Bayesian Networks approach to fault diagnosis of a hydroelectric generation system

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Abstract: This study focuses on the fault diagnosis of a hydroelectric generation system with hydraulic-mechanical-electric structures. To achieve this analysis, a methodology combining Bayesian Networks approach and fault diagnosis expert system is presented, which enables the time-based maintenance to transform to the condition-based maintenance. First, fault types and the associated fault characteristics of the generation system are extensively analyzed to establish a precise Bayesian Network. Then, the Noisy-Or modelling approach is used to implement the fault diagnosis expert system, which not only reduces node computations without severe information loss but also eliminates the data dependency. Some typical applications are proposed to fully show the

methodology capability of the fault diagnosis of the hydroelectric generation system.

Keywords: hydroelectric generation system; fault diagnosis; Bayesian Network; expert system; state evaluation

1. Introduction

2015 United Nations Climate Change Conference promised that the raise of global warming is almost 2 °C compared to pre-industrial levels, which greatly promotes the electricity generation to turn to renewable energy such as hydropower generations [1]. China is leading to a hydropower boom, followed by India, Europe, the United States and Japan [2]. Hydropower plants have been built in more than 160 countries, with a total number of 11000 plants equipped with 27000 hydro-turbine generator units at the end of 2017 [3]. In China, the hydropower capacity is expected to increase to 380 gigawatts by 2020 [4]. These hydropower plants are constructed at sites along rivers, including thirteen plants on the Salween or Nujiang, and twenty plants along the Brahmaputra [4]. In Brazil, 375 small hydropower plants with the total capacity of 4799 MW are currently running, and another 1701 MW installed capacity will be constructed in the next ten years [5]. Hydroelectric generation systems are under construction all over the world to ensure the enforcement of stricter energy and environmental policy. Obviously, the economic benefit and carbon dioxide mitigation of such hydroelectric generating systems are well known to the general public [6-11], but the stability and safety impacts of themselves still require enough attentions.

Faults in the hydroelectric generation systems (HGS) inevitably result in unexpected safety accidents with enormous maintenance costs [12-14]. National Energy Administration issued that 80% of HGS' faults are caused by the vibration of the hydraulic-mechanic-electric components [15-16]. In general, the vibration in the HGS is defined as a drastic reciprocating motion caused by unbalanced forces and uncertain disturbances [17-18]. For instance, 60% of the vibration faults are attributable to the out-of-balance rotating bodies and the pressure pulsation of flow passage components in Japan [19-20]. The current study of the HGS's faults mainly focuses on the constituent components (e.g. generators, hydro-turbines and pipelines) [21-23]. Additionally, the collection of the on-line monitoring data under the condition of fast information flow is another challenge for fault diagnosis of the HGS [24-25]. To adequately analyze the faults mechanism, to predict behavior of systems, to evaluate operating reliability and to decrease maintenance costs, are the challenging tasks. Hence, it is of primary importance to provide the powerful methodology for the fault diagnosis of HGSs not only of systems but also of data available.

Some popular efficient approaches, combining monitoring data and expert experiences, are developed for the fault diagnosis such as Fault-Tree Analysis (FTA), Event-Tree Analysis (ETA) and Bayesian Network (BN) [26-28]. FTA and ETA are applied to evaluate the reliability of systems, whereas these approaches lack lateral linkages between nodes and also require high-quality experts to cope with complicated computations [29]. In light of this, BN is widely used to overcome the limitations of FTA and ETA since it successfully incorporates expert experiences by means of lateral linkages [30-32]. However, the modelling of BN in practical applications is still difficult and tedious, especially for the complicated systems [33-34]. Thus, it is emergent to present suitable approaches to reduce node computations without severe information loss.

This study aims to provide an efficient computational methodology for the fault diagnosis of the HGS. To establish a precise Bayesian Network of the HGS, we fully analyze the complex fault types and their associated fault characteristics. The Noisy-Or modelling approach is used to eliminate the data dependency and to reduce node computations. The fault diagnosis expert system is proposed that is beneficial to the condition-based maintenance at the lowest cost. Finally, some typical applications are done to fully show the methodology capability of the fault diagnosis of the hydroelectric generation system.

This study is structured as follows. Section 2 describes the global methodology of the BN fault diagnosis of the HGS. Section 3 presents the BN fault diagnosis model considering the hydraulic, mechanical and electric factors. Section 4 performs the applications of the fault diagnosis model of the HGS. Conclusions and discussions in section 5 summary this study.

2. Methodology

This section is dedicated to the overall theoretical background of the methodology adopted in the present study. A brief description of BN, Noisy-Or model and expert system is presented.

2.1 Bayesian Network

BN is a statistical graphical model that combines the probability theory with the graphic theory [35]. A complete BN is comprised of nodes, connecting arrows and the Conditional Probability Tables (CPTs), which is represented by a Directed Acyclic Graph (DAG). The BN displays the cause and effect relationships between the network variables, as shown in Fig. 1.

Fig. 1 An example of BN.

The implementation of BN relying on the Bayes theorem is defined as: The exhaustive event set $\{B_1, B_2, ..., B_n\}$ and the event A exist in a sample space Ω, and they respectively meet the conditions of $P(B_i) > 0$ ($i = 1,2,3,...,n$) and $P(A) > 0$. Hence, we get [36-37]:

$$P(B_i \mid A) = \frac{P(A \mid B_i)P(B_i)}{\sum_{j=1}^{n} P(A \mid B_i)P(B_i)}, \quad i = 1,2,3,...,n \tag{1}$$

To enable the inference analysis of the BN, Eq. (1) is subject to the following conditional independence hypothesis:

The variable nodes ($X_1, X_2, ...X_n$) in the BN are conditionally independent for their father nodes. This means that the variable nodes satisfy the joint probability in Eq. (2).

$$P(X_1, X_2, ...X_n) = \prod_{i=1}^{N} P(X_i \mid pa_i), \tag{2}$$

where pa_i denotes the father node set of X_i.

2.2 Noisy-Or model

The major work of BN is to determine the CPT, whereas the deduction of the joint probability is growing exponentially with the increase of variable nodes. For the BN with *nth* binary discrete nodes, it generally requires $2^n th$ conditional probabilities to describe the network model. To reduce node computations, Noisy-Or modelling approach is applied in the BN calculation. A typical Noisy-Or model [38-39] is expressed as

$$\begin{cases} P_i = \dfrac{P(y \mid X_i) - P(y \mid \overline{X_i})}{1 - P(y \mid \overline{X_i})} \\ P(y \mid X_P) = 1 - \prod_{X_i \in X_T} (1 - P_i) \\ P(X_i = Tonly \mid Y) = \dfrac{P_i \cdot P(X_i = T)}{P(Y)} \end{cases}, \tag{3}$$

where y is a safety accident, X_P is the set of fault nodes expressed by $X_1, X_2, ...X_n$; X_T is the truth set of fault nodes; P_i is the probability of y if or only if X_i=True.

2.3 Fault diagnosis expert system

Fault diagnosis expert system is an intelligent tool that integrates expert experiences and Bayesian inferences, and it has significant advantages of the comprehensive collection of expert knowledge, the accurate simulation of expert thinking and the precision of fault diagnosis. The schematic diagram of the fault diagnosis expert system is performed in Fig. 2. The development of the efficient fault diagnosis expert system will be beneficial to the condition-based maintenance at the lowest cost.

Fig. 2 Schematic diagram of a fault diagnosis expert system.

2.4 Global methodology

Based on the above descriptions, Fig. 3 is plotted to show the global methodology of Bayesian fault diagnosis of the HGS. The calculation process plan is concluded in the following steps:

(1) Using expert experiences and monitoring data to collect the hydraulic, mechanical and electric fault types in the HGS and also to investigate their associated fault characteristics. Based on this, a fault diagnosis model of Bayesian network for the HGS is presented.

(2) The expert system gives the prior probabilities of nodes, and the Noisy-Or modelling approach is employed to reduce the node computations.

(3) Based on the Bayes theorem, we conduct the Bayesian fault diagnosis inference of the HGS. The obtained posterior probabilities are used to perform the diagnostic fault locations and the relevant fault characteristics. If the actual fault component is included in the diagnostic fault locations, the maintenance worker is able to solve the problem in time. Conversely, if the diagnostic result is “No”, the Bayesian network will reassessment the posterior probabilities of fault locations in light of the updated CPT.

(4) Summarizing the frequent fault locations and their corresponding fault characteristics to diminish the operation loss and maintenance loss in hydropower stations.

Fig. 3 The global methodology of fault diagnosis of the hydroelectric generation system. CPT refers to the condition probability table. HGS refers to the hydroelectric generation system.

3. Model

To model a BN of fault diagnosis, the critical task is to analyze the complex fault types and their associated fault characteristics in the HGS. we extensively collect the faults data of the HGS from literatures, on-site visit, and expert advice. In general, the HGS's fault refers to that the system works abnormally with enormous vibrations and can even lead to accidental shutdown or component damage since about 80 percent of HGS's faults are caused by component vibrations. Statistically, the disturbing forces (i.e. the rotational unbalanced force of rotors, the hydraulic unbalanced force and the unbalanced magnetic pull) with different magnitudes, directions and frequencies will influence the performance of vibrations. Based on the operating characteristic of the HGS, the disturbing forces are attributed to the hydraulic, mechanical and electric factors. Hence, the fault types and the associated fault characteristics can be performed in the fault diagnosis BN of the HGS, as shown in Fig. 4.

Fig. 4 The Bayesian network of the fault diagnosis of the HGS coupling with hydraulic, mechanical and electric factors.

4. Case Study

The mechanical fault, as the most important influence factor on the safety of the HGS, is selected as a case study for the application of the BN proposed in this work. The typical mechanical fault (i.e. the rubbing fault MF2, the misalignment fault of rotor MF3 and the mechanical axial crack MF4) and their associated fault characteristics (i.e. the vibration with doubled frequency F2F0 and the vibration with third frequency F3F0) are finally modeled a studied BN, as shown in Fig. 5. In the actual operation of hydropower stations, the rubbing fault (MF2) is triggered by improper assembly, shafting bend, rotor imbalance and mechanical looseness, resulting in enormous vibrations and noises. The misalignment fault of rotor (MF3) generally leads to the deformation of shaft and rotor swing, which significantly reduces the operating efficiency of the HGS. The mechanical axial crack (MF4) has obvious adverse effects on the stiffness of shaft, which can cause unexpected shaft-broken accidents with the increase of load and turbine speed.

Fig. 5 A simple BN of the hydraulic generating system with critical mechanical faults.

For the HGS's BN with critical mechanical faults performed in Fig. 5, the possible working states of the fault nodes are "normal" and "trouble", as well as the fault frequencies for their associated fault characteristics nodes include "high" and "low".

Example 4.1: Noisy-Or Model Applications

To reduce the complicated computations of CPT, the Noisy-Or model can significantly eliminate disturbing influences between the fault node and the associated fault characteristics nodes. Based on the Noisy-Or model (3), the CPT of node F2F0 and node F3F0 in Fig. 5 is calculated as:

i) CPT of node F2F0

According to expert experiences, the following probabilities are obtained as:

$P(MF2 = trouble) = 0.2$, $P(MF3 = trouble) = 0.2$, $P(MF4 = trouble) = 0.4$;

$P(y_1 | X_1) = P(F2F0 = high | MF2 = trouble) = 0.56$, $P(\overline{y_1} | \overline{X_1}) = P(F2F0 = low | MF2 = normal) = 0.82$;

$P(y_1 | X_2) = P(F2F0 = high | MF3 = trouble) = 0.44$, $P(\overline{y_1} | \overline{X_2}) = P(F2F0 = low | MF3 = normal) = 0.9$;

$P(y_1 | X_3) = P(F2F0 = high | MF4 = trouble) = 0.8$, $P(\overline{y_1} | \overline{X_3}) = P(F2F0 = low | MF4 = normal) = 0.92$.

For the Noisy-Or model (3), the matrix of $X_P = \{X_1 = normal, X_2 = trouble, X_3 = trouble\}$,

Substituting the above probabilities into the Noisy-Or model (3-1), we obtain

$$\begin{cases} P_1 = \dfrac{P(y_1 \mid X_1) - P(y_1 \mid \overline{X}_1)}{1 - P(y_1 \mid \overline{X}_1)} = \dfrac{0.56 - (1 - 0.82)}{1 - (1 - 0.82)} = 0.4634 \\ P_2 = \dfrac{P(y_1 \mid X_2) - P(y_1 \mid \overline{X}_2)}{1 - P(y_1 \mid \overline{X}_2)} = \dfrac{0.44 - (1 - 0.9)}{1 - (1 - 0.9)} = 0.3778 \\ P_3 = \dfrac{P(y_1 \mid X_3) - P(y_1 \mid \overline{X}_3)}{1 - P(y_1 \mid \overline{X}_3)} = \dfrac{0.8 - (1 - 0.92)}{1 - (1 - 0.92)} = 0.7826 \end{cases}. \tag{4}$$

Based on the Noisy-Or model (3-2) and Eq. (4), it can be obtained as

$$\begin{cases} P(y \mid X_P) = 1 - \prod\limits_{X_i \in X_T} (1 - P_i) = 1 - (1 - P_2)(1 - P_3) = 0.8647 \\ P(y \mid X_P) = 1 - \prod\limits_{X_i \in X_T} (1 - P_i) = 1 - (1 - P_1)(1 - P_3) = 0.8833 \\ P(y \mid X_P) = 1 - \prod\limits_{X_i \in X_T} (1 - P_i) = 1 - (1 - P_1)(1 - P_2) = 0.6661 \\ P(y \mid X_P) = 1 - \prod\limits_{X_i \in X_T} (1 - P_i) = 1 - (1 - P_1)(1 - P_2)(1 - P_3) = 0.9274 \end{cases}, \tag{5}$$

where the fault node set $X_P = \{X_1 = normal, X_2 = trouble, X_3 = trouble\}$ in Eq. (5-1), $X_P = \{X_1 = trouble, X_2 = normal, X_3 = trouble\}$ in Eq. (5-2), $X_P = \{X_1 = trouble, X_2 = trouble, X_3 = normal\}$ in Eq. (5-3), and $X_P = \{X_1 = trouble, X_2 = trouble, X_3 = trouble\}$ in Eq. (5-4).

Therefore, the CPT of node F2F0 is listed in table 1.

Table 1 CPT of node F2F0

MF2	normal				trouble			
MF3	normal		trouble		normal		trouble	
MF4	normal	trouble	normal	trouble	normal	trouble	normal	trouble
low	1.000	0.2174	0.6222	0.1326	0.5366	0.1167	0.3339	0.0726
high	0.0000	0.7826	0.3778	0.8647	0.4634	0.8833	0.6661	0.9274

ii) CPT of node F3F0

Based on expert experiences, the probabilities are obtained as follows:

$P(y_2 \mid X_1) = P(F3F0 = high \mid MF2 = trouble) = 0.74$, $P(\overline{y_2} \mid \overline{X_1}) = P(F3F0 = low \mid MF2 = normal) = 0.95$;

$P(y_2 \mid X_2) = P(F3F0 = high \mid MF3 = trouble) = 0.45$, $P(\overline{y_2} \mid \overline{X_2}) = P(F3F0 = low \mid MF3 = normal) = 0.92$;

$P(y_2 \mid X_3) = P(F3F0 = high \mid MF4 = trouble) = 0.35$, $P(\overline{y_2} \mid \overline{X_3}) = P(F3F0 = low \mid MF4 = normal) = 0.88$.

Then, based on the Noisy-Or model (3), we can get:

$$\begin{cases} P_1 = \dfrac{P(y_2 \mid X_1) - P(y_2 \mid \overline{X}_1)}{1 - P(y_2 \mid \overline{X}_1)} = \dfrac{0.74 - (1 - 0.95)}{1 - (1 - 0.95)} = 0.7263 \\ P_2 = \dfrac{P(y_2 \mid X_2) - P(y_2 \mid \overline{X}_2)}{1 - P(y_2 \mid \overline{X}_2)} = \dfrac{0.45 - (1 - 0.92)}{1 - (1 - 0.92)} = 0.4022 \\ P_3 = \dfrac{P(y_2 \mid X_3) - P(y_2 \mid \overline{X}_3)}{1 - P(y_2 \mid \overline{X}_3)} = \dfrac{0.35 - (1 - 0.88)}{1 - (1 - 0.88)} = 0.2614 \end{cases}, \tag{6}$$

$$\begin{cases} P(y \mid X_P) = 1 - \prod\limits_{X_i \in X_T} (1 - P_i) = 1 - (1 - P_2)(1 - P_3) = 0.5585 \\ P(y \mid X_P) = 1 - \prod\limits_{X_i \in X_T} (1 - P_i) = 1 - (1 - P_1)(1 - P_3) = 0.7978 \\ P(y \mid X_P) = 1 - \prod\limits_{X_i \in X_T} (1 - P_i) = 1 - (1 - P_1)(1 - P_2) = 0.8364 \\ P(y \mid X_P) = 1 - \prod\limits_{X_i \in X_T} (1 - P_i) = 1 - (1 - P_1)(1 - P_2)(1 - P_3) = 0.8792 \end{cases}, \tag{7}$$

where the fault nodes set $X_P = \{X_1 = normal, X_2 = trouble, X_3 = trouble\}$ in Eq. (7-1), $X_P = \{X_1 = trouble, X_2 = normal, X_3 = trouble\}$ in Eq. (7-2), $X_P = \{X_1 = trouble, X_2 = trouble, X_3 = normal\}$ in Eq. (7-3), and $X_P = \{X_1 = trouble, X_2 = trouble, X_3 = trouble\}$ in Eq. (7-4).

Thus, the CPT of node F3F0 is listed in Tab. 2.

Table 2 CPT of node F3F0

MF2	normal				trouble			
MF3	normal		trouble		normal		trouble	
MF4	normal	trouble	normal	trouble	normal	trouble	normal	trouble
low	1.000	0.7386	0.5978	0.4415	0.2737	0.2022	0.1636	0.1208
high	0.0000	0.2614	0.4022	0.5585	0.7263	0.7978	0.8364	0.8792

Example 4.2: BN-Based Fault Diagnosis of the HGS

Using Bayes theory presented in the methodology section, we establish the fault diagnosis expert system of the HGS that integrates expert experiences and Bayesian inferences. The BN inference is utilized to give some typical applications of the BN-Based fault diagnosis of the HGS. Six cases are performed as follows.

- Case 1: Assuming the fact is the increasing vibration with doubled frequency. That is, the probability of the fault characteristic node F2F0 in "high" state is 1. Using the Bayesian diagnosis inference (the definition is revealed in the literature [40]), its father nodes probabilities including the rubbing fault MF2, the misalignment fault of rotor MF3 and the mechanical axial crack MF4 in "trouble" states are 0.3110, 0.2892 and 0.7718, respectively. The calculated result indicates that the HGS's fault is most likely due to the mechanical axial crack with the occurrence of the increasing vibration with doubled frequency.
- Case 2: When the on-line monitoring system captures the increasing signal of the vibration with third frequency, the probability of the fault characteristic node F3F0 in "high" state equals to 1. Similarly, the nodes probabilities of the rubbing fault MF2, the misalignment fault of rotor MF3 and the mechanical axial crack MF4 in "trouble" states are therefore calculated as 0.5230, 0.3663 and 0.5665, respectively. This means that the mechanical rubbing and axial crack are able to result in the fault of the HGS.
- Case 3: The HGS shows the vibration with doubled frequency and third frequency. As a result, the probability for the fault characteristic nodes F2F0 and F3F0 in the "high" state is 1. The nodes probabilities of the rubbing fault MF2, the misalignment fault of rotor MF3 and the mechanical axial crack MF4 in "trouble" states are obtained as 0.5145, 0.3568 and 0.7013 by means of Bayesian diagnosis inferences, respectively. Therefore, the mechanical axial crack may be considered as the main influence factor on the operating safety of the HGS in this case.
- Case 4: Assuming the fault of the mechanical axial crack is found by maintenance workers, and the on-line monitoring system also captures the increasing signal of the vibration with doubled frequency. Based on the Bayesian support inference in literatures [40-41], its father nodes

probabilities of the rubbing fault MF2 and the misalignment fault of rotor MF3 in “trouble” states are 0.2181 and 0.2150, respectively. Meanwhile, the parallel node probability of the vibration with third frequency F3F0 in the “high” state is 0.4325.

Comparing with case 3, the probability for the occurrence of the rubbing fault and the misalignment fault of rotor significantly decreases if the fault of mechanical axial crack already exists in the HGS. Additionally, the hydropower station is suggested to develop the protection strategies to cope with the increase of the vibration with third frequency in advance.

- Case 5: If the fault of the mechanical axial crack and the fault characteristic of the increasing vibration with third frequency occur during the maintenance task, the CPT of neighbor nodes using the Bayesian support inference are obtained. Specifically, its father nodes probabilities of the rubbing fault MF2 and the misalignment fault of rotor MF3 in “trouble” states are 0.3881 and 0.2969, meanwhile the parallel node probability of the vibration with doubled frequency F2F0 in the “high” state is 0.8434.

Comparing with the separate occurrence of the increasing vibration with third frequency in case 2, the occurrence probability of the rubbing fault and the misalignment fault of rotor decreases when the fault of the mechanical axial crack and the fault characteristic of the increasing vibration with third frequency occur at the same time. In this situation, case 5 is easy to lead to the increase of the vibration with doubled frequency, which should be pay more attentions in the actual operation of hydropower stations.

- Case 6: For the HGS existing in the fault of the mechanical axial crack and the fault characteristic of the increasing vibrations with both third frequency and doubled frequency, the CPT of neighbor nodes are calculated using the Bayesian support inference. That is, the probabilities of the rubbing fault MF2 and the misalignment fault of rotor MF3 in “trouble” states are 0.4109 and 0.3113, respectively.

From the analysis of cases 3 and 6, when the HGS shows the same fault characteristic except for the mechanical axial crack, the occurrence probability of the rubbing fault and the misalignment fault of rotor will decrease.

In conclusion, the calculated results in cases 1 to 3 are validated in refs. [42-46], and the diagnostic results obtained in cases 4 to 6 are consistent with ref. [47].

5. Conclusions and discussion

In this work, the fault diagnosis method for the hydroelectric generation system coupling with hydraulic, mechanical and electric factors is presented. The methodology adopted in this work is based on the Bayesian Networks approach and the expert system. Herein a complete Bayesian network fault diagnosis model of the generating system is implemented that takes into consideration the comprehensive knowledge of the vibration fault types and the associated fault characteristics. The Noisy-Or modelling approach is used to calculate the CPT of the presented Bayesian network to overcome the limitation of the complicated node computations and data dependency in current approaches. The final implementation of the fault diagnosis expert system realizes the combination of expert experiences and Bayesian inferences. The obtained results allow to develop the time-based maintenance to the condition-based maintenance, which achieves the goal of the reduction of the maintenance costs in hydropower stations. In addition, historical data collected from a hydropower station is a good method to improve the accuracy of the diagnosis, while it is extremely difficult to obtain diagnosis from manufacturers since such data are confidential. To propel the future study of historical data parameter learning or other data-based methods, we are attempting to cooperate with potential hydropower stations to carry out some experiments of the generating system. The above illustrations have been added to the manuscript to guide our future work. Moreover, the future work is designed to the extraction of the common fault characteristics to improve the coupling relationship of the electric faults with the mechanical hydraulic fault network.

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Graphical Abstract: Global hydropower growth continues to accelerate with 25% of total capacity installed in just the last 10 years. This accelerating expansion and the important storage facility hydropower means it is increasingly important to understand the reasons for operational failures. Fault diagnosis of a hydroelectric generation system is a critical science and engineering problem to improve the safety of hydropower stations. To enable the risk quantification in the process of fault diagnosis, fault types and associated fault characteristics of a hydroelectric generation system are extensively analyzed to model a precise Bayesian Network. Noisy-Or modelling approach is used for the implementation of fault diagnosis expert system, which not only reduces the computation of nodes probability without severe information loss but also eliminate the data dependency. A typical application is proposed to fully show the capability of the presented methodology of the HGS's fault diagnosis. The graphical table is shown in Fig. 6.

Fig. 6 General technical route of this paper.