e. sensor validation and reasoning under uncertainty. Sensor validation plays a vital role in the ability of the overall system to correctly determine the state of a plant monitored by imperfect sensors (Sopocy, 1990). Two subsystems, Algorithmic (ASV) and Heuristic (HSV) Sensor Validation, separate activities according to the degree of plant knowledge required and represent Sensor Validation Expert System when combined. Uncertain information in sensory values is represented through probability assignments on three discrete states, High, Normal, and Low, and additional sensor confidence measures in ASV. 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 influence diagram represents the backbone of reasoning under uncertainty in Influence Diagram Knowledge Base.

KeyWords: Diagnosis, Expert Systems, Bayes Belief Network, Uncertainty Propagation

1. Introduction

Diagnosis consists of the two different but closely related procedures. The first step is to receive responses of the system through measuring devices, i. e., sensors. From the imperfect nature of sensors, uncertainties are naturally introduced in the responses. The second step is to make a decision on the state of the system based on the sensory values. Lots of uncertainties are introduced at this stage not only because we have to make a decision on information with a degree of uncertainty but because the decision itself depends on one's preference. However, we cannot afford a spectrum of different decisions based on the similar responses of the system by an operator, since the decision can be very critical both in economical and preventive point of view. In order to guarantee a uniform decision based on the in formation, researchers seek a way of using a computer to mimic human reasoning. Expert system technology is to analyze experts' reasoning under a certain circumstance and implement this knowledge to the computer in a form of rules, data base, etc. Monitoring and diagnostics have proven to be successful application areas of expert systems (Milne, 1987). There have been a number of sensor-driven applications in manufacturing and process control (Agogino, 1988; Paasch, 1991 and Kim, 1995) where the degree of validity of sensor readings proved to be a major factor in determining the accuracy of the diagnosis and the usefulness of the resulting corrective recommendations. The objective of this paper is to outline a framework and a set of tools for performing sensor validation and reasoning under uncertainty in expert systems and describe their implementation in HEATXPRT^{TM}, a data-driven online expert system for monitoring and diagnosing heat rate degradation problems in fossil power plants.

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In developing a framework for a diagnostic expert system, we set three essential tools as follows;

1. we need an analyzing tool for uncertain information, since sensory values are not deterministic. Thus, we have to utilize statistical methods in dealing with sensory values.
2. we need a representational tool for uncertain information, since the mapping from quantitative (numeric) value to qualitative (symbolic) value is not one-to-one.
3. we need a diagnosing tool for uncertain information, since the human reasoning is not well represented by the binary logic.

Sensor validation is a major concern for any on-line diagnostic expert system; the large number of inputs needed for enhancing the system performance has led to the development of a preprocessing module dedicated to analyzing and correcting sensor input. Various methodologies have been applied to assessing the degree of validity of sensory input in power generation (Irving, 1985 and Hashemian, 1988). Most calculate statistical features of sensory data for comparison to normal or previously identified abnormal situations. What is generally lacking is a coherent method for establishing and updating both the uncertainty in the data stream and the confidence to be placed in a given reading. In order to do this task, we develop a Sensor Validation Expert System (SenVES) as shown in Fig. 1.

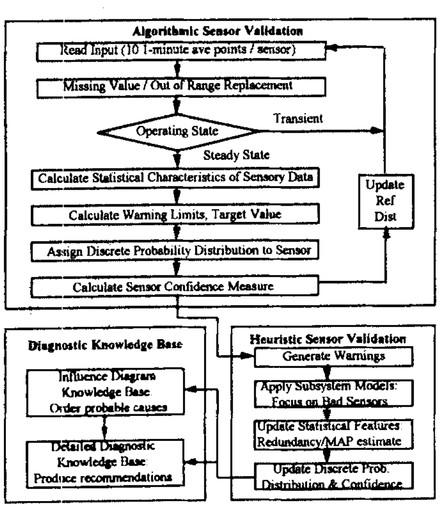

Fig. 1 Schematic diagram of main functional blocks of diagnostic expert system, HEATXPRT™ (Kim, 1994a)

The first level of SenVES in our framework, shown in Fig. 1, will be referred to as Algorithmic Sensor Validation (ASV) (Kim, 1994a). Various algorithmic schemes to assess these probabilities from the on-line data and the plant-specific data files will be described in the next section of this paper.

The second phase of our system, Heuristic Sensor Validation (HSV), investigates possible malfunctions for normal behavioral explanations (Kim, 1994b). Expert heuristic and first principle information of the plant physics (e. g. comparison of upstream and downstream values) are among methods used in HSV for updating probability distributions and sensor confidence measures. Another aspect of HSV concerns the fusion of information from redundant or coupled sensors measuring a single parameter. Previous approaches include: majority voting (Frogner, 1988), averaging with equal weights (IEEE, 1977), and averaging with unequal weights with conditional probabilities (Agogino, 1988). All of these techniques provide the means for determining a single virtual value for redundant sensors, but none takes into account integrity of the sensor reading. We present a method that combines multiple sensor readings with each sensor confidence measure.

The depicted framework ends with validated data and updated probability distributions being input into the Influence Diagram Knowledge Base (InDiaKB) (Kim, 1993). 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 (Kim, 1994a). 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 in Sec. 4.

2. Algorithmic Sensor Validation(ASV)

In identifying the statistical characteristics of sensors and their data, we need a key parameter so that we can make a prediction on other parameters based on it. The key parameter should have a good correlation with other parameters. Also the sensor for this key parameter should have a low precision errors in measuring the values. This key parameter turns out to be the gross generation, which is the output of the power plant. Figure 2 shows a strong correlation between gross generation and parameter. With this strong correlation, we can safely represent a specific parameter values as a function of gross generation. Also it turns out that the representation of parameter as a function of gross generation is the most efficient way in reducing calculation time and database storage.

The ASV module integrates several statistical methods for characterizing the sampled sensory data. A check for transient behavior is first performed to guarantee that all diagnoses are performed on steady state values; many of the algorithms and heuristic in HEATXPRT™ do not apply under transient conditions generated by start-up and large load swings. The elimination from consideration of data collected during such transients provides a stable basis from which trend analysis can be used to predict future states of the system, providing early warnings for potential failures and enabling early corrective action. Because transient operation must be defined so that normal load dispatch commands do not disable the expert system, a tuneable transient state detector has been implemented as part of ASV.

The need to represent the state of the plant over a time period of ten minutes forms the basis for ASV. An estimate is required which takes into account both variation in operation and uncertainty in measurement. Deterministic values certainly cannot accurately represent the state of a dynamic plant over a ten minute period; a statistical distribution is used to characterize the uncertainty in the data stream. Ten one-minute average data points generate a distribution that is discretized into three states: High, Normal, and Low, based on the upper and lower warning limits designated for each sensor. Analysis of typical plant data has shown that the Gaussian (normal) distribution can be used to represent sensor data without significant ($< 3\%$) integrated error (Kim, 1994a). Upper and lower warning limits used as probability density function integration limits for discretization are set to values which indicate a potential problem in the heat rate of the system. The nature of plant operation is such that these limits vary with operating point and so are represented by quadratic functions of gross generation (load). Warning limits are essential to the

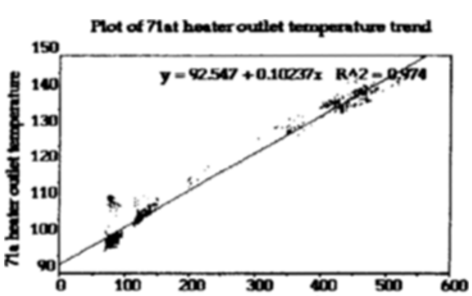

Fig. 2 Strong correlation between a parameter and gross generation (load)

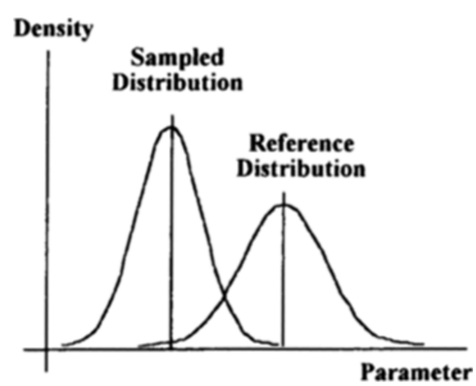

Fig. 3 Calculation of sensor confidence in two distributions including both mean and standard deviation (Kim, 1994a)

proper determination of process state and have required considerable attention from the heat rate experts.

The generation of warning limits based on the learning set is illustrated in other paper (Kim, 1994a). Warning limits are not the only aspect of operation that has been characterized by functions of load; target values and replacement limits are also represented by quadratic equations.

Some error correction does take place in the ASV module. Replacement limits represent parameter values which are never reached during plant operation and thus represent clear cases of sensor failure. In these cases and in cases where an input datum is missing, the target value is substituted. Probability distributions are generated using these target values (they vary according to load variation) and then analyzed by HSV.

The final responsibility of ASV is the assessment of the integrity of an input sensor value. One method for quantifying sensor confidence is to calculate the similarity of the data stream to a reference distribution of a typical sensor of the same class for a specific level of gross generation. A sensor confidence measure determines the reliability of sampled sensor value distribution based on a reference distribution. Sensor confidence measures are given in terms of a metric (distance) between two probability density functions (Fig. 3). The numeric value of sensor confidence represents the closeness between two distributions. If a scale over [0,1] is used, [0] implies completely independent distributions and [1] represents identical distributions. Due to its computational efficiency and empirical accuracy (Kaliath, 1967) (Bhattacharyya, 1943) (Matusita, 1955) (Kobayashi, 1967) for the class of distributions in our application, the Bhattacharyya Coefficient is chosen as an appropriate measure in HEATXPRT™.

Kim has developed the mathematics necessary to apply the Bhattacharyya Coefficient to our application (Kim, 1994a). As a distance measure, it has the desirable property that it decreases or increases accordingly to the probability of error as defined by the Kolmogorov Distance (Kaliath, 1967). This measure of confidence can also be easily updated in cases where HSV updates the initial probability distributions calculated by ASV. It is used by HSV as one of the criteria for further examination of the operation of a sensor.

3. Heuristic Sensor Validation

Heuristic Sensor Validation (HSV) synthesizes the results generated by ASV with system characteristics to differentiate sensor failures from process deviations. Ideally the output of HSV is a set of sensor values, probability distributions, and confidence measures that represents all of the deviations from normal caused by operational problems and none of those caused by sensor malfunctions. The following techniques are used by HSV to accomplish this separation (Kim, 1992) :

- Performance experience
- Connectivity of subsystems
- Sensor redundancy
- First principles

Exploiting these sources of knowledge, HSV updates the sensor probability distributions and confidence measures when inconsistencies are identified. These modified distributions are then used as input to the influence diagram knowledge base and the rest of the HEATXPRT™ knowledge base.

3.1 Connectivity of subsystems and its examples

The scope of analysis performed in ASV is limited to data readings from a single sensor and a probability distribution on past readings. Power plants contain many subsystems which are represented inside the expert system as a set of operationally interdependent parameters. In addition these subsystems are interconnected to make up the overall plant, extending the scope of subsystem models to neighboring subsystems. There exists a wealth of information usable for validation that cannot be applied on a single sensor basis as in ASV. In our framework, it is the job of HSV to exploit these additional sources of knowledge.

Fortunately, there are some desirable features

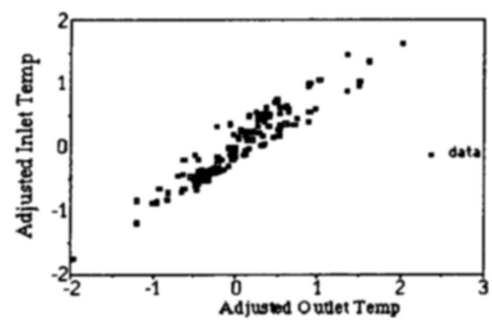

Fig. 4 Load-adjusted inlet temp vs. adjusted outlet temp

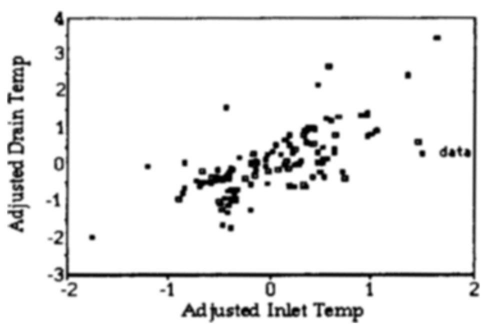

Fig. 5 Load-adjusted drain temp vs. adjusted inlet temp

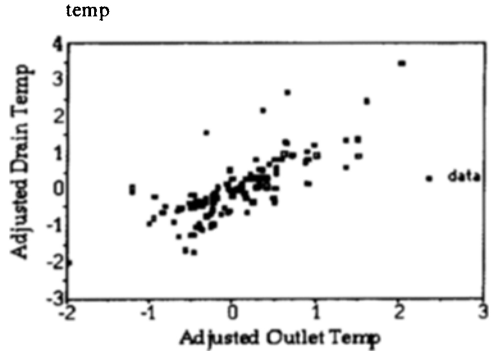

Fig. 6 Load-adjusted drain temp vs. adjusted outlet temp

of data we have seen in our prototype development of a feedwater heater expert system. While plant operating points vary widely over time, a repeatable pattern of parameter behavior with respect to gross generation as explained in the previous section is present. Subsystem parameters closely follow quadratic polynomial relationships to gross generation. Once gross generation is parameterized out of the data stream, a further relationship among the data can be recognized: subsystems of the power plant operate in a multivariate Gaussian distribution with strong covariance within equipment and across equipment connections. This distribution forms the backbone of HSV, allowing the discrimination between sensor faults and process deviation through relatively simple calculations. Covariance among parameters provides for us a large set of relationships for cross-checking plant operation versus sensor behavior.

A multivariate Gaussian probability density function can be used to represent parameter value (corrected for plant load) behavior in equipment groupings:

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

where: p=the probability density function
x=the vector of subsystem parameter values (normalized)
R=the covariance matrix

The performance of the plant can be analyzed with respect to its predicted behavior described by a quadratic 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 (Kim, 1994b).

Of note in Figs. 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 Figs. 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:

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

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 in the curve fits, seasonal operating changes, and missing data with approximation. In cases where data does not cluster as well as seen in Figs. 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.

3.2 Sensor redundancy

Redundant sensors cause problems of their own in the operation of a plant; in the words of an expert, *if you have one sensor, you know exactly what is going on. Add a second sensor and you' re not quite sure.* HSV improves the evaluation of single sensor data through the use of a load independent multivariate Gaussian distribution on subsystem operation. The same distribution can be used in several ways to merge multiple measurements of the same process variable. The subsystem distribution can be coupled to good parameter values to provide a prior distribution of process variable values. If a probability distribution of sensor behavior (including likely failure modes) given variable value can be constructed, Bayes' rule can be used to combine evidence from redundant sensors.

Barlow et al. (Barlow, 1986) investigated this situation and developed an appropriate utility function, based on the idea that the decision maker only exercises minimal judgment relative to random quantities of interest. This idea is similar to that of sensor confidence, which was investigated in the previous section, where the sensor confidence is calculated between probability distributions among sampled and a reference distribution (Kim, 1994a). Thus using the normalized sensor confidence as the weights in Barlow's equation, we can provide a better consensus on the posterior distribution by the decision maker.

$$f(x)=\sum_i w_i f_i(x),\ \text{where } w_i \geq 0 \text{ and } \sum_i w_i = 1$$

$$w_i=\frac{\rho_i}{\sum_{i=1}^{N}\rho_i^2} \tag{2}$$

where ρ_i sabscript is the i-th sensor confidence.

The sensor confidence is calculated by Eq. (2). One of the advantages that the sensor confidence method described here has over the method proposed by Barlow et al. is that it uses a continuous density function as the distance measure, and thus can be used for a range of uncertainties in the feature values from the sensor signal.

Bayes' rule is applied to create an updated probability density function given all sensor values recorded for the parameter in question along with its subsystem model (Winkler, 1972). The general form of Bayes rule for this case is given:

$$p(y|x)=\frac{p(x|y)p(y)}{p(x)} \tag{3}$$

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 are 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. (3) can be applied to multiple redundant sensors. Eq. (4) is the resulting probability density function for the parameter value after sensor fusion. In addition, all scaling constants have been grouped together as K (Kim, 1994b).

$$p(y|x_1 \ldots x_N)=Ke^{-\frac{1}{2}\left[ay^2+by+c+\sum_{i=1}^{N}\frac{(y-x_i)^2}{\sigma_{acc}^2}\right]} \tag{4}$$

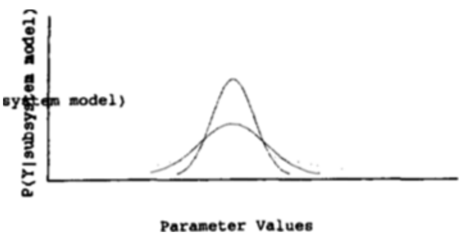

Fig. 7 Probability distribution of process variable, Y, given the subsystem model and other parameter values.

Unlike the case of a MAP estimate where a single maximum value of the distribution is used, other characteristics of the distribution are captured in Bayesian sensor fusion. Figure 7 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 the error associated with this value. Thus, the predictive quality of the subsystem model is used to determine the best parameter value estimate. An ML estimate requiring that an actual sensor be associated with the parameter value cannot exploit this information (Kim, 1994b).

4. Influence Diagram Knowledge Base

Diagnosis is the process of determining the state of a system based on system observable (Paasch, 1991). 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 mapping and in the observable themselves (Milne, 1987). 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 (Pearl, 1988). Knowledge engineering schemes (Moore, 1985) 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 operator's 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) (Pearl, 1988). The IDES (Influence Diagram Based Expert System (Moore, 1985; Agogino, 1987 and Agogino, 1990), developed at UC Berkeley, was used as a preprocessor to create the run-time version of the influence diagram knowledge base in HEATXPRT™. This is stored as a matrix of numerical solutions for every combination of qualitative ranges on the input sensor values.

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 Bayesian 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

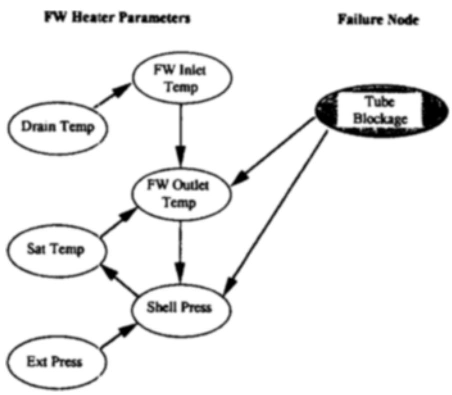

Fig. 8 Influence Diagram for Tube Blockage (Kim, 1993)

constructing the model, 3) a causal model allows for parametrizing the prior probabilities of failures to take into account individual utility in 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. The major knowledge acquisition tasks are listed. (Kim, 1993)

An example influence diagram is shown in Fig. 8. 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 experts and from statistical data supplied by EPRI.

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 and Tube Blockages (Kim, 1993). Later, the resulting probabilities of each failure in the feedwater heater are calculated over a different set of parameter states. The results of this calculation is listed in Table 1. (Kim, 1993)

Table 1 Calculation of resulting probabilities for two failures with similar symptoms (Kim, 1993)

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 Bolckage	(0.01, 0.99)	(0.24, 0.76)	(0.01, 0.99)	(0.24, 0.76)

5. Conclusion

This paper outlines a framework and methodology for performing sensor validation in HEATX-PRT™, a data-driven on-line expert system for monitoring and diagnosing heat rate degradation problems in fossil power plants (Sopocy, 1990). The sensor validation system consists of both algorithmic and heuristic modules, including both qualitative and quantitative approaches. We believe that the architecture and techniques described can be applied to any number of on-line expert system applications in which the degree of validity of sensor readings is a major factor in determining the accuracy of the diagnosis and the usefulness of the resulting corrective recommendations.

Acknowledgments

The author would like to acknowledge Professor Alice Agogino and Dr. Bill Wood's contributions to the overall project development and in the development of the Heuristic Sensor Validation system, in particular.

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