Original Article

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Component Fault Diagnosis Using Bayesian Network Model

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Abstract

The failure in power systems is often related to the problem of component fault diagnosis. Various methods and models have been proposed in the diagnosis before but most have -been either ineffective or impractical. This paper presents a proposal of a Bayesian network as a feasible statistical diagnosis model. The model incorporates the learning of network parameters by a proposed Particle Swarm Optimization Algorithm. As such, the model's framework comprises two constructs, that is, the Noisy-Or and Noisy-And structure. In the model, the 4-level Bayesian network predicts the fault in power systems using appropriately given parameters. The methodology used in this research is an empirical case study. The case study presents a characteristic problem of diagnosing component faults in a power system using the proposed method. The outcomes of the empirical case study prove the efficacy of the proposed model.

Key words: Bayesian networks, Power system, Parameters learning, Component fault diagnosis

INTRODUCTION

Fault diagnosis has grown to become a critical issue that attracts the public attention given the current continuous expansion of various power systems as well as the increase in the complexity of the corresponding network structures (Askarian, Zarghami, Jalali-Farahani, & Mostoufi, 2016). The diagnosis can help in the location of the faults or faulty conditions in a timely manner as to enable the restoration and adjustment of the system operating mode, thereby achieving the power system security as well as stable operation (Weber, Medina-Oliva, Simon, & Iung, 2012).

The whole process is aided by an alarm information emitted by an assortment of remote terminate units located at the dispatch center. The emergence of new energy power systems such as solar system and wind power system have attracted considerable problems in system security and stability, as compared to the conventional energy forms (Patton, Frank, & Clark, 2013). As such, fault diagnosis has grown in significance to a higher degree than before to offer a dependable and long lasting solution to such problems (Cai et al., 2014). The paper presents a literature review of various scholarly sources that have shed considerable light on the issue of fault diagnosis and the efforts that have so far been made to rectify frequent faults in power systems.

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Literature Review

In the content of current literature, the structure of diagnosing faults in power system has been predominantly based on methods of artificial intelligence such as rough set methods, Bayesian networks, neural networks, and expert systems (Seshadrinath, Singh, & Panigrahi, 2014). The rough set theory solves alarms processing and the problem of fault power systems (Korbicz et al., 2012).

Similarly, wavelet entropy and neural networks also solve problems of power system fault diagnosis. In both cases, the real-time and accurate measurement of disturbances in power systems is a critical step towards controlling, controlling, fault diagnosis, power metering, and power quality monitoring, particularly in electric power systems (Dejaeger, Verbraken, & Baesens, 2013).

The use of artificial neural networks has also been seen in fault diagnosis of power transmission lines (Tobon-Mejia, Medjaher, & Zerhouni, 2012). Similarly, the estimation of fault section in power systems has been achieved through

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a genetic algorithm. On the other hand, the expert system has been mainly applied to the control of power system equipment and on-line as well as off-line fault diagnosis of power systems (Zheng et al., 2013). One of the most popular expert systems is Multi-BP expert system.

Empirical studies have shown the use of Bayesian network in fault diagnosis for power systems (Zhang, Wang, & Wang, 2013). This paper draws its basis from former studies that have shown the effectiveness of Bayesian network with Noisy-Or and Noisy-And node as the constituent model frameworks. In this case, the learning of the network parameters is achieved through a particle swarm optimization (PSO) algorithm that is specifically designed (Gao, Cecati, & Ding, 2015).

The subsequent segments incorporate four sections. The first section introduces Bayesian network model while the second section highlights the particle swarm optimization. The third section highlights the proposed method, which is an empirical case study to validate the proposed methods. The final section is the analysis of the results and a conclusion that recaps the main points in the paper and issues further recommendations.

Bayesian Network Model

According to the Bayesian network model, the conditional probability table associated with each node is learned from a specific network structure that characteristically incorporates independent assumptions (Zhao, Xiao, & Wang, 2013). Noisy-Or and Noisy-And models have been mostly used by researchers to deal with this matter.

Noisy-Or model. In the Bayesian network, the Noisy-Or node is almost synonymous to the logic "or" although disparities exist between the two concepts (Muruganatham et al., 2013). The probability of Nj, according to the independence hypothesis, to be affirmative is a monotonic function of n (Schumann et al., 2013). The formula for of Nj is as shown below taking cij=1–qij as the degree of conditional probability from Ni to Nj.

$$P(N_j = x) = \begin{cases} \prod_i (1 - c_{ij} P(N_i = \text{True})) & x = \text{False} \\ 1 - \prod_i (1 - c_{ij} P(N_i = \text{True})) & x = \text{True} \end{cases}$$

A typical graphical representation of the Noisy-Or model is as shown in the Figure 1 below.

Noisy-And model. In the Bayesian network, the node Noisy-And is synonymous to the logic "and." (Medjaher, Tobon-Mejia, & Zerhouni, 2012) The model works in a similar way as the Noisy-Or model described above (Yu & Rashid, 2013). The formula for calculation of Nj for this model is as shown below.

$$P(N_j = x) = \begin{cases} 1 - \prod_i (1 - c_{ij} (1 - P(N_i = \text{True}))) & x = \text{False} \\ \prod_i (1 - c_{ij} (1 - P(N_i = \text{True}))) & x = \text{True} \end{cases}$$

A graphical representation of the model (Figure 2) is shown below.

Particle swarm optimization (PSO). For the last two decades, PSO has been widely used as an evolutionary optimizer to solve optimization problems in practical engineering (Ye et al., 2013). Some of the merits that underline its widespread use include fast convergence, high searching accuracy, and its easy usability. Two steps make up the searching loop in PSO (Nelles, 2013). They are the updating of location as well as the velocity of particles continuously to the point that satisfies the ultimate convergence condition (Lee et al., 2014). The formula for updating the location is:

$$x_{iu}^{k+1} = x_{iu}^{k} + \gamma v_{iu}^{k+1}$$

On the other hand, the updating of the particle velocity is achieved using the formula shown below:

$$v_{iu}^{k+1} = w v_{iu}^{k} + c_1 \xi (p_{iu}^{k} - x_{iu}^{k}) + c_2 \eta (p_{gu}^{k} - x_{iu}^{k})$$

In both formulas, w = coefficient vector that keeps the original velocity as the inertia,
c1 = the weight coefficient for which the particles track the best value for their individual search history.
c2 = is the weight coefficient for which the particles track the global best attached to the entire population.
ξ, η = random noise factors created within the intervals [0,1].
γ = constraint factor.

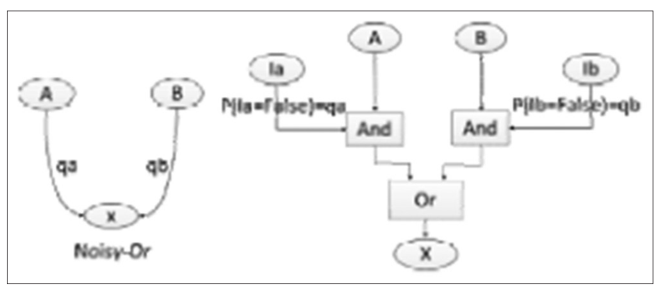

Figure 1: Noisy-Or Graph

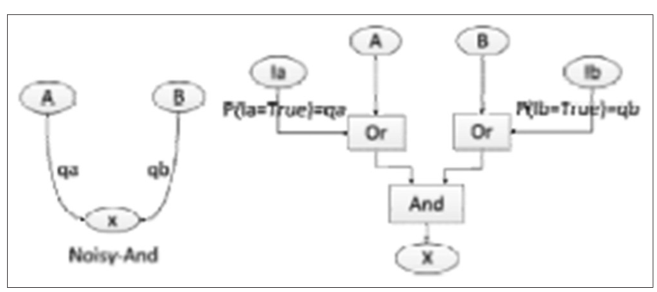

Figure 2: Noisy-And Graph

MATERIAL AND METHODS

Case Study

For purposes of validating the effectiveness of the proposed technique, a numerical example is utilized as the empirical case study in the case of the paper.

Problem Description

The paper uses an empirical study presented by Shi et al. (2013) in their research. The paper applies PSO in learning the parameters and integrates a three-stage (I, II and III) protection of transmission lines used in power systems. Figure 3 below portrays the tie lines that Shi et al. (2013) used in the experiment.

Various symbols used in the figure represent specific aspects of the three stage.
m = main protection (I segment)
p = first backup protection (n segments)
s = second backup protection (III segment)
S = protection of export, left of the line
R = protection of export, right of the line.

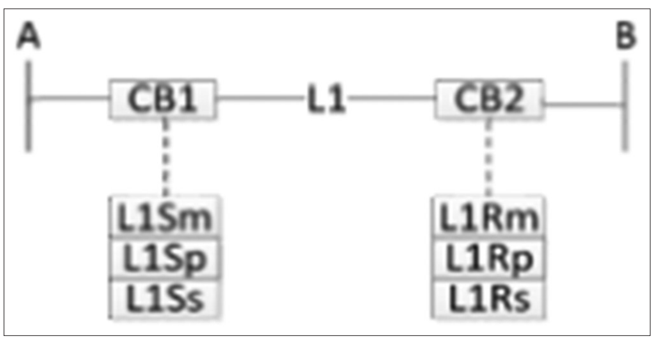

Figure 3: Wiring diagram of power lines

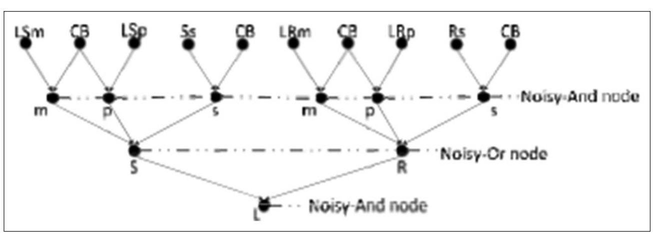

Figure 4: Bayesian Network Topology

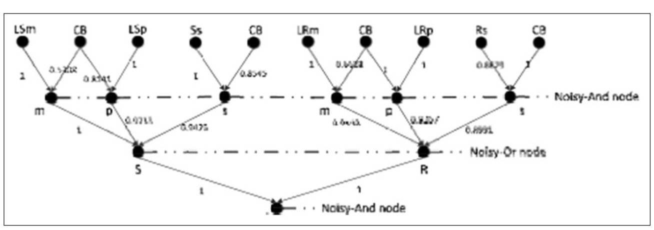

Figure 5: Bayesian network topology after PSO optimization

The corresponding Bayesian network topology for the case study is shown in Figure 4 while the learning samples of network parameters are outlined in Table 1 below.

The experimental procedure was conducted using a PC with specifications that include a 2GB RAM, and a processor of Intel Core i3 M-370.

RESULT AND DISCUSSION

The outcomes of the parameters of the Bayesian network after optimization with PSO is shown in Figure 5. The outcomes of the line fault diagnosis after optimization are shown in Table 3 below and compared with the results in Table 2. PSO shows a closer output to the desired outcome, which validates the effectiveness of the technique.

CONCLUSION

The paper proposed a Bayesian network that uses PSO based parameters learning algorithm to perform fault diagnosis in power systems. The paper highlighted the framework of the model and the algorithm process to be used in the empirical case study, which is the methodology

Table 1. Parameters setting

LSm	CB	LSp	Ss	CB	LRm	CB	LRp	Rs	CB	Desired output
1	1	0	0	0	1	1	0	0	0	0.95
1	1	0	0	0	0	1	1	0	0	0.93
1	1	0	0	0	0	0	0	1	1	0.90
0	1	1	0	0	1	1	0	0	0	0.93
0	1	1	0	0	0	1	1	0	0	0.90
0	1	1	0	0	0	0	0	1	1	0.87
0	0	0	1	1	1	1	0	0	0	0.90
0	0	0	1	1	0	1	1	0	0	0.87
0	0	0	1	1	0	0	0	1	1	0.85
0	0	0	0	0	0	0	0	0	0	0
1	1	1	1	1	0	0	0	0	0	0
0	0	0	0	0	1	1	1	1	1	0

Table 2: Expected outcomes of line fault diagnosis mode

Parameters	Population size	Maximum generation	Dimension	c_1	c_2	w	v_{max}	*gamma*
Set value	100	500	20	2	2.1	0.5	0.1	1

Table 3: Outcomes of line fault diagnosis mode after optimization

Theoretical output	0.95	0.93	0.90	0.93	0.90	0.87	0.90	0.87	0.85	0	0	0
AFA output [11]	0.9538	0.9256	0.8986	0.9255	0.8982	0.8721	0.8987	0.8721	0.8467	0.0002	0.0157	0.0158
PSO output	0.9540	0.9267	0.8991	0.9267	0.9001	0.8734	0.8991	0.8734	0.8474	0	0	0

used to validate the effectiveness of the Bayesian network and the proposed algorithm. The simulation results after optimization using PSO tallied with the desired outcome, which proves the effectiveness of the model.

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