Bayesian Network for Fault Diagnosis and Prognosis

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1. Introduction

To prevent unexpected failure and reduce economic loss, numerous studies have been in the field of prognostics and health management (PHM). Many good review papers investigated recent state-of-the-art of PHM [1-3]. Most of the researches show their feasibility by applying to the real field. Although component-level PHM becomes mature, many operator and maintenance practitioners are more interested in the system-level PHM. As industrial systems become more and more complex, they consist of multiple components that are connected. In addition to this, the combination of a small amount of degradation of several components can be combined and lead to much larger severe effects on a whole system. Therefore, one of the major challenges of system-level PHM is how to deal with the dependency effect of multiple components to accomplish accurate fault diagnosis and prognosis. This study introduces system-level fault diagnosis and prognosis using a Bayesian network. To verify the effectiveness of the proposed approach, simple numerical examples is to be utilized.

2. Bayesian Network

Bayesian Network is a promising tool to integrate various uncertainty sources and heterogeneous information [4]. Bayesian network contains nodes and links which represent random variables and casual relationships between nodes, respectively. Fig. 1. Illustrates a simple Bayesian network that consists of four nodes. According to this structure, the joint probability of the system can be written as

$$P(X_1, X_2, X_3, X_4) = P(X_1)P(X_2)P(X_3|X_1, X_2)P(X_4|X_3) \quad (1)$$

Once the user obtains the conditional probability between random variables, the joint probability of the system can be calculated. The basic process of fault diagnosis and prognosis using Bayesian network is to identify its conditional probability table (CPT) which gives the likelihood for all possible status combination that defined by the node and its immediate precedent. Table 1 shows an example of a CPT of X_1, X_2, and X_3. CPT assumes that 0 and 1 represent normal and fault state of random variables, respectively. According to Table 1, when X_1 and X_2 show 0 and 1 respectively, X_3 will be 0 with a chance of 0.46. In practice, random variables are modeled as components or subsystem and their health condition can be probabilistically estimated based on the constructed CPT.

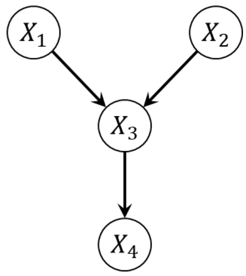

Fig. 1. Simple Bayesian network model

Table 1 Condition probability table

X_1	X_2	X_3	$P(X_3\|X_1, X_2)$
0	0	0	0.02
0	0	1	0.98
0	1	0	0.54
0	1	1	0.46
1	0	0	0.12
1	0	1	0.88
1	1	0	0.76
1	1	1	0.24

3. Conclusion

To realize an effective system-level diagnosis and prognosis, dependencies between multiple components that are combined to operate as a system should be considered properly. This paper introduced diagnosis and prognosis approaches using the Bayesian network to identify the causal relationship between these components. For practical application, uncertainty quantification of system-level and their propagation will be explored as future work.

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