BAYESIAN NETWORK FOR FAULT DIAGNOSIS

C.H. Lo, Y.K. Wong and A.B. Rad
Department of Electrical Engineering, The Hong Kong Polytechnic University
Hung Hom, Kowloon, Hong Kong
Fax: +852 2330 1544
Email: eechlo@inet.polyu.edu.hk, {eeykwong, eeabrad}@polyu.edu.hk

Keywords: Probability reasoning, Bayesian networks, Bond graph, Model-based fault diagnosis

Abstract

Fault diagnosis based on artificial intelligence techniques often deals with uncertain knowledge and incomplete input data. Probability reasoning is a method to deal with uncertain information, and Bayesian network is a tool that brings it into the real world applications. This paper describes the application of Bayesian network for diagnosing faulty components from engineered systems. A general procedure for constructing the Bayesian network structure on the basis of a bond graph model is proposed. We demonstrate how the resulting Bayesian network can be applied to fault diagnosis in an engineered system.

1 Introduction

The complexity and sophistication of modern engineering systems, and the growing demand for system's safety and reliability; motivate the development of robust fault diagnosis algorithm. Early approaches to fault diagnosis are inherently rule-based. They are proved to be inflexible, incomplete, and required comprehensive a prior knowledge of the fault characteristics, rather than actually deducing the fault themselves. Most advanced fault diagnosis algorithms now concern of using model that is derived from system's structure and behavior in order to establish the cause of system malfunction. These model-based fault diagnosis algorithms [2, 9, 13] enables more complex cause-effect reasoning and hence a more robust diagnostic system can be developed.

A number of different model-based fault diagnosis algorithms had been proposed in the past decades, capable of dealing with different diagnostic problems. Quantitative and qualitative were the two major approaches to model-based fault diagnosis. In quantitative fault diagnosis, precise mathematical model was used to monitor system states, detect abnormal behaviors and diagnose the failures. The main problems with such methodologies are the intricacy and overheads of obtaining precise numerical models and the sensitivity of the diagnostic system to modeling error. Usually, the effects of modeling errors obscure the effects of faults and cause false alarms [8, 13]. Qualitative fault diagnosis which dominates in the AI community, without the use of precise numerical model and capable of dealing incomplete information, alleviate some problems encountered by quantitative approach. However, the lack of precision in the representation, and ambiguities introduced during the inference process, limit the application of the qualitative approach to complex systems [4].

Fault diagnosis based on AI techniques often deals with uncertain knowledge and incomplete input data. Probability reasoning is a method to deal with uncertain information, and Bayesian network is a tool that brings it into the real world applications. In this paper, we proposed an alternative approach to model-based fault diagnosis, where Bayesian network is adopted to model the system and diagnose the failures. Bayesian network is a directed, acyclic graph (DAG), which embeds cause-effect relationship between variables (nodes). The representation framework of Bayesian network allows reasoning under uncertainty. Component failure probability of a system is computed by sequential evidence-propagation inference among conditional probability distributions that have been specified at each variable (node) [3].

The goal of the model-based fault diagnosis is to detect and localize faulty components in a system. Hence, the model used should incorporate structural information about the system and bond graph was such a representation. In this paper, a general procedure for constructing a Bayesian network structure on the basis of a bond graph model is proposed. Some researchers have proposed to learn the Bayesian network structure from data [5, 10]. However, the accuracy of the learned Bayesian network is largely affected by the 'richness' of the data and the prior knowledge of the network ordering. There are several advantages of using bond graph model as the skeleton to construct the Bayesian network for fault diagnosis. The task of identifying system variables to construct Bayesian network is completed and the localization of faulty components from Bayesian network is enhanced since they are already represented in the bond graph model. Bayesian network based fault diagnosis contributes to the possibility of ranking possible failures, handling multiple simultaneous failures and uncertainty symptoms of certain faults.

The paper is organized as follows. In Section 2, fundamental knowledge of Bayesian network is reviewed. Section 3 describes the construction issues of a Bayesian network on the basis of a bond graph model. In Section 4, fault diagnostic scheme based on Bayesian network and its result are presented. Finally, the paper is concluded in Section 5.

2 Bayesian Network

Bayesian network, also known as probability network or belief network [5], are well established as a representation of relations among a set of random variables that are connected by edges and given conditional probability distribution at each variable. Bayesian network is a directed, acyclic graph (DAG) where nodes represent random variables. Causal relations are represented as a directed edge between variables, leading from the cause variable to the effect variable. As shown in Figure 1, an edge from B to A indicates that B causes A.

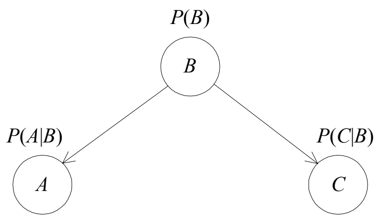

Figure 1: A simple Bayesian network.

Conditional probability distribution (CPD) is specified at each node that has parents, while prior probability is specified at node that has no parents (the root node). As shown in Figure 1, the CPDs of variables A and C, are $P(A|B)$ and $P(C|B)$ respectively; and the prior probability of B is $P(B)$. The edges in the Bayesian network represent the joint probability distribution of the connected variables. For example, the joint probability distribution for the edge (B, A) is $P(A, B)$ which represents the probability of joint event $A \wedge B$. The fundamental rule of probability calculus shown that,

$$P(A, B) = P(A|B) \cdot P(B). \tag{1}$$

,and in general, the joint probability distribution for any Bayesian network, given nodes $\boldsymbol{X} = X_1, \ldots, X_n$, is,

$$P(\boldsymbol{X}) = \prod_{i=1}^{n} P(X_i | parents(X_i)). \tag{2}$$

,where $parents(X_i)$ is the parent set of node X_i. Equation (2) is known as the chain rule, which indicates the joint probability distribution of all variables in the Bayesian network as the product of the probabilities of each variable given its parents' values.

Inference in the Bayesian network is the task of computing the probability of each variable when other variables' values are known. That means once some evidence about variables' states are asserted into the network, the effect of evidences will be propagated through the network and in every propagation the probabilities of adjacent nodes are updated. The situation is mathematically formalized as the Baye's theorem,

$$P(X|Y) = \frac{P(Y|X) \cdot P(X)}{P(Y)}. \tag{3}$$

,which represents the probability of node X given evidence Y. The term $P(X|Y)$ denotes the posterior probability of node X and can be computed when the likelihood ($P(Y|X)$) and prior probability ($P(X)$) are known; and $P(Y)$ denotes a normalizing factor, which is determined as follow,

$$P(Y) = P(Y|X) \cdot P(X) + P(Y|\neg X) \cdot P(\neg X). \tag{4}$$

,where $\neg X$ denotes the complement of variable X. In fault diagnosis application, variable X may be interpreted as the hypotheses of fault and evidence Y is the observed symptoms.

Fault diagnosis in a qualitative sense is the reasoning of the cause-effect or fault-symptom relations and in almost all cases single symptom will be caused by several faults, while single fault will exhibit several symptoms [7]. This is also the case in the medical diagnosis. In this situation, Bayesian network provides an alternative approach to tackle the diagnosis problem. Every fault and even symptom is modeled by a random variable in the network with a probability distribution. When observed symptoms (evidences) are input to the network, probabilities of every fault are computed according to the Baye's rule, Equation (3). So, ranking of different faults with the given symptoms is possible and the possibility of eliminating possible fault candidates as in the case of qualitative reasoning is reduced.

3 Building Model

The performance of model-based fault diagnosis will be greatly impaired when a poor model is used. Traditionally, the construction of Bayesian network is by intuition. The resulting network model will be incomplete and the causal relations will be incorrect. Recently, some researchers proposed to automate the construction process by learning the network structure through data [5, 10]. However, the accuracy of the learned Bayesian network is largely affected by the 'richness' of the data and the prior knowledge of the network ordering. Moreover, when the number of variables in the network is increased, the learning algorithm rapidly becomes computationally infeasible and 'enormous' data is necessary [10]. To overcome this problem, bond graph model is proposed to generate the required Bayesian network. Before discussing this construction process, basic procedures for constructing a Bayesian network are briefly reviewed.

2.1 Modeling elements

The construction of a Bayesian network consists of the following procedures

1. Identify hypothesis events and achievable information to the network and represent them into a set of random variables, i.e., hypothesis variables and information

variables, respectively.

2. Establish directed links between variables for a causal network. Mediating variables (neither hypothesis variables nor information variables) are often introduced to facilitate the acquisition of CPDs, reflecting independence properties in the domain, or other purposes [5].
3. Specify the conditional probability distributions (CPDs) at each variable.

The purpose of Bayesian network is to estimate certainties of events that are unobservable or costly to observe (i.e., hypothesis variables) when evidences (i.e., information variables) are given. The variables in Bayesian network may be discrete, having a finite number of states, or they may be continuous. Mediating variables are introduced in order to have a more refined network model of the domain. If the introduction of mediating variables serves no purpose, we should eliminate them from the model or they may menace performance [5]. Historical data and expert knowledge are employed to specify the conditional probabilities at each node. Figure 2 shows the Bayesian network model constructed from the above procedures.

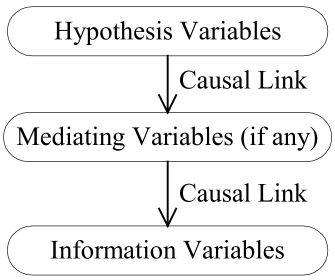

Figure 2: Typical Bayesian network model.

2.2 Bond graph

Bond graph provides a systematic and unified framework to model systems in different energy domain. It simply consists of subsystems linked together by lines representing power bonds. Power variable is the product of effort (e) and flow (f). A half arrow indicates positive energy flow from one variable to other. Usually, effort represents either: force, voltage or pressure; and flow represents either: current, flow or velocity. Each bond in the bond graph is numbered so as their corresponding flow and effort. The construction of bond graph is based on nine primitive entities: three are 1-port elements, namely, resistance (R), capacitance (C) and inertia (I); two are 2-port elements, transformer (TF) and gyrator (GY); two are 3-port elements, parallel junction (*0-junction*) and serial junction (*1-junction*); and the rest are the ideal effort (S_e) and flow (S_f) sources. Extensive review of bond graph theory can be found in [6].

As mentioned in the previous subsection, hypothesis and information variables are necessary for the construction of Bayesian network and they can be readily identified in a bond graph model. Any efforts or flows in a bond graph that are observed can be identified as information variables. For example, the liquid level in a tank (hydraulic domain), the input flow rate to a tank (hydraulic domain), and the voltage of a capacitor (electrical domain), can be information variables once they are observed. The state of hypothesis variables is what we are interested in when giving the state of information variables. They can be represented in bond graph as C, I, or R elements or any effort and flow variables that their states are of interest. The directed links between variables in Bayesian network can be obtained from a set of qualitative equations that are derived from bond graph model. The detailed formulation of qualitative equations is omitted here and interested readers can find the information in [13].

2.3 Implementation

The structure of a Bayesian network has some similarities to a bond graph model. Hence in this section, the transformation from bond graph model to Bayesian network will be discussed and the tank system is used as an illustration. Figure 3 shows the structure of the tank, with an input flow source Q_{in}, an output control valve R and the capacity of the tank C. The measured variable is the height h of the tank (liquid level) which is related to the pressure as $P = f(h)$. In this example, volume flow rate and pressure are the flow and effort variables respectively. The qualitative bond graph equations are derived from Figure 3 and described as follow:

$$\begin{aligned} e_1 &= e_2 = e_3 \\ f_1 &= f_2 + f_3 \\ f_2(t) &= C \times (e_2(t) - e_2(t-1)) \\ e_3 &= R \times f_3 \end{aligned} \tag{5}$$

All power variables are considered at time t unless specified.

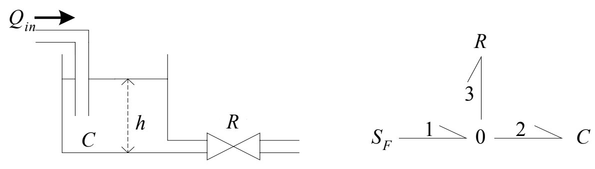

Figure 3: A tank system and its bond graph.

Following the procedures of constructing a Bayesian network as aforementioned, we are first to identify the information and hypothesis variables. From Equation (5), the only information variable is e_2 (the liquid level in tank) and the hypothesis variables are elements C and R; since in a diagnostic application, the state of a component in the system is of concern. A mediating variable, f_2, is also necessary in order to express the causal relation between variables f_2 and e_2. Hence, the resulting Bayesian network describing the diagnosis process of the tank system is shown in Figure 4.

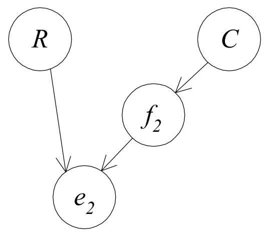

Figure 4: Bayesian network constructed from bond graph in Figure 3 to effect fault diagnosis.

In order to construct a simple Bayesian network that still captures all the necessary information to perform fault diagnosis, the unnecessary variables like, f_1, $e_2(t\text{–}1)$, f_3, are omitted in the network. Whenever an information variable is on the R.H.S. of the equation (such as the third one in Equation (5)), a variable on the L.H.S. (in this case, f_2) should be introduced as a mediating variable to represent the causal relation as shown in Figure 4. Bayesian network constructed from bond graph model is nowready for fault diagnosis application.

4 Fault Diagnosis Scheme and Results

Fault diagnosis scheme based on Bayesian network proposed in this paper is designed to localize the faulty components that cause the abnormal behaviors of a system or process. Rather than generating an initial fault candidates' set, such as in [13], a probability distribution, which is computed through the Bayesian network with given evidence, is attached to each component. Hence, ranking of faulty components can be achieved. Faulty components to be localized are represented as hypothesis variables in the network and system measurements are input to the network through the corresponding information variables. This has a close relation with bond graph model. Components in the bond graph are represented as *C*, *I*, or *R*, elements, while system measurements are represented as corresponding effort or flow variables in the bond graph. As a result, the structure of a Bayesian network for performing fault diagnosis can be readily derived from a bond graph model as mentioned in Section 3.

Figure 5 illustrates the fault diagnosis scheme based on Bayesian network. A bond graph model from a system concerned is used to construct a Bayesian network for localizing faulty components. Once the structure of the diagnostic Bayesian network is known and the necessary CPDs are acquired from either historical data or expert knowledge or both, the Bayesian fault diagnosis module is now ready to infer probabilities of faulty components. System measurements are provided to the Bayesian fault diagnosis module as evidences input to the network. Evidences are propagated through the network and the probability distributions for each hypothesis variable are inferred. Subsequent advices through ranking the faulty components by their corresponding probability distributions can be given to the system operators. The proposed approach is better than traditional fault diagnosis approaches [2, 9, 13] because probability distribution is computed for each component. This can provide the system operators a priority checking and maintenance schedule for system components. Also, the approach can be applied to localize multiple faulty components that will be correlated to exert a single symptom since it is the strength of Bayesian network.

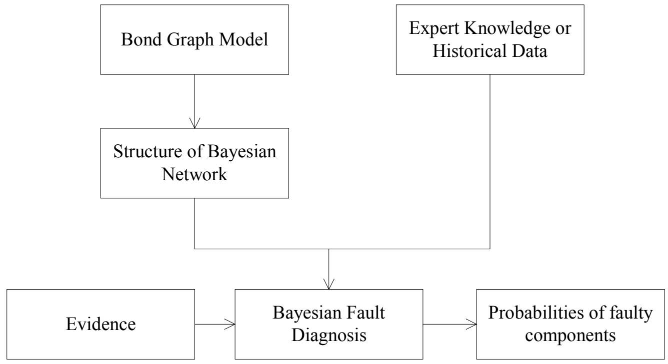

Figure 5: The fault diagnosis scheme based on Bayesian network.

4.1 Results

The performance of the fault diagnosis based on Bayesian network is evaluated by simulation. Exact inference is used for propagating evidences through the network. In the literatures [1, 5, 11, 12], there are many inference algorithms, such as, junction tree, variable elimination, Monte Carlo, Gibbs sampling, etc and each has its advantage over other in different situation. Discrete probability is adopted as the prior probabilities and CPDs for variables in the network and it can be extended to deal with continuous probability.

The single tank system is firstly used to evaluate the performance of the proposed fault diagnosis algorithm. Figures 3 and 4 show the tank system and its Bayesian network derived from bond graph model respectively. The information variable is only the measured liquid level in the tank (e_2) and its state is either true (T: maintain at the desired level) or false (F: deviate from desired level). Component faults, such as, *R* and *C*, are identified as the cause of the abnormality which are represented as hypothesis variables in the network. The state of components *R* and *C* is either true (T: no fault) or false (F: faulty). The prior probability for hypothesis variables *R* and *C* are both [0.5 (T), 0.5 (F)]. Figure 6 shows the result of the proposed diagnosis algorithm to the tank system. When information variable e_2 is observed to be abnormal (with state: F), the probabilities for both hypotheses *R* and *C* decreases below the prior. The probability of *R* is lower than *C* because *R* has a direct causal relation with e_2 and it is not the case for *C* component, and it has already reflected in the Bayesian network shown in Figure 4. A direct causal relation shows that *R* component will have a greater influence to the system rather than component C. When information variable e_2 is observed to be normal (with state: T), probabilities for both hypotheses R and C increases above the prior. Correct localization of faulty component can be achieved in this simulation.

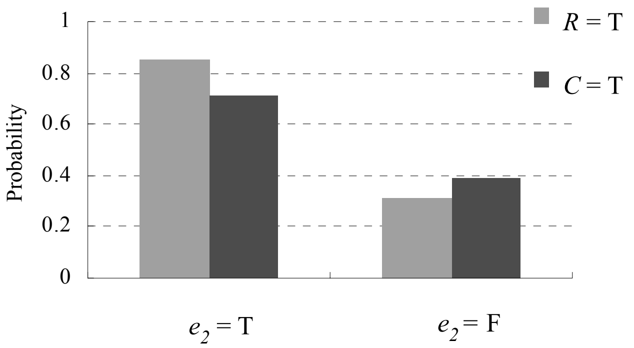

Figure 6: Fault diagnosis result for the tank system.

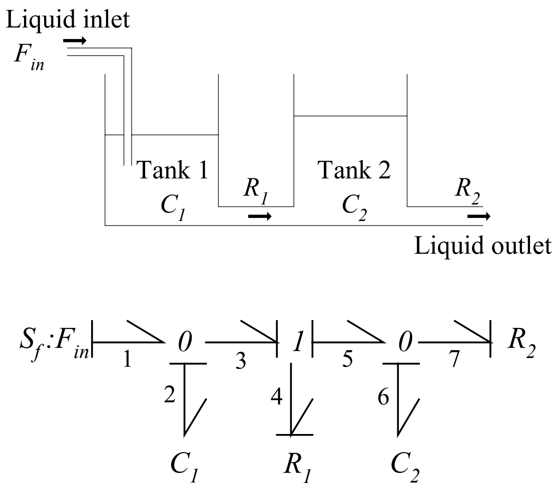

Figure 7: The coupled-tank system and its bond graph.

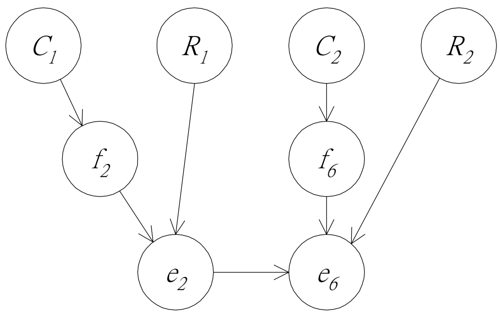

Figure 8: Bayesian network of the coupled-tank system for fault diagnosis.

Next, localization of faulty components for the coupled-tank system will be studied. Figure 7 shows the structure of the coupled-tank system and its bond graph. The bond graph model derived from the system is transformed to the Bayesian network which is shown in Figure 8. In this case, two information variables are identified and they are e_2 and e_6 that represent the liquid level in tank 1 and tank 2 respectively. Four hypothesis variables are recognized as R_1, C_1, R_2 and C_2. The prior probability for hypothesis variables is all set to [0.5 (T), 0.5 (F)]. Figure 9 shows the diagnosis result for the coupled-tank system. All combinations for different states of information variables are simulated. As before, the diagnosis algorithm can localize faulty component accurately. When e_2 is F and e_6 is T (the second case in Figure 9), the probabilities of R_1 and C_1 at T is much lower than R_2 and C_2. It indicates that the influence of components R_1 and C_1 to tank 1 is higher than component R_2 and C_2. Similar argument can be applied to the situation when e_2 is T and e_6 is F (the third case in Figure 9). In both cases, the probabilities for R elements (R_1 and R_2) to be normal are lower than C elements (C_1 and C_2), it shows that the state of R elements have a direct influence towards the liquid level. When both the observed vraibles are faulty, i.e., e_2 = F and e_6 = F, the probabilities for all elements to be normal are lower than the priors. The probabilities for R_1 and C_1 to be normal are lower than the other two because these two elements have a large influence towards both faulty liquid levels in Tank 1 and Tank 2. For elements R_2 and C_2, their effects are relatively confined and local to Tank 2 and only show a small influence toward the liquid level in Tank 1.

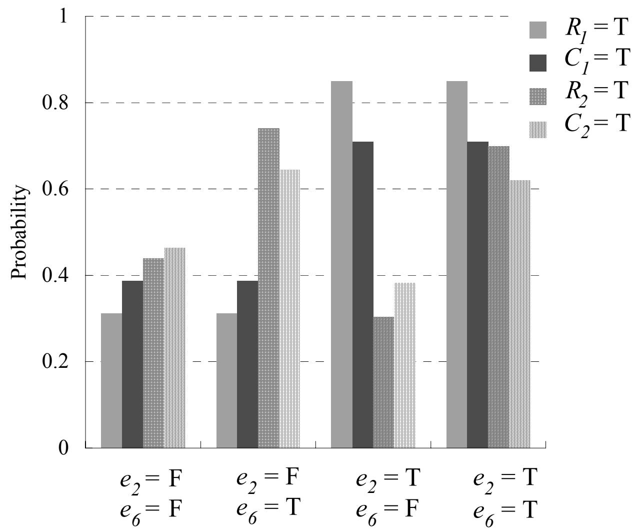

Figure 9: Fault diagnosis result for the coupled-tank system.

From simulation studies, the proposed fault diagnosis algorithm based on Bayesian network is feasible. Construction of Bayesian network used to be a difficult task is now alleviated with the help of bond graph model. Bond graph provides a formal, systematic and unified approach to model systems in different energy domain. Similarities can be found between Bayesian network and bond graph model especially when applied to fault diagnosis. The hypothesis variables in the Bayesian network can be readily identified from a bond graph model as the elements R, C, and I.

Qualitative interpretation among the set of qualitative equations after identifying information and hypothesis variables generates the required Bayesian network. Mediating variablesare sometimes inserted to the Bayesian network for its completeness and correctness. The property of Bayesian network in reasoning under uncertainty resolves the problems of uncertainty and ambiguity that may be encountered during fault localization. The proposed algorithm can be applied to refine a set of fault candidates that is generated from qualitative reasoning without extra measurements [13].

5 Conclusions

This contribution presents a novel approach on constructing a Bayesian network from a bond graph model. Information and hypothesis variables are first identified. The causal links between variables are generated from qualitative interpretation through the set of qualitative equations. Specification of prior and CPDs can be completed by expert knowledge and learning from historical data. Simulation studies on the single tank and coupled-tank systems show that the proposed fault diagnosis based on Bayesian network is feasible. Faulty components can be localized correctly without extensive computation which is a major criteria for on-line fault diagnosis.

Acknowledgement

The authors appreciate the generous assistance from Dr. Zeke Chan. The authors also gratefully acknowledge the financial support from the Hong Kong Polytechnic University through grant G-V872.

References

[1] Y. L. Chang, L. C. Lander, H. S. Lu and M. T. Wells. “Bayes analysis for fault location in distributed systems”, *IEEE Transactions on Reliability*, **43**(3), pp. 457-469m (1994).

[2] J. Chen and R. J. Patton. *Robust Model-based Fault Diagnosis for Dynamic Systems*, Boston: Kluwer Academic Publishers, (1999).

[3] C. F. Chien, S. L. Chen and Y. S. Lin. “Using Bayesian Network for Fault Location on Distribution Feeder”, *IEEE Transactions on Power Delivery*, **17**(13), pp. 785-793, (2002).

[4] W. Hamscher, L. Console and J. de Kleer. *Readings in Model-Based Diagnosis*. San Mateo, CA: Morgan Kaufmann, (1992).

[5] F. V. Jensen. *Bayesian Networks and Decision Graph*, New York: Springer-Verlag, (2001).

[6] D. C. Karnopp, D. L. Margolis and R. C. Rosenberg. *System Dynamics: Modeling and Simulation of Mechatronic Systems*, 3rd edition, NY: JohnWiley & Sons, , (2000).

[7] H. Kirsch and K. Kroschel. Applying “Bayesian Networks to Fault Diagnosis”, In *Proceedings of the IEEE Conference on Control Applications*, pp.895-900, (1994).

[8] P. J. Mosterman, and G. Biswas. “Diagnosis of continuous valued systems in transient operating regions”, *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, **29**(6), pp. 554-564, (1999).

[9] R. J. Patton, P. M. Frank and R. N. Clark. *Issues of Fault Diagnosis for Dynamic Systems*, London: Springer-Verlag, (2000).

[10] M. Singh and M. Valtorta. “Construction of Bayesian Network Structures form Data: A Brief Survey and an Efficient Algorithm”, *International Journal of Approximate Reasoning*, **12**, pp. 111-131, (1995).

[11] T. A. Stephenson. “An Introduction to Bayesian Network Theory and Usage”, *Dalle Molle Institute for Perceptual Artificial Intelligence Research Report, IDIAP-RR-00-03*, pp. 1-29, (2000).

[12] H. Wang. “Fault diagnosis and fault tolerant control for non-gaussian stochastic systems with random parameters”, In F. Caccavale, L. Villani eds., *Fault Diagnosis and Fault Tolerance for Mechatronic Systems*, Berlin: Springer-Verlag, pp. 59-84, (2003).

[13] H. Wang and D. A. Linkens. *Intelligent Supervisory Control: A Qualitative Bond Graph Reasoning Approach*, Singapore: World Scientific Publishing, (1996).