Proceedings of the Korean Nuclear Society Spring Meeting
Seoul, Korea, May 1998

A Belief Network Approach for Development of A Nuclear Power Plant Diagnosis System

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Abstract

Belief network(or Bayesian network) based on Bayes' rule in probabilistic theory can be applied to the reasoning of diagnostic systems. This paper describes the basic theory of concept and feasibility of using the network for diagnosis of nuclear power plants. An example shows that the probabilities of root causes of a failure are calculated from the measured or believed evidences.

1. Introduction

Bayes' Rule is a mathematical formula in probabilistic theory to express a conditional probability of the form $Pr(A|B)$ into the reversed conditional probability in the form of $Pr(B|A)$[1,2,3]. It is represented as

$$Pr(A|W) = \frac{Pr(W|A)Pr(A)}{Pr(W|A)Pr(A) + Pr(W|\sim A)Pr(\sim A)}$$
$$= \frac{Pr(W|A)Pr(A)}{Pr(W|A)Pr(A) + Pr(W|B)Pr(B) + Pr(W|C)Pr(C) + \ldots\ldots}, \quad (1)$$

where, $U = \{A, B, C, \ldots\ldots\}$.
On the other hand, probabilistic chain rule [2] can be represented as

$$Pr(A, B, C, D) = Pr(A|B, C, D)\, Pr(B|C, D)\, Pr(C|D)\, Pr(D). \quad (2)$$

A Bayesian network [2,4] uses Eq.(1) and Eq.(2) this process to draw a network representing or modeling the events and/or phenomena of the world by making certain random variable pairs uncorrelated once the information of some other random variables is known. If a set of events U satisfies the following Eq.(3) , then it is interpreted as A is determined by $C1, \ldots, Cn$ regardless of U. Therefore, if $C1, \ldots, Cn$ is known, A is conditionally independent from U.

$$Pr(A|C1, \ldots, Cn, U) = Pr(A|C1, \ldots, Cn) \quad (3)$$

These independence conditions make it possible to replace the terms in the chain rule with the simpler conditional probability terms. In Eq.(2), if A is determined only by B, B is only determined by C, and C is determined only by D, then Eq. (2) becomes

$$Pr(A,B,C,D) = Pr(A|B,C,D)\ Pr(B|C,D)\ Pr(C|D)\ Pr(D)$$
$$= Pr(A|B)\ Pr(B|C)\ Pr(C|D)\ Pr(D) \quad (4).$$

A Bayesian network is a directed diagram of conditional probability relationships. Directed lines between random variables indicate conditional dependencies. If all the parents of event A are defined, then A is conditionally independent of the remaining events except descendants of A. An example is illustrated in Fig. 1. The diagram is drawn from the following set of rules. [5,6]

- *If sea-water is leaking from condenser, then the sodium concentration of the condensate extraction pump(CEP) outlet is high ,*
- *If the sodium of makeup water is high, then the sodium of CEP outlet is high ,*
- *If the sodium of CEP outlet is high, then cation conductivity of blowdown is high*

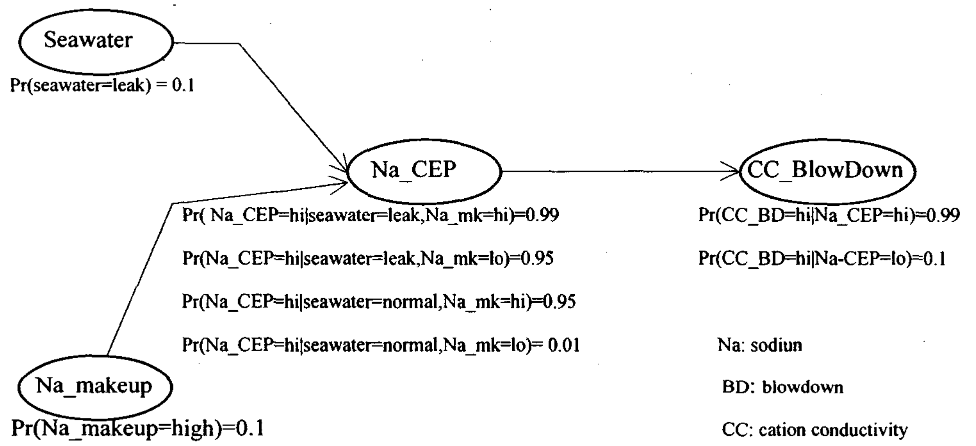

Fig.1 An example of Bayesian Network

From Fig.1, for an example of conditional independence, it is said that the state of the cation conductivity of blowdown is only dependent of sodium of CEP, no matter what other random variables of Fig.1 are. Thus, $Pr(CC\_BD=high \mid Na\_CEP=high, Na\_makeup=high, seawater=leak) = Pr(CC\_BD = high \mid Na\_CEP = high)$. It means that the cation conductivity is only determined by the sodium in the CEP outlet regardless of the conditions of the other variables. The states of *Na_makeup* and *seawater* only determine the state of *Na_CEP*, not the state of *CC_BlowDown*.

2. Network Calculations

From the independent probabilities of the parent node and conditional probabilities in node A, the probabilities of node A can be calculated according to the total probability raw as Eq.(6)[1,3]

$$Pr(A) = Pr(A|B)Pr(B) + Pr(A|\sim B)Pr(\sim B) \quad (5)$$

If B, C, D,…… subdivide the universe U, then

$$Pr(A) = Pr(A|B)\,Pr(B) + Pr(A|C)\,Pr(C) + Pr(A|D)Pr(D) + \ldots\ldots \quad (6)$$

Therefore, in Fig. 1, the probability of '*Na_CEP = high*' is

$$\begin{aligned} Pr(\,Na\_CEP{=}high\,) &= Pr\,(Na\_CEP{=}hi \mid seawater{=}leak,\ Na\_mk{=}hi)\ Pr(seawater{=}leak,\ Na\_mk{=}hi) \\ &+ Pr\,(Na\_CEP{=}hi \mid seawater{=}leak,\ Na\_mk{=}lo)\ Pr(seawater{=}leak,\ Na\_mk{=}lo) \\ &+ Pr\,(Na\_CEP{=}hi \mid seawater{=}normal\ Na\_mk{=}hi)\ Pr(seawater{=}normal,\ Na\_mk{=}hi) \\ &+ Pr\,(Na\_CEP{=}hi \mid seawater{=}normal,\ Na\_mk{=}lo)\ Pr(seawater{=}normal,\ Na\_mk{=}lo) \\ &= 0.19. \end{aligned} \quad (7)$$

With the same manner, the probability of other variables can be calculated.

2.1. Belief Revision and Belief Update[2]

There are two types of computational methods with Bayesian networks. One is the belief revision concerned with the maximum joint probability of the network. It gives the most satisfactory explanation for the given evidence. If W is the set of all random variables in the given Bayesian network and e is the identified evidence, i.e., e represents a set of results made from a subset of W, then any complete set of instantiations of all the variables in W consistent with the given e will be an explanation or interpretation of the measured e. Belief revision is a process to find w^* such that

$$Pr(w^* \mid e) = max\ Pr(w \mid e). \quad (8)$$

w^* can be called "*maximum probable instantiation*". For belief revision, it is necessary to construct a set of complete instances consistent with e whose joint probability is maximal. For example, in Fig. 1, if the measured evidence is '*CC_BlowDown = high*', then our assignment for belief revision is to find the set of events that maximize the joint probability including the evidence '*CC_BlowDown = high*'. The solution will be

$$\begin{aligned} &Pr(CC\_BlowDown{=}high,\ Na\_CEP{=}high,\ seawater{=}leak,\ Na\_makeup{=}normal\,) \\ &= Pr(CC\_BlowDown{=}high|Na\_CEP{=}high) * Pr(Na\_CEP{=}high|seawater{=}leak,Na\_makeup{=}\ normal) \\ &\quad * Pr(seawater{=}leak,\ Na\_makeup{=}normal) = 0.085. \end{aligned} \quad (9)$$

Belief updating is a recalculation of the probability of subset events of random variable W based on the measured or identified evidence. In other words, it is a process to compute a reverse conditional probability or posteriori probability from priori conditional probabilities by Bayes' rule. When someone finds that the cation conductivity of the blowdown is high, what he is going to estimate is whether the seawater is leaking or not. The probability computation can be performed by Bayes' rule in the backward direction from node to node. Thus,

$$Pr(seawater = leak \mid CC\_BlowDown{=}high)$$

$= 0.354$ (10)

3. Belief Network for a Feedwater Diagnosis

Belief networks are able to describe various physical system or phenomena of the world. Particularly, they are useful representing the cause-effect relationships of complex events [2,3]. One or several root causes affect to the intermediate events and/or observable evidences. In many cases, failures propagate from a small root cause to middle events and observable evidences. One of the important purposes of a diagnostic system is to find out the root cause of the existing failure situation from measured evidences. When a Bayesian network simulates properly the physical propagation process of failure with measurable evidences, the failure probability of each node is calculated on the condition of the measured evidences. Thus the most probable candidate root cause can be identified on the basis of the observed evidences. Fig. 2 is illustrating a Bayesian network representing a feedwater chemistry behavior. It is constructed with a commercial belief network tool, called Netica [4]. The probabilities of input nodes(root cause nodes in Fig 2. For example, condenser leak) and conditional probability table of the other nodes will be able to be determined on the basis of operational experiences, failure rate data from the manufacturer, design data, or intuitive approximation etc. For example, one of the conditional probability of *Sea_water_leak* node, *Pr(sea_water_leak = leak | condenser_leak = leak),* is 1.0 in Fig. 2.

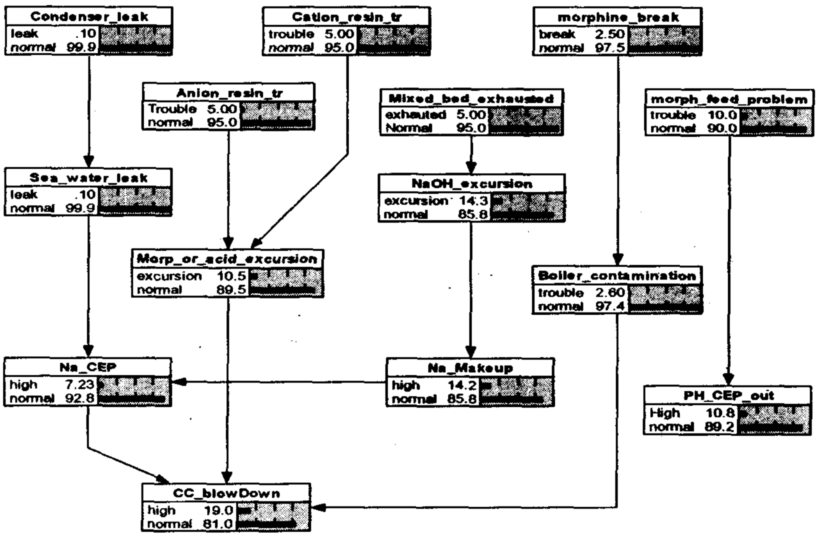

Fig.2 A Belief Network for Feed Water Chemistry

Thus, Fig. 2 shows normal probabilities of each node when any evidence is not considered. Let's assume the cation conductivity of blowdown (*CC_blowDown*) is measured very high. Based on the measured evidence, the new modified probability, that is, the conditional probability conditioned on '*CC_blowDown is High*', is calculated for each node. The updated probability of each node gives the belief information of "*Conditioned on the observed evidence(s), what would be the probability of abnormality of the node?*" If additional evidences are observed, more realistic probability will be put to the other nodes. Fig. 3 illustrates the updated probabilities, conditioned on '*CC_blowdown*' is high. It gives the information that the probabilities of '*Cation_resin = trouble*', '*Anion_resin = trouble*', and '*Mixed_bed = exhausted*' have changed to very high in comparison with the probabilities in Fig. 2.

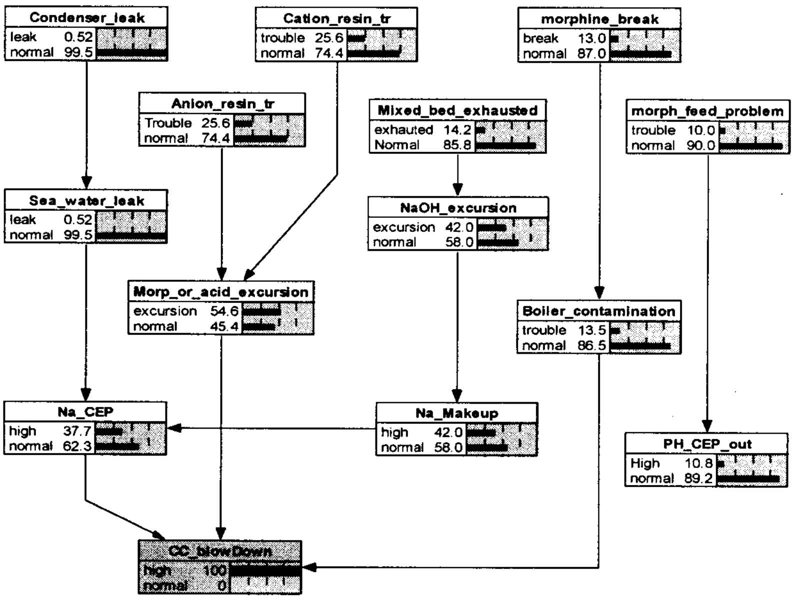

Fig.3. Updated probabilities on the condition of a measured evidence

4. Conclusion

A belief network is an useful expert system tool for diagnosis, prediction, statistical analysis, probabilistic modeling, risk management, etc. This paper described its basic theory and illustrated an application example for feedwater chemistry control. This technology is comparable to a general expert system. In an expert system, the engineer tries to implement the reasoning process with IF-THEN rules. When an expert system grows with a lot of rules to express a complex phenomenon, it is very hard to figure out why and how the physical system is modeled with the rules because of the complexity of rules. However, a belief network captures the expert's understanding of the modeled system under a certain knowledge domain and constructs influence relationships on the basis of the understanding. It is not necessary to develop all reasoning rules from observed evidences or conditions for diagnosis. A belief network system only tries to express a causal relationship of what is to be modeled with conditional probability information. Therefore, users could understand the overall relationships of subsets in the knowledge domain with in the belief network approach system more easily than IF-THEN rule-based system. The diagnostic information is indicated as a value of probability on the basis of observed evidences or measurements. For more useful applications of belief networks as a diagnosis tool, it is required to be equipped with various user interface functionality, capability of data interface or connectivity with other software, and other utilities.

REFERENCES

1. Peyton Z. Peebles, Jr. Probability, Random Variables, and Random Signal Principles, Second Edition, McGraw-Hill, 1987.
2. Air Force Institute of Technology Artificial Intelligent Laboratory, "Bayesian Networks Tutorial"
3. Gelb, A et al, Applied Optimal Estimation, MIT Press
4. Norsys Software Corp., Netica^{TM}, Application for Belief Networks and Influence Diagrams – User's Guide, 1997.
5. Khartabil, L et al , "FW-COMPAS: An On-line Intelligent System for Monitoring, Diagnosis and Prediction of Corrosion Product Generation and transport into Steam Generatos", AECL Ontario.
6. Barber,D. and Van Belo,J.P., An Introduction to CANDU Chemistry (Training course manual), 1996