Bayesian Networks for Fault Diagnosis of Large Power Generating Stations

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Abstract – In this paper, a simplified Bayesian networks with Noisy-OR and Noisy-AND nodes fault diagnosis system is proposed to estimate the faulty item of power generation station that includes; generation units, power transformers, station service transformers, autotransformers and station bus bars. The proposed method utilizes the final information of protective relays and corresponding circuit breakers to construct the Bayesian networks for each section/item. The proposed method can deal with the incomplete information and uncertainties imposed on fault section/item diagnosis. The learning algorithm for network parameters is analogous to the back propagation algorithm of artificial neural networks. Taking the sum of the mean-squared error between the expected values and the computed results of target variables as the minimizing optimization function, it adjusts the network's parameters continuously. By comparing the results believe of possible fault sections/item; the faulty section(s) is candidate. Computer simulation of High Dam power generation station (Hydro Plants Generation Company HPGC) in Egypt shows that type of fault diagnosis has powerful error tolerance ability, rapid reasoning, less storage memory and processing time. It is also flexible and can be applied into control center of the actual large power generation station for online fault diagnosis to make the reasonable decision in critical situations.

I. INTRODUCTION

Fault diagnosis plays a crucial role in power system. Traditionally, human operator performs the fault diagnosis in power generation station. It is essential for the operators of power generation station to estimate quickly the faulty section, decrease the outage time and so ensure stable supply of electric power for the power system. Therefore, the operators should have the capability to estimate and restore the fault section/item after removing the fault, if any, with the best way at the first step in the restoration situation. With the development of power system itself, regarding the power stations, the complexity of the power station fabric is increased and the power station automation has become a major issue. In this situation, it is rather difficult to diagnose quickly and exactly the fault case only by human operator with their experience. In order to give out the fault diagnosis results quickly, clearly, operators should be assisted and supported by a fault diagnosis system to diagnose the power system faults.

The researchers have been proposed many fault diagnosis system for solving the power system fault diagnosis problem, such as; rule-based and logic expert systems (ES) [1-3] respectively, fuzzy relations [4,5], neural network [6], genetic algorithm (GA) [7]. Their purposes are focused to diagnose faults timely on-line to provide an accurate judging rule for dispatch operators.

Due to many of uncertain signals, which are caused by many factors, such as mal-operation and no-operation of circuit breakers or relays, data-transmission error or data-loss, the inaccurate timing of protective relay operation, power system fault diagnosis scheme needs uncertainty reasoning. Among the existing uncertainty reasoning approaches, Bayesian networks (belief networks, causal networks, influence diagrams, probabilistic networks) is more accurate and has a solid theoretical foundation based on probability theory [8]. Bayesian network based approach, mainly used for representing and reasoning with uncertainty, has been successfully used in many fields, such as business and finance, computer games, computer vision, medicine, natural language processing, planning, speech recognition, vehicle control and malfunction diagnosis, weather forecasting [8], fault diagnosis of power system networks [9-10] and fault location on distribution feeder [11].

Since general Bayesian networks are impractical for many large problems because it requires for each variable the conditional probabilities of the variable given all possible combinations of values of its parents. For a network where all variables are binary-valued, a variable with $n$ parents would require $2^n$ conditional probabilities to be specified. This makes general Bayesian networks inference exponential in the fan-in of the nodes. Then, they are it is need more storage memory and processing time [12].

The Noisy-OR and Noisy-AND models of Bayesian networks [13] avoid the above problem providing a way to compute the conditional probability of a variable given a combination of values of its parents from just the conditional probabilities of the variable given the value of each of its parents in isolation. In this paper, a simplified Bayesian networks with Noisy-OR and Noisy-AND models utilize the final information of protective relays and corresponding circuit breakers to construct the Bayesian networks for each section and estimate the faulty section of a power generation station includes; generation unit, step up power transformer, station service transformer, autotransformer and station bus bar. They can deal with uncertain incomplete data. The structures and initial parameters of the Bayesian networks depend on the prior knowledge of the domain experts. The learning algorithm for network parameters is analogous to the back propagation algorithm of neural networks.
The proposed method has been tested on High Dam power station 500/220/15.75/11 kV (Hydro Plants Generation Company HPGC). Testing results have shown that the proposed method is rapid reasoning, correct, efficient and can use flexibly in a large power generation station for on-line fault diagnosis.

II. BAYESIAN NETWORK [14]

A. Brief Introduction to Bayesian Network

A Bayesian network is defined by two components. The first is a directed acyclic graph (DAG), where each node represents a random variable, and directed link or arrow connects pairs of nodes represents a probabilistic dependence. If link is drawn from a node $Y$ to a node $X$, then $Y$ is a parent of $X$, and $X$ is a descendent of $Y$. Each node is conditionally independent of its nondescendents in the graph, given its parents. The second component defining a belief network consists of one conditional probability table (CPT) for each variable. The CPT for a variable $X$ specifies the conditional distribution $P(x | Parents(X))$, where $Parents(X)$ are the parents of $x$. The conditional probability of each value is the possible combination of values of its parents [14].

B. The Noisy-OR Model

A Noisy-OR node in a Bayesian network is a generalization of a logical or [14]. As in the case of the logical or, an event represented by a Noisy-OR node $N_j$ is presumed to be false (i.e. $P(N_j = \text{true}) = 0$) if all the conditions that cause $N_j$ are false. However, unlike a logical or, if one of the causes of the event $N_j$ is true, it does not necessarily imply that $N_j$ is definitely true. The inputs $N = (N_1, ..., N_i, ..., N_n)$ are the parents of $X$ in the Bayesian networks, and they normally represent explanations or enabling conditions that may account for the occurrence of $X$. The inhibitors $I = (I_1, ..., I_i, ..., I_n)$ represent exceptions or abnormalities that interfere with the normal relationship between $N$ and $X$. These are normally not represented by nodes in Bayesian networks but are summarized implicitly by the link matrix $P(x | n_1, ..., n_i, ..., n_n)$. That is mean; each condition $N_i$ causing the event $N_j$ can be thought to have an associated inhibitory influence, which is active with a probability $q_{ij}$. Thus, if $N_j$ is the only cause of $N_j$ that is true, then $N_j$ is true with a probability $(1 - q_{ij})$. Moreover, the inhibitory influences are assumed to be mutually independent. The likelihood of $N_j$ being true is a monotonic function of the number of its causal conditions that are true. The parameter $c_{ij} = 1 - q_{ij}$ is the degree to which an isolated cause $N_i$ of an event $N_j$ can endorse the event. These parameters can be used to construct a Conditional Probability Table (CPT) for the node, if needed. Fig. 1 shows the conceptual view of a Noisy-OR node.

![Conceptual view of Noisy-OR node.](image)

The belief degree in a node $N_j$ is given by

\[
Bel(N_j = x) = \begin{cases} 
1 - \prod_i (1 - c_{ij}(1 - Bel(N_i = True))) & \text{if } x = \text{False} \\
\prod_i (1 - c_{ij}(1 - Bel(N_i = True))) & \text{if } x = \text{True} 
\end{cases}
\]  

where, $c_{ij}$ is the parameter on the link from node $N_i$ to node $N_j$.

C. The Noisy-AND Model

A Noisy-AND node is the dual of a Noisy-OR node [14]. It is a generalization of a logical and. As in the case of the logical and, an event represented by a Noisy-AND node $N_j$ is presumed to be true (i.e. $P(N_j = \text{true}) = 1$) if all the conditions that cause $N_j$ are true. However, unlike a logical and, if one of the causes of the event $N_j$ is false, it does not imply that $N_j$ is definitely false. The inputs $N = (N_1, ..., N_i, ..., N_n)$ are the parents of $X$ in the Bayesian networks, and they normally represent explanations or enabling conditions that may account for the occurrence of $X$. The inhibitors $I = (I_1, ..., I_i, ..., I_n)$ represent exceptions or abnormalities that interfere with the normal relationship between $N$ and $X$. These are normally not represented by nodes in Bayesian networks but are summarized implicitly by the link matrix $P(x | n_1, ..., n_i, ..., n_n)$. That is mean; each condition $N_i$ causing $N_j$ can be thought to have an associated enabling influence, which is active with a probability $q_{ij}$. Thus, if $N_i$ is the only cause of $N_j$ that is false, then $N_j$ is false with a probability $(1 - q_{ij})$. The likelihood of $N_j$ being false is a monotonic function of the number of its causes that are false. The parameter $c_{ij}$ is the degree to which disproving an isolated cause of an event disproves the event itself. Fig. 2 shows the conceptual view of a Noisy-AND node.

The belief degree in a node $N_j$ is given by

\[
Bel(N_j = x) = \begin{cases} 
\prod_i (1 - c_{ij}(1 - Bel(N_i = True))) & \text{if } x = \text{False} \\
\prod_i (1 - c_{ij}(1 - Bel(N_i = True))) & \text{if } x = \text{True} 
\end{cases}
\]
where, 
\( c_{ij} \) is the parameter on the link from node \( N_i \) to node \( N_j \).

III. NOISY-OR AND NOISY-AND BAYESIAN NETWORK FOR POWER GENERATION STATION

The proposed Bayesian Noisy-OR and Noisy-AND networks has been tested on High Dam power generation station [15], as shown in Fig. 3 which includes the case studies fault locations too. The text symbols used to represent the operating relays in the figures are explained as follows. The letters U, T, A and M denote to generation unit, transformer, auxiliary generator and main generator, after them the protection relay number. Moreover, the letters TS, B, HV and BB denote to service transformer, block bus bar “three units with their step up transformers form a block”, high voltage and bus bar number. The system comprises:

1. 36 faulted unit/sections (U1…U12, T1…T12, B1BB…B4BB, TS1…TS4, HVBB1 and HVBB2, T13 and T14).
2. 40 circuit breakers (12 for units, 8 for blocks, 8 for service transformers, 4 for double circuit transmission lines, 6 for autotransformers at 500 kV and 220 kV side, 2 bus tie circuit breakers at 220 kV side).
3. 428 protective relays (240 for units, 84 for power transformers, 4 for blocks bus bar, 12 for TS1 and TS3, 16 for TS2 and TS4, 40 for T13 and T14, 2 for HVBB1 and HVBB2, 30 for breaker failures).

A. Bayesian Fault Diagnosis of Generation Unit

As an example of Bayesian Noisy-OR and Noisy-AND application on generation unit is the generation unit of High Dam power station, Aswan, Egypt. The protection system of generation unit of High Dam power station is more complex since it has two cascaded generators to produce the output voltage. Moreover, each generator has protection relays to protect itself, so more complex protection scheme with corresponding CBs are extracted. The typical generation unit 7 (U7) of High Dam power station shown in Fig. 4 [5,15] is used to illustrate the procedure of electrical protection and also illustrate how it is connected to the other elements (main power transformers and service transformer).
TABLE I
KINDS OF PROTECTIVE RELAY OF THE GENERATION UNIT 7

<table>
<thead>
<tr>
<th>Kinds of Protective Relay</th>
<th>The Generator</th>
<th>Auxiliary Generator</th>
<th>Main Generator</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main fast protective relays as main generator protection MGP without time delay.</td>
<td></td>
<td>A87M diff. protection</td>
<td>M87M diff. protection</td>
</tr>
<tr>
<td>Primary Generator Protections PGP with time delay</td>
<td>M51BTV transverse differential protection</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Primary Generator Protections against Abnormal Operating Conditions GPAOC</td>
<td>M59G stator ground fault</td>
<td>M24 over excitation</td>
<td></td>
</tr>
<tr>
<td>Generator backup protections GBP</td>
<td>M81O over frequency, M50IE inadvertent energization, emergency protection (load shedding), M40 loss of excitation</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

TABLE II
THE TRAINING RESULTS AND SAMPLES OF THE FAULT DIAGNOSIS MODEL OF GENERATION UNIT 7

<table>
<thead>
<tr>
<th>Sample Number</th>
<th>MGP</th>
<th>U7CB</th>
<th>PGP</th>
<th>GPAOC</th>
<th>GBP</th>
<th>B3CB1</th>
<th>B3CB2</th>
<th>TS3CB</th>
<th>U8CB</th>
<th>U9CB</th>
<th>Desired Output</th>
<th>Trained Output</th>
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<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>1</td>
<td>1</td>
<td>0.61</td>
<td>0.6319</td>
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<td>0</td>
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<td>0</td>
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<td>1</td>
<td>0</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
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<td>0.8155</td>
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<tr>
<td>5</td>
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<td>1</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.9</td>
<td>0.9157</td>
</tr>
</tbody>
</table>

Due to many kinds of generation unit protective relays and make the diagnosis process with more realistic, the protective relays of generation unit 7 are divided into four kinds as shown in Table I. Because both a relay and its corresponding CBs should operate if the generation unit is faulty, the relay operation and its corresponding CB operation form the parents nodes of a Noisy-AND node. Moreover, because each relay of generation unit is designed to respond to the fault and that trips its CB, all of the relays and their breakers' operations are made up of Noisy-OR node. Fig. 5 shows the Bayesian fault diagnosis of High Dam generation unit, and all parameters are shown in the figure are obtained from Table I through parameters learning algorithm, which explain in the next section. If U7CB do not work, its breaker failure relay should operate [16].

B. Bayesian Fault Diagnosis of Step up Power Transformer
As application of Bayesian Noisy-OR/AND on step up power transformer, the step up power transformer of High Dam power station is used. There are many protective relays and different tripping scheme for these protective relays. The protective relays are divided into four kinds:

1. Main fast protective relays as Main Transformer Protections MTP without time delay include; harmonic restrained differential protection 87T, unrestrained differential protection 87H and Buchholz relay 63B.
2. Primary Transformer Protections PTP1 include; bushing leakage current TKHB and oil temperature OT.
3. Primary Transformer Protections PTP2 include; neutral over current protection first stage T51N I.
4. Primary Transformer Protections PTP3 include; neutral over current protection second stage T51N II.

When MTPs or PTPs operate that, confirm the transformer is faulty section. Fig. 6 illustrates the Bayesian fault diagnosis model of step up transformer.
C. Bayesian Fault Diagnosis of Block Bus Bar
Three-generation units with their step up power transformers at side 500 kV are connected to form a block with common bus bar. That common bus bar is protected by the following protective relays:

1. Main fast protective relays as Main Bus Bar Protection MBP without time delay include; differential protection 87B.
2. Primary Bus Bar Protections PBP1 include; over current with voltage controlled protection “50P and 51VC” for block generation units.
3. Primary Bus Bar Protections PBP2 include; instantaneous over current second stage 50P II and phase time over current second stage 51P II for the service transformer of block.
4. Primary Bus Bar Protections PBP3 include; step up power transformer neutral over current protection second stage 51N II.

Fig. 7 illustrates the Bayesian fault diagnosis model of High Dam block 3 bus bar.

IV. BAYESIAN NOISY-OR/AND PARAMETER LEARNING ALGORITHM
The parameter-learning algorithm used by the Bayesian Noisy-OR/AND is analogous to the standard back propagation algorithm used to learning a multilayer feed forward neural network. Gradient descent method is used to minimize the mean square deviation between the actual value and the computed value of certain target variables. The gradient is computed according to the mean square deviation between the actual and the computed values of certain target variables and taking its partial derivative with respect to the parameters.

\[ \delta_j = \frac{1}{2} \sum_{i} (y_{ij} - \tilde{y}_{ij})^2 \]  

where \( y_{ij} \) is the actual belief that the \( j \)th target variable \( N_j \) is true, and \( \tilde{y}_{ij} \) is the presently calculated value of the belief that the \( j \)th target variable is true.

For hidden nodes in a Bayesian network, the error propagated to \( N_j \) from its child node \( N_k \) is shown in “(5),” at the top of the next page, where \( \delta_k \) is the error at node \( N_k \).

In addition to Noisy-OR and Noisy-AND nodes, the networks could include negation nodes [10]. These are probabilistic nodes, with a single parent corresponding to the variable being negated. The belief of a negated node is computed according to

\[ \text{Bel}(N_j = \text{True}) = 1 - \text{Bel}(N_j = \text{True}) \]  

where \( N_j \) is a negation node, and \( N_i \) is its sole parent.

Before the parameter leaning, the value of \( c_{ij} \) (the parameter on the link from node \( N_i \) to node \( N_j \)) must be initialized randomly or depended on the prior knowledge of the domain experts. The parameters of the fault diagnosis model of generation unit can be trained and learned by the samples shown in Table II and the above mentioned gradient algorithm equation “(3),”“(6),” for parameter adjustment and the learning results (conditional probability \( c_{ij} \)) have been respectively shown in Fig. 5. As for each fault sample of the samples shown in Table II, the training process is repeated for 36 iterations and takes 1 sec. until the required prospective output is realized. For the fault samples, the training output values should be between 0.6 and 0.95, but for those no-fault samples, the training output values should be between 0.0 and 0.1.

Similarly, the parameters of the Bayesian fault diagnosis models for step up transformers, service transformer, block bus bar, autotransformer and main bus bar of station can be revised, the learning results (conditional probability \( c_{ij} \)) for transformer and block’s bus bar have been shown in Fig. 6 and Fig. 7 respectively.

V. DIAGNOSIS METHODOLOGY
The real-time information of the circuit breakers and protective relays are adopted to identify the system topology structures before and after fault, then the difference between them are the faulty power area and the fault element candidates must be in that area.
\[
\Delta c_{ij} = \left\{ \begin{array}{ll}
\eta \delta_i \text{Bel}(N_j = \text{True}) \times \prod_{m \neq i} (1 - c_{mj} \text{Bel}(N_m = \text{True})) \\
- \eta \delta_i (1 - \text{Bel}(N_j = \text{True})) \times \prod_{m \neq i} (1 - c_{mj} (1 - \text{Bel}(N_m = \text{True})))
\end{array} \right.
\]

(3)

\[
\delta_j = \left\{ \begin{array}{ll}
\delta_k \prod_{i \neq j} (1 - c_{ki} \text{Bel}(N_j = \text{True})) \\
- \delta_k c_{kj} (1 - \text{Bel}(N_j = \text{True}))
\end{array} \right.
\]

(5)

After identification the faulty power area, put the information of the relevant protective relays and the operation of the corresponding circuit breakers of each element into the fault diagnosis model “which has been trained”, then compute the fault belief degree of each element in the faulty area according to “(1),” and “(2),”.

Through a large number of diagnosis cases to many actual faults that happened in High Dam power station and operating conditions of each protective relays, the following results are obtained: 1) If the fault belief degree of an element is higher than 0.7, this element must be faulty. 2) If the fault belief degree of an element is between 0.1 and 0.7, this element may be faulty. 3) If the fault belief degree of an element is lower than 0.1, this element is normal. A low cost personnel computer PC (Pentium(R) 3.02 GHz, 1.99) used to proposed method. The flow chart of the Bayesian fault diagnosis program is shown in Fig. 8 and the program is written in MATLAB package.

![Flow chart of the Bayesian fault diagnosis program](image)

VI. CASE STUDIES

High Dam power generation station is used as the test system to testify the effectiveness of Bayesian networks Noisy-OR and Noisy-AND nodes as fault diagnosis system. As shown in Fig. 3, the single line fault diagram of actual part of High Dam power station that includes the locations of different fault cases. These actual several studies are collected from High Dam's accidents and fault archive that happened in the station. The diagnosis results of four cases are shown as follows:

**Case 1) Fault on Generation Unit**

The fault occurred at 22:13, 02/07/2008

**Operated Relay** : U7M59G.

**Tripped CBs** : U7CB.

**HPGC's Analysis** : M59G stator ground fault protection right operation.

**Bayesian Diagnosis** : The faulted section is unit 7 with fault belief degree is 0.8154.

The ensuring faulted section is unit 7 because its faulted belief degree is higher than 0.7. If the control room receives only the operation information of M59G or unit 7 circuit breaker, the inference result of unit 7 is 0.1337 and 0.2287 respectively, so unit 7 may be faulty section because its fault belief degree is higher than 0.1. Then the proposed fault diagnosis has certain capability of generalization and error tolerance.

**Case 2) Fault on Generation Unit**

The fault occurred at 18:15, 22/5/2003

**Operated Relay** : Unit 12 over current 50P with voltage controlled 51VC “50P and 51VC”.

**Tripped CBs** : Unit 10CB, unit 11CB, unit 12CB, block 4 CB1 and CB2.

**HPGC's Analysis** : Right operation of the protective relay.

**Bayesian Diagnosis** : The results are shown in Table III.

![Table III](image)

**TABLE III**

<table>
<thead>
<tr>
<th>Section</th>
<th>U10</th>
<th>U11</th>
<th>U12</th>
<th>T10</th>
<th>T11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault Belief Degree</td>
<td>0.3890</td>
<td>0.3890</td>
<td>0.6319</td>
<td>0.2609</td>
<td>0.2609</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Section</th>
<th>T12</th>
<th>B4BB</th>
<th>HVBB1</th>
<th>HVBB2</th>
<th>-------</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault Belief Degree</td>
<td>0.2609</td>
<td>0.1947</td>
<td>0.1600</td>
<td>0.1600</td>
<td>-------</td>
</tr>
</tbody>
</table>
The proposed method ensures the fault occurred on block 4 because there are many candidates of station faulty sections due to their belief degree between 0.1 and 0.7. The higher belief degree of faulty section is unit 12 by its operation of protective relay over current 50P with Voltage Controlled 51VC, so it is the faulty section; and the other sections may be faulty section but less possibility because their belief degree between 0.1 and 0.7.

The operation of 50P and 51VC for unit 12 only from block 4 means that fault was in the grid due to a swing occurrence. Unit 10 and 11 do not operate because the operating conditions for them are not the same but the protective relay and corresponding circuit breakers for unit 12 are operated, so it has higher fault certainty. In addition, this protection is considered as back up protection for unit generator against down stream faults, so that the proposed method can train the generation unit parameters fault diagnosis model to give it a belief degree of 0.6 as the target output when operated.

So, can reduce/raise the expected output value of the fault section, or reduce/raise the expected output value of the non-fault section, by parameter learning algorithm. Thus, the capability of generalization will be more powerful and has error tolerance.

**Case 3) Fault on Step up Power Transformer**

The fault occurred at 17:06, 22/11/2007

**Operated Relay**

- Transformer 9 Buchholtz relay and differential protection “T9 63B” and “T9 87H” respectively.

**Tripped CBs**

- Unit 9CB, block 3 CB1 and CB2 and service transformer 3CB.

**HPGC’s Analysis**

- Right operation of the protective relay.

**Bayesian Diagnosis**

- The results are shown in Table IV.

<table>
<thead>
<tr>
<th>Section</th>
<th>U7</th>
<th>U8</th>
<th>U9</th>
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<th>T8</th>
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<td>Fault Belief Degree</td>
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<td>0.3890</td>
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<table>
<thead>
<tr>
<th>Section</th>
<th>T9</th>
<th>B3BB</th>
<th>HVBB1</th>
<th>HVBB2</th>
<th>TS3</th>
</tr>
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<tbody>
<tr>
<td>Fault Belief Degree</td>
<td>0.9054</td>
<td>0.2599</td>
<td>0.1600</td>
<td>0.1600</td>
<td>0.1917</td>
</tr>
</tbody>
</table>

The fault occurred on the block 3 of High Dam power generation station. There are many possibilities of faulty sections. Then, the proposed fault diagnosis method compute their fault belief degrees that shown in Table IV. The confirmed faulty section is transformer 9 because its fault belief degree is higher than 0.7; the other sections are possible faulty because its degree is between 0.1 and 0.7; and finally the other sections of High Dam station are normal because its degrees is less than 0.1.

The diagnosis result shows the faulty transformer lead to variant belief degrees of the other sections for the faulted area due to its shared tripped circuit breakers only.

**Case 4) Faults on Transformer and Station Bus Bar 500 kV**

This case is an example of multiple fault.

**Operated Relay**

- High Voltage Station Bus Bar 1 500 kV differential protection “HVBB1 87H” and transformer 1 differential protection “T1 87H”.

**Tripped CBs**

- Autotransformer 13 CB, block 1 CB1, block 1 CB2, block 2 CB1, block 3 CB1, block 4 CB1, line 1 CB1, line 2 CB1. unit 1CB, unit 2CB, unit 3CB, service transformer 1 CB.

**Bayesian Diagnosis**

- The results are shown in Table V.

<table>
<thead>
<tr>
<th>Section</th>
<th>U1</th>
<th>U2</th>
<th>U3</th>
<th>T1</th>
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<td>Fault Belief Degree</td>
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<table>
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<th>Section</th>
<th>T2</th>
<th>T3</th>
<th>TS1</th>
<th>B1BB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault Belief Degree</td>
<td>0.2609</td>
<td>0.2609</td>
<td>0.1917</td>
<td>0.2599</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Section</th>
<th>L1</th>
<th>L2</th>
<th>HVBB1</th>
<th>HVBB2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault Belief Degree</td>
<td>0.0269</td>
<td>0.0269</td>
<td>0.9160</td>
<td>0.1600</td>
</tr>
</tbody>
</table>

This case is considered as multiple fault case that can occur in the power system and makes confusion to the operators due to many tripped circuit breakers that follows the outage of faulted sections and so the loss of a large part of the system.

The fault occurred in High Voltage bus bar 1 (HVBB1) by High Voltage bus bar differential relay operated (HVBB1 87B). Following the relay operation many circuit breakers are tripped these circuit breakers are: the first circuit breaker for block no. 1 (B1CB1), block no. 2 (B2CB1), block no. 3 (B3CB1), block no. 4 (B4CB1), High Dam/Nag Hammadi transmission line 1 (HDL1CB1), High Dam/Nag Hammadi transmission line 2 (HDL2CB1) and autotransformer no. 13 (T13CB). At the same time, the differential protection of main transformer no. 1 (T187H) is operated and tripped the following circuit breakers: the first and second circuit breaker of block no. 1 (B1CB1, B1CB2), the circuit breakers of units no. 1, 2 and 3, and service transformer circuit breaker no. 1 (TS1CB).

Table V shows the faulty sections and its belief degrees. The ensuring faulty sections are High Voltage Bus bar 1 (HVBB1) and main Transformer (T1) because their belief degrees are higher than 0.7. The sections; unit 1, unit 2, unit 3, transformer 2, transformer 3, block’s bus bar 1, High voltage bus bar 2 are probable faulty sections because their belief degrees between 0.1 and 0.7 and their values come from their shared tripped circuit breakers. The sections; service transformer 1, High Dam/Nag Hammadi transmission line 1, High Dam/Nag Hammadi transmission line 2 are not faulty sections because its belief degrees are less than 0.1 although there is one of their circuit breakers are tripped.
TABLE VIII
COMPARISON OF THE PROPOSED BAYESIAN NETWORKS AND FUZZY RELATIONS

<table>
<thead>
<tr>
<th>Method</th>
<th>Bayesian Noisy-Or/And Networks</th>
<th>Fuzzy Relations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generality of the Fault Diagnosis System</td>
<td>(Excellent) A section oriented fault diagnosis model that consists of Noisy-OR/AND nodes is suitable for any section of this kind in a power generation station.</td>
<td>(Good) The fuzzy relations fault diagnosis models of power generation station which are not the same to the other fuzzy relations fault diagnosis models of power generation stations and need to a little modification of these models.</td>
</tr>
<tr>
<td>Efficiency</td>
<td>(Excellent) It takes a maximum of 1 sec. to diagnose the different faults cases for the same power station.</td>
<td>(Good) It takes a relatively long time due to large amount of fuzzy relations of the power station.</td>
</tr>
<tr>
<td>Parameters Learning Ability</td>
<td>(Excellent) The relationship parameters between causal nodes and the parameters can be easily revised through sample training.</td>
<td>(Bad) No need to parameters learning.</td>
</tr>
<tr>
<td>Size of Applied Power System</td>
<td>(Very Large) The Bayesian Noisy-OR/AND fault diagnosis models are universal to the same kinds of sections.</td>
<td>(Very Large) The fuzzy relation fault diagnosis models are universal to the same kinds of sections.</td>
</tr>
</tbody>
</table>

VII. COMPARISON OF THE PROPOSED BAYESIAN NETWORKS AND FUZZY RELATIONS

A comparison of the proposed Bayesian Noisy-OR/AND networks and the fuzzy relations [5] in the qualities and performances for power generation station and transmission lines are listed in Table VIII.

VII. CONCLUSION

To aid and support the operator in the control room to make correct decisions during critical situations and reduce the delay of restoration after emergency, a simplified Bayesian networks with Noisy-OR and Noisy-AND nodes are used to deal with the uncertainties, incompleteness of protective relays and circuit breakers information, as well as the great number of alarms and tripping signals which send to the power station's control room.

The paper proposed a fault diagnosis models for power generation station which includes; generation unit; step up transformer and bus bars based on the Noisy-OR/AND nodes, and the error back propagation training algorithm that is analogous to back propagation neural network to revise the network parameters. The fault diagnosis models do not vary with the change of the network structure. If there are many complete practical fault sections to train the fault diagnosis models, not only the parameters can be revised, but also the structure can also be revised easily.

The proposed method has been tested for actual faults on High Dam power generation station to verify the system performance. The tested results demonstrate that the proposed method has many merits such as clear defined semantics, rapid reasoning, less memory storage and process time, fast convergence, powerful error tolerance ability. It can be applied for actual on-line fault diagnosis of large power generation station.

The proposed method can be used flexibly in any power station by changing and training network's parameters of different sections to give the desired values according to the configuration, requirements and special conditions for each power station. Moreover, the paper presents a complete protection scheme for large power generation station with complex configuration.

REFERENCES