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## RESEARCH ARTICLE

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# Bayesian network 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 network 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 modeling 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

Bayesian network, expert system, fault diagnosis, hydroelectric generation system, state evaluation

Beibei Xu and Huanhuan Li contribute equally to this paper.

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## 1 | INTRODUCTION

2015 United Nations Climate Change Conference promised that the raise of global warming is almost  $2^{\circ}\text{C}$  compared to pre-industrial levels, which greatly promotes the electricity generation to turn to renewable energy such as hydropower generations.<sup>1</sup> China is leading to a hydropower boom, followed by India, Europe, the United States, and Japan.<sup>2</sup> Hydropower plants have been built in more than 160 countries, with a total number of 11 000 plants equipped with 27 000 hydro-turbine generator units at the end of 2017.<sup>3</sup> In China, the hydropower capacity is expected to increase to 380 gigawatts by 2020.<sup>4</sup> These hydropower plants are constructed at sites along rivers, including thirteen plants on the Salween or Nujiang and twenty plants along the Brahmaputra.<sup>4</sup> 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 10 years.<sup>5</sup> 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,<sup>6-11</sup> 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.<sup>12-14</sup> National Energy Administration issued that 80% of HGS' faults are caused by the vibration of the hydraulic-mechanic-electric components.<sup>15,16</sup> In general, the vibration in the HGS is defined as a drastic reciprocating motion caused by unbalanced forces and uncertain disturbances.<sup>17,18</sup> 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.<sup>19,20</sup> The current study of the HGS's faults mainly focuses on the constituent components (eg, generators, hydro-turbines, and pipelines).<sup>21-23</sup> 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.<sup>24,25</sup> 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).<sup>26-28</sup> 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.<sup>29</sup> 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.<sup>30-32</sup> However, the modeling of BN in practical applications is still difficult and tedious, especially for the complicated systems.<sup>33,34</sup> 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 modeling 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 discussion in Section 5 summarize 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.<sup>35</sup> A complete BN is comprised of nodes, connecting arrows and the conditional

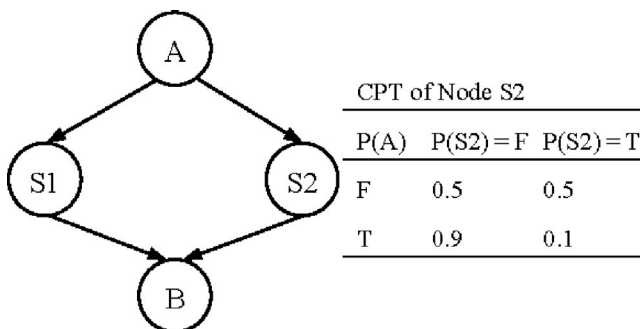


FIGURE 1 An example of BN

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 Figure 1.

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

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

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

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

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^N P(X_i|pa_i), \quad (2)$$

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  $n$ th binary discrete nodes, it generally requires  $2^n$ th conditional probabilities to describe the network model. To reduce node

computations, Noisy-Or modeling approach is applied in the BN calculation. A typical Noisy-Or model<sup>38,39</sup> is expressed as

$$\begin{cases} P_i = \frac{P(y|X_i) - P(y|\bar{X}_i)}{1 - P(y|\bar{X}_i)} \\ P(y|X_p) = 1 - \prod_{X_i \in X_T} (1 - P_i) \\ P(X_i = \text{Only}|Y) = \frac{P_i \cdot P(X_i = T)}{P(Y)} \end{cases}, \quad (3)$$

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

### 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 Figure 2. The development of the efficient fault diagnosis expert system will be beneficial to the condition-based maintenance at the lowest cost.

### 2.4 | Global methodology

Based on the above descriptions, Figure 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:

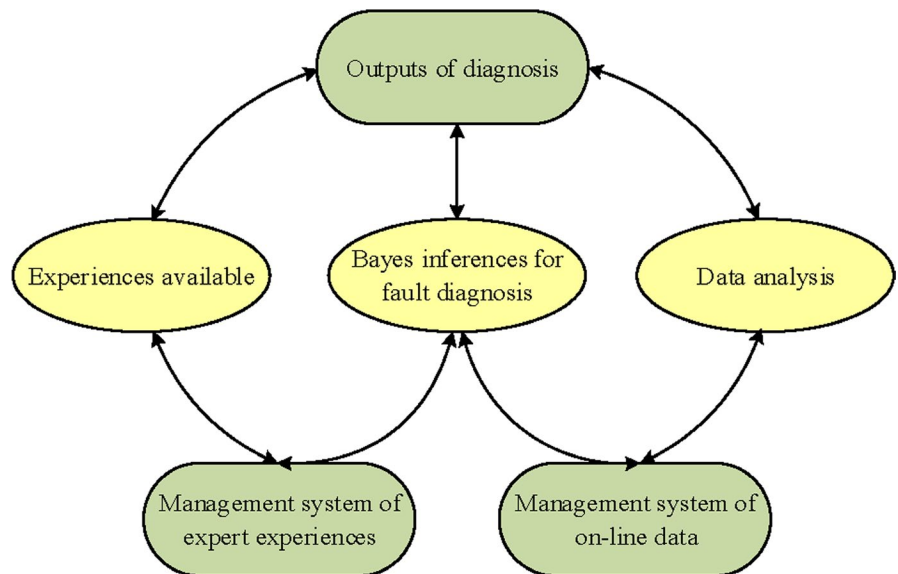
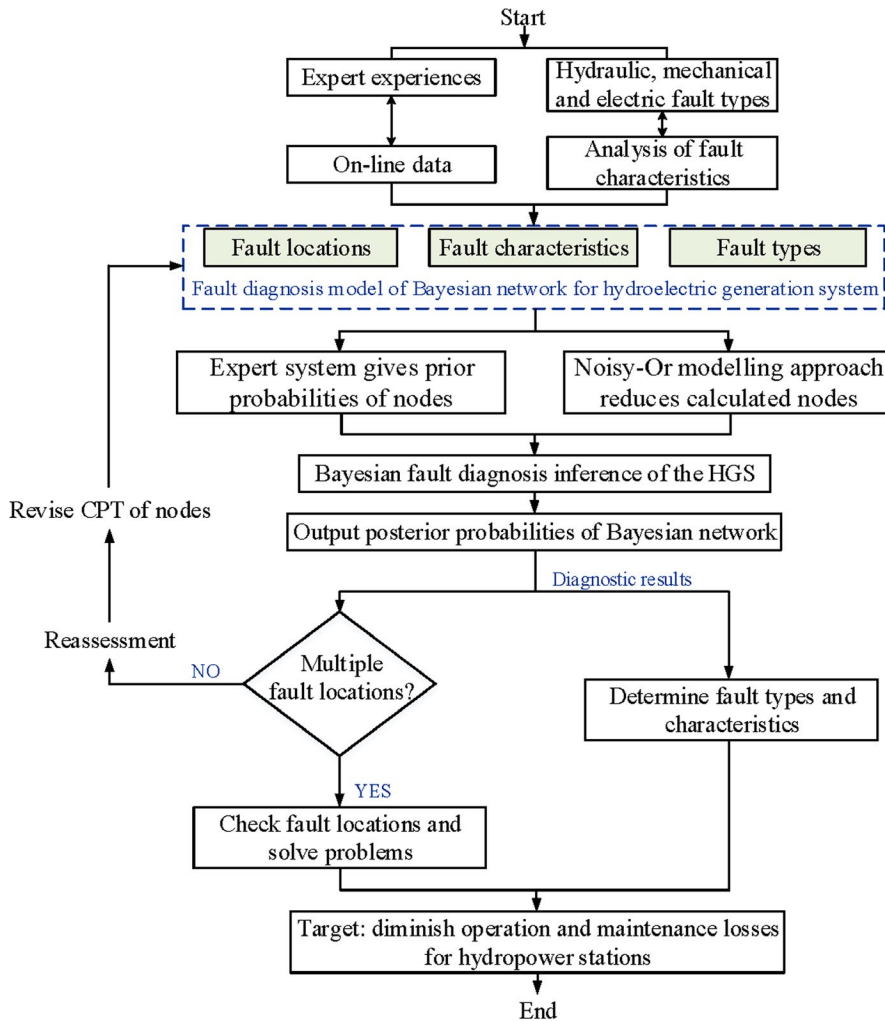


FIGURE 2 Schematic diagram of a fault diagnosis expert system

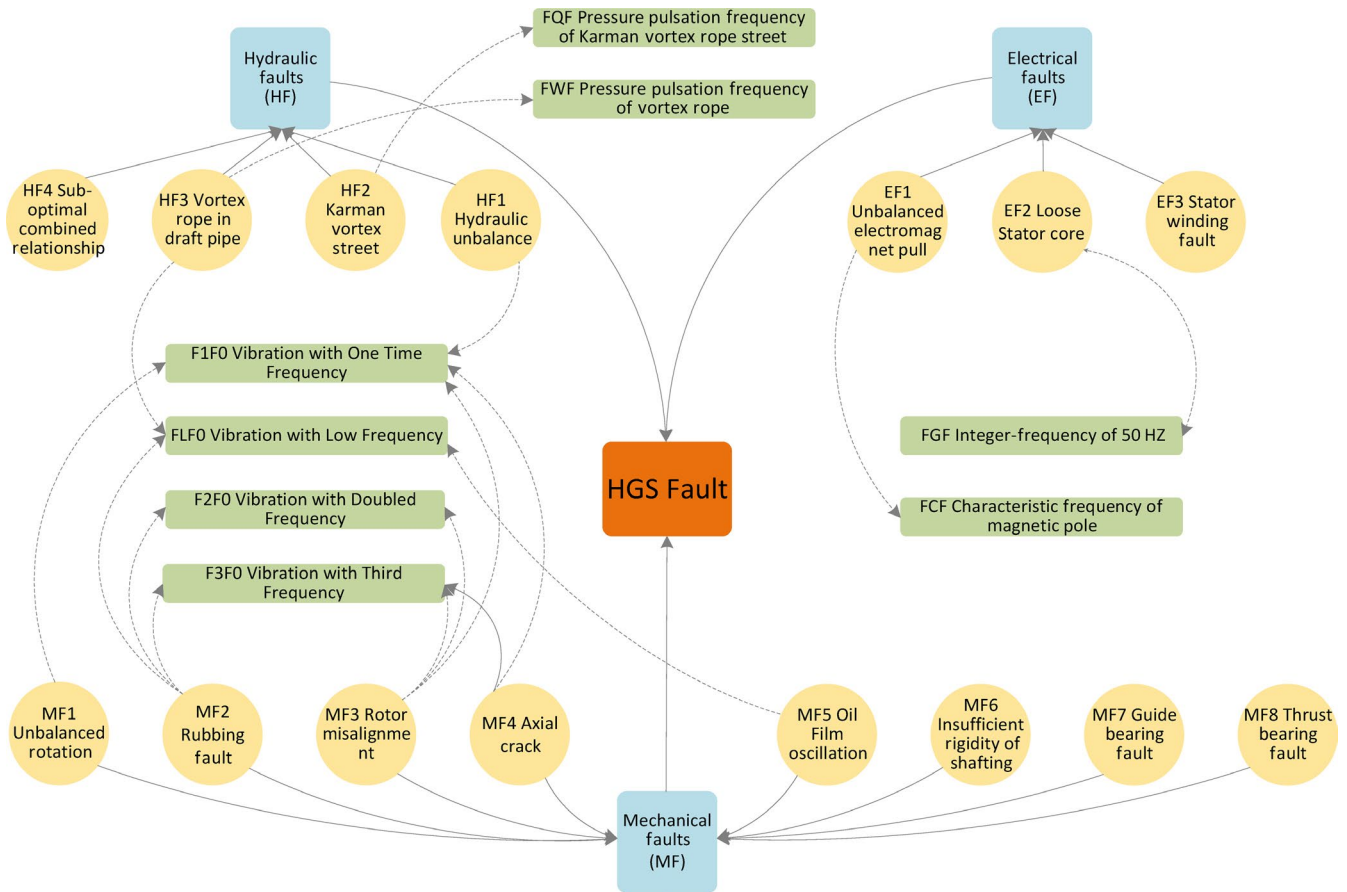


**FIGURE 3** The global methodology of fault diagnosis of the hydroelectric generation system. conditional probability table refers to the conditional probability table. HGS refers to the hydroelectric generation system

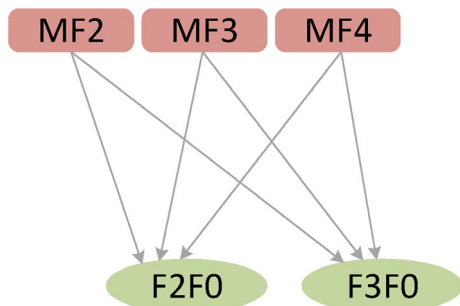
1. Using expert experiences and monitoring data to collect the hydraulic, mechanical, and electric fault types in the HGS and also to investigate their associated fault characteristics. Based on this, a fault diagnosis model of Bayesian network for the HGS is presented.
2. The expert system gives the prior probabilities of nodes, and the Noisy-Or modeling 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.

### 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% of HGS's faults are caused by component vibrations. Statistically, the disturbing forces (ie, 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 Figure 4.



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



**FIGURE 5** A simple BN of the hydraulic generating system with critical mechanical faults

## 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 (ie, the rubbing fault MF2, the misalignment fault of rotor MF3, and the mechanical axial crack MF4) and their associated fault characteristics (ie, the vibration with doubled frequency F2F0 and the vibration with third frequency F3F0) are finally modeled a studied BN, as shown in Figure 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.

For the HGS's BN with critical mechanical faults performed in Figure 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 Figure 5 is calculated as:

1. CPT of node F2F0

TABLE 1 Conditional probability table of node F2F0

MF2	Normal				Trouble			
	Normal		Trouble		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

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

$$\begin{aligned}
 P(MF2 = trouble) &= 0.2, & P(MF3 = trouble) &= 0.2, \\
 P(MF4 = trouble) &= 0.4; \\
 P(y_1 | X_1) &= P(F2F0 = high | MF2 = trouble) = 0.56, \\
 P(\bar{y}_1 | \bar{X}_1) &= P(F2F0 = low | MF2 = normal) = 0.82; \\
 P(y_1 | X_2) &= P(F2F0 = high | MF3 = trouble) = 0.44, \\
 P(\bar{y}_1 | \bar{X}_2) &= P(F2F0 = low | MF3 = normal) = 0.9; \\
 P(y_1 | X_3) &= P(F2F0 = high | MF4 = trouble) = 0.8, \\
 P(\bar{y}_1 | \bar{X}_3) &= P(F2F0 = low | MF4 = normal) = 0.92.
 \end{aligned}$$

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

$$\begin{cases}
 P_1 = \frac{P(y_1 | X_1) - P(y_1 | \bar{X}_1)}{1 - P(y_1 | \bar{X}_1)} = \frac{0.56 - (1 - 0.82)}{1 - (1 - 0.82)} = 0.4634 \\
 P_2 = \frac{P(y_1 | X_2) - P(y_1 | \bar{X}_2)}{1 - P(y_1 | \bar{X}_2)} = \frac{0.44 - (1 - 0.9)}{1 - (1 - 0.9)} = 0.3778 \\
 P_3 = \frac{P(y_1 | X_3) - P(y_1 | \bar{X}_3)}{1 - P(y_1 | \bar{X}_3)} = \frac{0.8 - (1 - 0.92)}{1 - (1 - 0.92)} = 0.7826
 \end{cases} \quad (4)$$

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

$$\begin{cases}
 P(y | X_p) = 1 - \prod_{X_i \in X_r} (1 - P_i) = 1 - (1 - P_2)(1 - P_3) = 0.8647 \\
 P(y | X_p) = 1 - \prod_{X_i \in X_r} (1 - P_i) = 1 - (1 - P_1)(1 - P_3) = 0.8833 \\
 P(y | X_p) = 1 - \prod_{X_i \in X_r} (1 - P_i) = 1 - (1 - P_1)(1 - P_2) = 0.6661 \\
 P(y | X_p) = 1 - \prod_{X_i \in X_r} (1 - P_i) = 1 - (1 - P_1)(1 - P_2)(1 - P_3) = 0.9274
 \end{cases} \quad (5)$$

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

(5-3), and  $X_p = \{X_1 = trouble, X_2 = trouble, X_3 = trouble\}$  in Equation (5-4).

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

2. CPT of node F3F0

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

$$\begin{aligned}
 P(y_2 | X_1) &= P(F3F0 = high | MF2 = trouble) = 0.74, \\
 P(\bar{y}_2 | \bar{X}_1) &= P(F3F0 = low | MF2 = normal) = 0.95; \\
 P(y_2 | X_2) &= P(F3F0 = high | MF3 = trouble) = 0.45, \\
 P(\bar{y}_2 | \bar{X}_2) &= P(F3F0 = low | MF3 = normal) = 0.92; \\
 P(y_2 | X_3) &= P(F3F0 = high | MF4 = trouble) = 0.35, \\
 P(\bar{y}_2 | \bar{X}_3) &= P(F3F0 = low | MF4 = normal) = 0.88.
 \end{aligned}$$

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

$$\begin{cases}
 P_1 = \frac{P(y_2 | X_1) - P(y_2 | \bar{X}_1)}{1 - P(y_2 | \bar{X}_1)} = \frac{0.74 - (1 - 0.95)}{1 - (1 - 0.95)} = 0.7263 \\
 P_2 = \frac{P(y_2 | X_2) - P(y_2 | \bar{X}_2)}{1 - P(y_2 | \bar{X}_2)} = \frac{0.45 - (1 - 0.92)}{1 - (1 - 0.92)} = 0.4022 \\
 P_3 = \frac{P(y_2 | X_3) - P(y_2 | \bar{X}_3)}{1 - P(y_2 | \bar{X}_3)} = \frac{0.35 - (1 - 0.88)}{1 - (1 - 0.88)} = 0.2614
 \end{cases} \quad (6)$$

$$\begin{cases}
 P(y | X_p) = 1 - \prod_{X_i \in X_r} (1 - P_i) = 1 - (1 - P_2)(1 - P_3) = 0.5585 \\
 P(y | X_p) = 1 - \prod_{X_i \in X_r} (1 - P_i) = 1 - (1 - P_1)(1 - P_3) = 0.7978 \\
 P(y | X_p) = 1 - \prod_{X_i \in X_r} (1 - P_i) = 1 - (1 - P_1)(1 - P_2) = 0.8364 \\
 P(y | X_p) = 1 - \prod_{X_i \in X_r} (1 - P_i) = 1 - (1 - P_1)(1 - P_2)(1 - P_3) = 0.8792
 \end{cases} \quad (7)$$

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

**TABLE 2** Conditional probability table of node F3F0

MF2	Normal				Trouble			
	Normal		Trouble		Normal		Trouble	
MF3	Normal		Trouble		Normal		Trouble	
	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

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

#### 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<sup>40</sup>), 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 node 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,<sup>40,41</sup> 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 CPTs 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 paid 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 CPTs 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.,<sup>42-46</sup> and the diagnostic results obtained in cases 4 to 6 are consistent with ref.<sup>47</sup>

## 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 modeling 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 are 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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## REFERENCES

1. Turner B. *United Nations Framework Convention on Climate Change*. London: Palgrave Macmillan UK; 2012.
2. Ran L, Lu XX. Cooperation is key to Asian hydropower. *Nature*. 2011;473:452.
3. IHA (International Hydropower Association). 2018 Hydropower status report (Fifth Edition). Launched 24 May 2018. <http://hydropower.org/status2018>
4. Xu L, Chen NC, Chen ZG. Will China make a difference in its carbon intensity reduction targets by 2020 and 2030? *Appl Energy*. 2017;203:874-882.
5. Ferreira J, Camacho JR, Malagoli JA, Júnior S. Assessment of the potential of small hydropower development in Brazil. *Renew Sustain Energy Rev*. 2016;56:380-387.
6. Yu YQ, Chang ZY, Qi YG, Xue X, Zhao JN. Study of a new hydraulic pumping unit based on the offshore platform. *Energy Sci Eng*. 2016;4:352-360.
7. Zeiner-Gundersen DH. Turbine design and field development concepts for tidal, ocean, and river applications. *Energy Sci Eng*. 2015;3:27-42.
8. Afshar MH, Rohani M, Taheri R. Simulation of transient flow in pipeline systems due to load rejection and load acceptance by hydroelectric power plants. *Int J Mech Sci*. 2010;52(1):103-115.
9. Azizipour M, Afshar MH. Adaptive hybrid genetic algorithm and cellular automata method for reliability-based reservoir operation. *J Water Resour Plan Manage-ASCE*. 2017;143(8).
10. Li FF, Qiu J, Wei JH. Multiobjective optimization for hydro-photovoltaic hybrid power system considering both energy generation and energy consumption. *Energy Sci Eng*. 2018;6(5):362-370.
11. Gosens J, Kaberger T, Wang YF. China's next renewable energy revolution: goals and mechanisms in the 13th Five Year Plan for energy. *Energy Sci Eng*. 2017;5(3):141-155.
12. Aggidis GA, Zidonis A. Hydro turbine prototype testing and generation of performance curves: Fully automated approach. *Renew Energy*. 2014;71:433-441.
13. Karlsen-Davies ND, Aggidis GA. Regenerative liquid ring pumps review and advances on design and performance. *Appl Energy*. 2016;164:815-825.
14. Goyal R, Gandhi BK. Review of hydrodynamics instabilities in Francis turbine during off-design and transient operations. *Renew Energy*. 2018;116:697-709.
15. Cheng JT, Wang L, Xiong Y. An improved cuckoo search algorithm and its application in vibration fault diagnosis for a hydroelectric generating unit. *Eng Optimiz*. 2018;50(9):1593-1608.
16. Wu QQ, Zhang LK, Ma ZY. A model establishment and numerical simulation of dynamic coupled hydraulic-mechanical-electric-structural system for hydropower station. *Nonlinear Dynam*. 2017;87:459-474.



17. Xu BB, Chen DY, Zhang H, Zhou R. Dynamic analysis and modeling of a novel fractional-order hydro-turbine-generator unit. *Nonlinear Dynam.* 2015;81(3):1263-1274.
18. Li HH, Chen DY, Gao X, Wang XY, Han QS, Wu CZ. Fast-slow dynamics of a hydropower generation system with multi-time scales. *Mech Syst Signal Proc.* 2018;110:458-468.
19. Riasi A, Tazraei P. Numerical analysis of the hydraulic transient response in the presence of surge tanks and relief valves. *Renew Energy.* 2017;107:138-146.
20. Li HH, Chen DY, Zhang H, Wu CZ, Wang XY. Hamiltonian analysis of a hydro-energy generation system in the transient of sudden load increasing. *Appl Energy.* 2017;185:244-253.
21. Xia X, Ni W, Sang YJ. A novel analysis method for fault diagnosis of hydro-turbine governing system. *Proc Inst Mech Eng Part O-J Risk Reliab.* 2017;231(2):164-171.
22. Thiery F, Gustavsson R, Aidanpaa JO. Dynamics of a misaligned Kaplan turbine with blade-to-stator contacts. *Int J Mech Sci.* 2015;99:251-261.
23. Xu BB, Chen DY, Behrens P, Ye W, Guo PC, Luo XQ. Modeling oscillation modal interaction in a hydroelectric generating system. *Energy Conv Manag.* 2018;174:208-217.
24. Egusquiza M, Egusquiza E, Valero C, Presas A, Valentín D, Bossio M. Advanced condition monitoring of Pelton turbines. *Measurement.* 2018;119:46-55.
25. Chen LY, Arzaghi E, Abaei MM, Garaniya V, Abbassi R. Condition monitoring of subsea pipelines considering stress observation and structural deterioration. *J Loss Prev Process Ind.* 2018;51:178-185.
26. Dobrivoje C, Milomir G, Mile S, Jasna G. Fault tree analysis of hydraulic power-steering system. *Int J Veh Des.* 2014;64(1):26-45.
27. Yuan NQ, Yang WL, Kang B, Xu SX, Wang XL, Li CJ. Manifold learning-based fuzzy k-principal curve similarity evaluation for wind turbine condition monitoring. *Energy Sci Eng.* 2018;6(6):727-738.
28. Alireza P, Riasi A. Quasi-two-dimensional numerical analysis of fast transient flows considering non-newtonian effects. *J Fluid Eng-T ASME.* 2016;138(1):011203.
29. Jong CG, Leu SS. Bayesian-network-based hydro-power fault diagnosis system development by fault tree transformation. *J Mar Sci Technol-Taiwan.* 2013;21(4):367-379.
30. Li HJ, Graham DJ, Majumdar A. Effects of changes in road network characteristics on road casualties: an application of full Bayes models using panel data. *Saf Sci.* 2015;72:283-292.
31. Xu W, Zhang C, Peng Y, Fu GT, Zhou HC. A two stage Bayesian stochastic optimization model for cascaded hydropower systems considering varying uncertainty of flow forecasts. *Water Resour Res.* 2014;50(12):9267-9286.
32. Alam J, Kim D, Choi B. Uncertainty reduction of seismic fragility of intake tower using Bayesian Inference and Markov Chain Monte Carlo simulation. *Struct Eng Mech.* 2017;63(1):47-53.
33. Boksteen SZ, van Buijtenen JP, Pecnik R, van der Vecht D. Bayesian calibration of power plant models for accurate performance prediction. *Energy Conv Manag.* 2014;83:314-324.
34. Hu JQ, Zhang LB, Ma L, Liang W. An integrated method for safety pre-warning of complex system. *Saf Sci.* 2010;48:580-597.
35. Cai BP, Liu YH, Fan Q, et al. Multi-source information fusion based fault diagnosis of ground-source heat pump using Bayesian network. *Appl Energy.* 2014;114:1-9.
36. Cai BP, Liu Y, Xie MA. dynamic-Bayesian-network-based fault diagnosis methodology considering transient and intermittent faults. *IEEE Trans Autom Sci Eng.* 2017;14:276-285.
37. Cai BP, Zhao YB, Liu HL, Xie MA. data-driven fault diagnosis methodology in three-phase inverters for PMSM drive systems. *IEEE Trans Power Electron.* 2017;32:5590-5600.
38. Zhou K, Martin A, Pan Q. The belief noisy-OR model applied to network reliability analysis. *Int J Uncertainty Fuzziness Knowledge Based Syst.* 2016;24(6):937-960.
39. Hu YJ, Xiao ZH, Zhou YF, Sun ZH. Study of hydropower units fault diagnosis based on Bayesian network Noisy OR model. *Journal of Hydroelectric Engineering.* 2015;34(6):197-203 (in Chinese).
40. Stern HS. A test by any other name: P values, Bayes factors, and statistical inference. *Multivariate Behav Res.* 2016;51(1):23-29.
41. Atchade YF. A computational framework for empirical Bayes inference. *Stat Comput.* 2011;21(4):463-473.
42. Shen D, Chu FT, Chen S. Diagnosis and identification of vibration accident for hydrogenerator unit. *Journal of Hydrodynamics.* 2000;15(1):129-133 (in Chinese).
43. Xu BB, Chen DY, Li HH, et al. Priority analysis for risk factors of equipment in a hydraulic turbine generator unit. *J Loss Prevent Proc.* 2019;58:1-7.
44. Xiao ZH, He XY, Fu XQ, Malik OP. ACO-Initialized wavelet neural network for vibration fault diagnosis of hydroturbine generating unit. *Math Probl Eng.* 2015;2015:1-7.
45. Fu WL, Zhou JZ, Li CS, Xiao H, Xiao J, Zhu WL. Vibrant fault diagnosis for hydro-electric generating unit based on support vector data description improved with fuzzy K nearest neighbor. *Proceedings of the CSEE.* 2014;34(32):5788-5795 (in Chinese).
46. Peng WJ, Luo XQ, Zhao DL. Vibrant fault diagnosis of hydro-turbine generating unit base on spectrum analysis and RBF network method. *Proceedings of the CSEE.* 2006;26(9):155-158 (in Chinese).
47. Cheng JZ, Zhu C, Fang X, Wang CX, Sun J, Xiong Z. Fault diagnosis of hydropower unit based on fuzzy cognitive Bayesian network model. *Water Resources and Power.* 2018;36(8):135-138 (in Chinese).

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