# Fault Diagnosis in Power Transmission Networks Using Bayesian Networks

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**Abstract.** In this paper we present an approach to detect and diagnose single or multiple faults in power transmission networks using Bayesian Networks (BNs). A BN model of the power system is generated by taking in account the relationships existing between the nodes in the network and the primary and secondary protection elements. The diagnostic system is implemented by using two different inference algorithms: a first-order logic theorem prover (used by the Independent Choice Logic framework), and an approximate inference method based on rejection sampling and likelihood weighting sampling. The input to the diagnostic system is a set of discrete alarms coming from the status of breakers at the moment of failure. The output of the system is a set of explanations to the observed symptoms. In both cases, the theorem prover and the approximate method, the main interest lies on the most likely explanation. The approach is tested by diagnosing faults in a simulated electrical power network with 12 nodes and 32 protection breakers.

## 1 Introduction

The purpose of monitoring a process or system operation is to reduce the occurrence of sudden or dangerous shutdowns, equipment damage, and personal accidents and to assist in the operation of the maintenance program. In any of these cases, appropriate and timely action becomes crucial, hence the importance of developing algorithms that gives an optimal trade-off between finding an exact solution and finding it quickly.

It is no surprise that the problem of process monitoring and fault diagnosis has become an important area of research in the Artificial Intelligence community. In general terms, a monitoring system for process operation should consider not only early detection and diagnosis, but also robustness, adaptability and reasonable storage and computational resources.

As the need to solve more complex real world decision problems has increased, the adequate treatment of uncertainty has become fundamental. This is especially true in large, highly interconnected systems such as power transmission networks, where for a given fault scenario, hundreds or thousands of alarms are

generated. The complexity and high degree of interconnection present in electrical power networks, can lead to an overwhelming array of alarms and status messages being generated as a result of a disturbance. This can have a negative impact on the speed with which operators can respond to a contingency, and therefore it becomes necessary to use automated tools that can help the operator to speed up the resolution process.
In the last decade, different AI algorithms have been proposed for solving the diagnosis problem in power networks: alarm processing aids have relied on the use of Expert Systems [4,5], Neural Networks [10], Fuzzy Logic [1] or Petri Nets [9]. More recently, the need to develop more powerful approaches has motivated the development of systems based on Bayesian Networks [11,12] that can deal very efficiently with uncertainty inherent to power systems. BNs are powerful graphical probabilistic models that encode in a compact way multivariate probability density functions.
In this paper we describe an approach to automate fault diagnosis in electrical power transmission networks using a discrete Bayesian network formalism. In order to perform the inference within the BN model, two different approaches are used: a theorem prover for a probabilistic first-order logic framework, and an approximate method based on rejection sampling and likelihood weighting. The general idea is to explore the possibility of having a diagnostic system able to perform online diagnosis. The input to the diagnostic system is a set of discrete alarms representing the status of protection breakers. The system generates explanations consistent with the discrete observations: each explanation contains the hypothesized nodes in a faulty state. We show results from experiments in a simulated power network with 12 nodes and 32 protection breakers.
The paper is organized as follows: Section 1 provided a general introduction. In section 2 we describe the necessary background regarding BNs and inference methods. In Section 3 we develop a case study. In section 4 we analyze the related work, and finally section 5 sets forth our conclusions.

## 2 Background

### 2.1 Bayesian Networks

BNs are directed acyclic graph (DAG) in which nodes represent random variables and arcs determine the probabilistic information needed to specify the joint probability distribution of all network variables, as shown in figure 1. In this BN model, every node has a set of discrete states and the functional relationships between power network nodes and protection breakers nodes are specified by the arcs. To specify the probability distribution of a BN, one must provide also the prior probabilities of all root nodes, and the conditional probabilities of the rest of the nodes given all the possible combinations of their direct predecessors (see for instance table 1).

A BN constitutes an efficient representation of a joint probability distribution over domain variables. Formally, it can be stated in this way: given a set of random variables $X_1, X_2, \ldots X_n$ , each of which has a domain $Dom[X_i]$ of

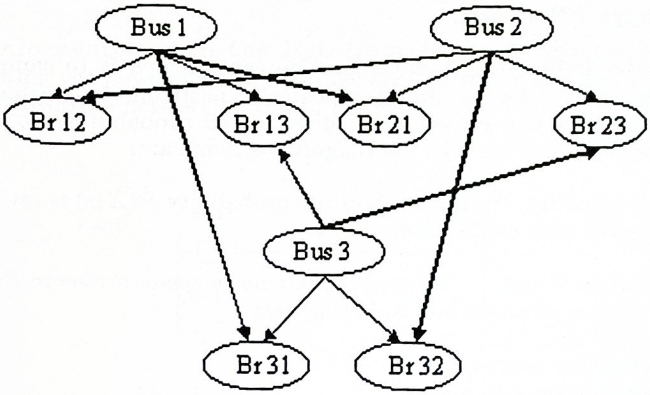


**Fig. 1.** Bayes network representation of the power network

**Table 1.** Probability distribution for breaker *Br12* node in the power network

| **Bus 1** | **Ok** | | **Fault** | |
|---|---|---|---|---|
| **Bus 2** | **Ok** | **Fault** | **Ok** | **Fault** |
| **Normal** | *1* | *0.9* | *0* | *0* |
| **Open** | *0* | *0.1* | *0.95* | *0.95* |
| **Fail** | *0* | *0* | *0.05* | *0.05* |

possible values, then the full joint distribution of a BN is specified by the *chain rule*:

$$p(X_1,\ldots,X_n) = \prod_{i=1}^{n} p(X_i|Parents(X_i)). \quad (1)$$

BNs allow causal representations of observation dependencies as well as efficient algorithms for probabilistic inference; as a result, they are useful in modeling situations in which causality plays an important role but there is incomplete information. In these cases, BN's provide a potentially useful probabilistic representation. To perform inference over BNs, there are different methods such as: exact methods, first-order logic theorem provers and approximate methods. Exact methods allow an accurate calculation of probabilities, but are not adequate for large BN models due to excessive computing time. Theorem provers are adequate when **BN** models are translated to first-order logic as in the Independent Choice Logic (**ICL**) framework [7]. Theorem provers have been used in the past with large **BN** models [2]. Approximate methods take samples from **BNs** considering the existing evidence. These methods are more adequate to apply over large BN models.

**Approximate Inference Methods.** The central idea is to sample the **BN** model $N$ times in order to obtain a posterior probability distribution $\hat{P}$ and show whether there is a convergence of estimated probabilities to actual ones. The sampling methods used in the diagnosis scheme are:

**Rejection Sampling.** In this method the probability $\hat{P}(X|e)$ is estimated from samples agreeing with evidence $e$.

**function** Rejection Sampling $(X, e, bn, N)$ **returns** an approximation to $P(X|e)$
  N[X] $\leftarrow$ a vector of counts over X, initially zero.
  for $j = 1$ to $N$ do
    $x \leftarrow PriorSample(bn)$
    if x is consistent with e then
      $\mathbf{N}[x] \leftarrow \mathbf{N}[x] + 1$ where $x$ is the value of $X$ on $x$
**return** Normalize $N[X]$

**Likelihood Weighting.** This method relies on fixing evidence variables, sampling only non-evidence variables, and weighting each sample by the likelihood according to evidence.

**function** WeightedSample $(bn, e)$ **returns** an event and a weight
  x $\leftarrow$ an event with $n$ elements; $w \leftarrow 1$
  for $j = 1$ to $n$ do
    if $X_i$ has a value $x_i$ in e
    then $w \leftarrow w \times P(X_i = x_i | Parents(X_i))$
    else $x_i \leftarrow$ a random sample from $P(X_i = x_i | Parents(X_i))$
**return** $x, w$

**function** LikelihoodWeighting $(X, e, bn, N)$ **returns** an approximation to $P(X|e)$
  W[X] $\leftarrow$ a vector of counts over X, initially zero.
  for $j = 1$ to $N$ do
  $x, w \leftarrow WeightedSample(bn)$
    $\mathbf{W}[x] \leftarrow \mathbf{W}[x] + w$ where $x$ is the value of $X$ on $x$
**return** Normalize $W[X]$

## 2.2 The Independent Choice Logic.

The Independent Choice Logic is used for modeling multiple agents acting under conditions of uncertainty. **ICL** was proposed and developed by David Poole [7]. **ICL** is inspired by game theory, Bayesian networks, probabilistic Horn abduction, Markov decision processes, agent modeling and dynamical systems. In **ICL**, knowledge representation is provided by a symbolic modeling language which guides the user how to model the domain. In order to use an **ICL** framework for fault diagnosis, it is necessary to represent the power network with a logical model.

**System representation in the ICL framework.** To illustrate the process of representing the power transmission network in the **ICL** framework, consider the simplified power network shown in figure 2.

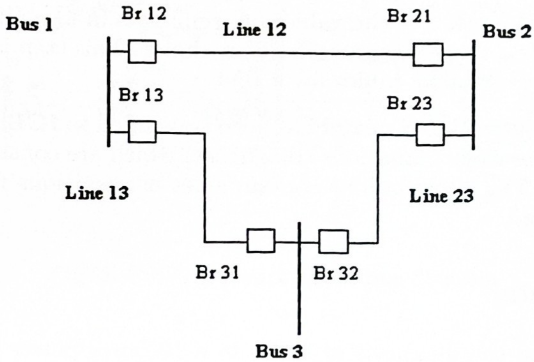


**Fig. 2.** Single line diagram of a small power network

The first step is constructing the BN to model the dependency between network elements. The random variables without parents are the nodes or buses, and for simplicity, they are assumed to be the only source of faults. The breakers have two parents (buses), because they are the main protection for one bus and the backup protection for another one - for instance breaker Br12, is the main protection for bus1 and the backup protection for bus2 (see figure 1). This scheme of backup protection allows the isolation of a bus fault, even in the event of a main breaker malfunction. From the BN, the following translation procedure is used to model the power network in the **ICL** framework. The procedure is similar to the one developed in [13].

1. The random variables with no parents are encoded as random choices. For instance, *Bus 1* is represented as:

   *random([bus1(ok):0.9,bus1(faulted):0.1])*

   The last representation states that Bus1 has a 0.9 probability to be in normal state and 0.1 probability to be in a faulted state. Prior probabilities may be estimated by a human expert or extracted from complete reliability methods.

2. For each random variable $Br_i(V)$ with $n$ parents, there is a rule of the form:

$$Br_i(V) \leftarrow bus_1(V_1) \wedge \cdots \wedge bus_n(V_n) \wedge c_{B}r_i(V, V_1, \ldots, V_n)$$

   The intended interpretation of $c_{B}r_i(V, V_1, \ldots, V_n)$ is that $Br_i$ has a value $V$ because $bus_1$ has value $V_1$, ..., and $bus_n$ has value $V_n$. For instance, the rule for Breaker *Br12* is:

$$Br12(StBr) \leftarrow bus1(StB1) \wedge bus2(StB2) \wedge c_{B}r_{12}(StBr, StB1, StB2)$$

3. For each combination of the values of arguments in $c_{B}r_i(V, V_1, \ldots, V_n)$ variables, there is an assertion as a random choice. This step is similar to filling conditional probability tables for a BN.

Once the power network BN model has been translated to **ICL**, a theorem prover is applied to generate explanations (diagnoses) which are consistent with the set of observations. The explanations contain a set of suspicious faulty elements in the power network.

## 3 Case Study

The case study is the diagnosis of faults in a 12-buses power transmission network. This is a portion of the network described in [3]. The single line diagram of the tested transmission network is shown in figure 3. The system consist of 12 buses, 16 lines and 32 breakers. The BN representation for the power network is shown on figure 4.

We implement two different methods for inference in **BNs**, to test the performance of each one. In the first implementation we use a probabilistic logic representation (**ICL**) with inference computed by a theorem prover and in the second we use an implementation of the BN on MatLab with inference computed by approximate methods. Single and multiple faults were considered with clean evidence (complete information given by the correct status of protection breakers) and noisy evidence (missed information of some breakers and fail-to-open status in main breakers). Every fault scenario was repeated 10 times for both implementations and average time was recorded.When using **ICL** representation, most likely explanation was used, and in all cases the correct diagnosis was found. In the other case, with approximate inference algorithms, time of diagnosis was recorded when correct diagnosis probability exceeded a 0.5 value threshold. To run the experiments we use a 800 MHz AMD Turion 64 computer with Windows XP operating system and 384 MB of RAM. The approximate inference algorithms were implemented in MatLab v7.2, and the **ICL** code was taken from [8].

The results of experiments show that approximate method by Likelihood Weighting sampling outperform in most cases the other two inference algorithms (see tables 2, 3, 4, and 5). In the other hand, Rejection Sampling performance

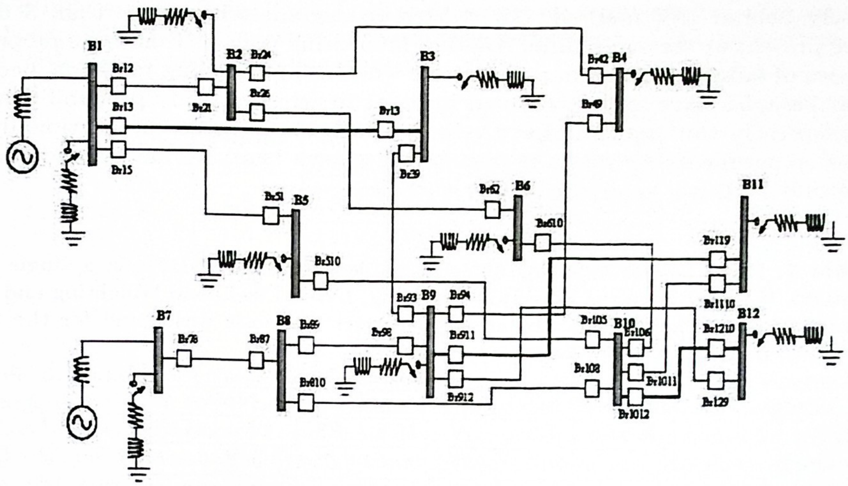


**Fig. 3.** Power Network single line diagram

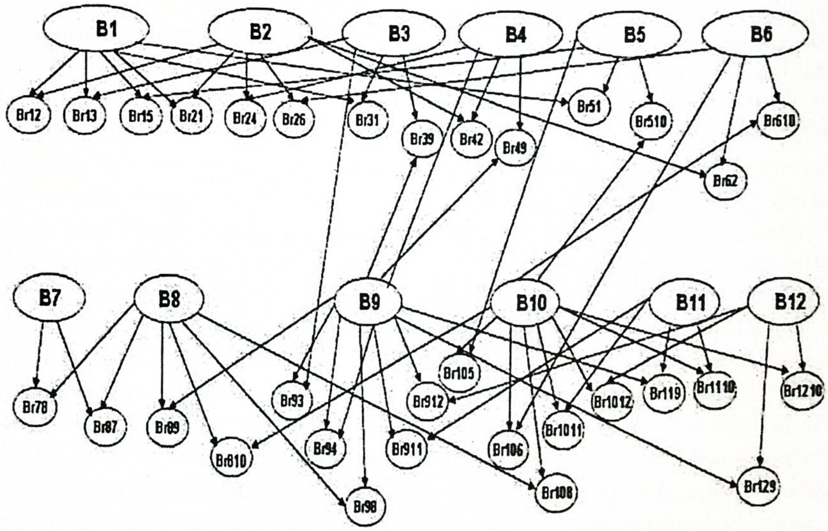


**Fig. 4.** BN model of the power network

seems competitive when using clean evidence, but is not adequate when noisy evidence is given, as it shows poor results. **ICL** approach performance followed closely behind **LW** method, but started to degrade when more than 3 faults were present at the same time. Another interesting point is that extreme probabilities of failure plays an important role when using sampling methods, because more samples have to be generated in order to achieve steady probabilities and consequently running time for a reliable diagnosis increases proportionally. In other experiments we perform (results not shown here) we have found that in this case **ICL** is a good alternative of choice.

**Table 2.** Runtime (seconds) for different implementations of BNs in a single fault scenario. Where **RS** means Rejection Sampling, **LW** is Likelihood Weighting and **ICL** is Independent Choice Logic. In all cases correct diagnosis was found for the three methods, and **LW** was the fastest approach

| Faulted | without Noise | | | with Noise | | |
|---|---|---|---|---|---|---|
| Node | RS | LW | ICL | RS | LW | ICL |
| 2 | 0.047 | 0.013 | 0.305 | 0.039 | 0.002 | 0.266 |
| 6 | 0.052 | 0.006 | 0.174 | 0.034 | 0.006 | 0.141 |
| 9 | 0.048 | 0.006 | 0.79 | 0.063 | 0.005 | 0.77 |
| 11 | 0.041 | 0.013 | 0.17 | 0.075 | 0.002 | 0.142 |

**Table 3.** Runtime (seconds) for different implementations of BNs in a scenario with two faults. Where **RS** means Rejection Sampling, **LW** is Likelihood Weighting and **ICL** is Independent Choice Logic. In all cases correct diagnosis was found for the three methods, and **LW** was the fastest approach

| Faulted | without Noise | | | with Noise | | |
|---|---|---|---|---|---|---|
| Nodes | RS | LW | ICL | RS | LW | ICL |
| 2,3 | 0.175 | 0.025 | 0.638 | 2.589 | 0.025 | 0.47 |
| 8,9 | 0.036 | 0.023 | 2.167 | 0.042 | 0.030 | 1.586 |
| 3,7 | 0.039 | 0.025 | 0.458 | 0.036 | 0.025 | 0.287 |
| 1,10 | 0.030 | 0.017 | 3.928 | 0.3.35 | 0.023 | 3.344 |

## 4 Related Work

The closest works to ours are stated in [11,12]. In [11] Bayesian networks with Noisy-or and Noisy-and are used to avoid the specification of big conditional

**Table 4.** Runtime (seconds) for different implementations of **BNs** in a scenario with three faults. Where **RS** means Rejection Sampling, **LW** is Likelihood Weighting and **ICL** is Independent Choice Logic. In all cases correct diagnosis was found for the three methods, and **LW** was the fastest approach. The performance of **RS** method was very poor with noisy evidence and was omitted

| Faulted | without Noise | | | with Noise | |
|---|---|---|---|---|---|
| Nodes | RS | LW | ICL | LW | ICL |
| **2,3,4** | *0.223* | *0.020* | *0.575* | *0.234* | *0.322* |
| **7,8,9** | *0.364* | *0.255* | *3.233* | *0.227* | *0.892* |
| **1,3,7** | *0.519* | *0.152* | *1.049* | *0.275* | *0.514* |
| **5,8,12** | *0.275* | *0.152* | *1.00* | *0.230* | *0.600* |

**Table 5.** Runtime (seconds) for different implementations of **BNs** in a scenario with three faults. Where **RS** means Rejection Sampling, **LW** is Likelihood Weighting and **ICL** is Independent Choice Logic. In all cases correct diagnosis was found for the three methods, and **LW** was the fastest approach. The performance of **RS** method was very poor with noisy evidence and was omitted

| Faulted | without Noise | | | with Noise | |
|---|---|---|---|---|---|
| Nodes | RS | LW | ICL | LW | ICL |
| **1,2,3,4** | *0.670* | *0.995* | *1.106* | *1.320* | *0.409* |
| **7,8,9,10** | *1.378* | *4.945* | *8.430* | *0.227* | *2.666* |
| **2,6,8,10** | *0.970* | *0.600* | *16.028* | *0.770* | *4.902* |
| **3,7,9,12** | *0.530* | *0.509* | *3.603* | *0.881* | *1.006* |

probability tables. In our case, conditional probability tables are bounded because we just consider two possible states in power network nodes (normal and faulted) and three states on breaker devices (normal, open and faulted). They implemented different models for elements of the power network, such as transformers, busbars and transmission lines, whereas we just consider a single model for the whole network. Another difference is that they apply an algorithm to verify and learn parameters (probabilities) in the models, while in this work this feature is not considered. In [12] a **BN** model similar to the one presented here is proposed but in this case the main difference is that they consider other possibilities, such as failures on the transmission lines. In this work a MonteCarlo approximate inference algorithm is used, although no specification of running times for the analyzed fault scenarios are given. The size of power network used in their experiments is similar to our network.

Although in both papers realistic cases were tested, no further analysis is made about the quality of evidence or the performance when multiple faults are present on the system.

## 5 Conclusions

A Power networks fault diagnosis approach, based on Bayesian networks has been presented. We have tested the method on a power network with realistic proportions. We have also implemented two different inference methods which offer different strengths and weaknesses under different circumstances. Rejection Sampling showed a good performance when clean evidence was present, whereas likelihood weighting was the best method with and without noisy evidence. In the other hand, **ICL** method based on a theorem prover seems to be more appropriate when extreme probabilities of failure are used and approximate methods increase in a significant way their running times.

## References

1. T. Bi, Y. Ni, and F. Wu: Distributed Fault Section Estimation System for Large-Scale Power Networks. Power Engineering Society Winter Meeting 2002. pp. 1350-1353, vol. 2.
2. L. Garza (2001) : Hybrid Systems Fault Diagnosis with a Probabilistic Logic Reasoning Framework. Instituto Tecnolgico y de Estudios Superiores de Monterrey. PhD thesis 2001.
3. Reliability Test System Task Force, Application of Probability Methods Subcomitee. IEEE Reliability Test System. IEEE Transactions on Power Apparatus and Systems, Vol. 98, No. 6, pp. 2047-2054, 1979.
4. Malheiro, N., Vale Z., Ramos C., Marques A., and Couto V.: On-line Fault Diagnosis with Incomplete Information in a Power Transmisin Network. Proceedings of the 13th International Conference on Intelligent Systems Application to Power Systems 2005. pp. 169-174.
5. McArthur S., and Davidson E.: Automated Post-fault Diagnosis of Power System Disturbances. In Proceedings of the IEEE Power Engineering Society Meeting 2006.
6. Microtran Power Systems Analysis Corporation. Microtran Reference Manual, Vancouver, BC Canada 1997.
7. Poole D.: The Independent Choice Logic for Modeling Multiple Agents under Uncertainty. Artificial Intelligence, Vol. 94, No. 1-2, special issue on economic principles of multi-agent systems, pp. 7-56, 1997.
8. Poole D.: Independent Choice Logic Interpreter version 0.2.1 PROLOG CODE. Technical Report, Dept. of Computer Science, University of British Columbia, 1998.
9. H. Ren, Z. Mi: Power System Fault Diagnosis Modeling Techniques based on Encoded Petri Nets. Power Engineering Society general Meeting 2006.
10. Xu L., and Chow M.: Power Distribution Systems Fault Case Identification using Logistic regression and Artificial Neural Network. Proceedings of the 13th International Conference on Intelligent Systems Application to Power Systems 2005. pp. 163-168.
11. Z. Yongli, H. Limin, and L. Jinling: Bayesian Networks-based Approach for Power systems Fault Diagnosis. IEEE Transactions on Power Delivery, Vol. 21, No. 2, April 2006.
12. W. Zhao, X. Bai, J. Ding, Z. Fang, Z. Li, and Z. Zhou: A New Uncertain Fault Diagnosis Approach of Power System Based on Markov Chain Monte Carlo Method. International Conference on Power System Technology 2006.