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Study on Bayesian Network Parameters Learning of Power System Component Fault Diagnosis Based on Particle Swarm Optimization

Qingxi Shi[a], Sujie Liang[a], Wei Fei[a], Yongfeng Shi[b], Ruifeng Shi[b]*

[a] *Linyi Power Supply Company, Shandong Electric Power Corporation, No. 130, Jinque RD, Linyi 276000, China*
[b] *School of Control and Computer Engineering, North China Electric Power University, Beijing 102206, China*

Abstract

Power system component fault diagnosis problem is a key issue in case of the failure of the power system. A Bayesian network, in which the network parameters are learnt by a particle swarm optimization algorithm, is proposed in this paper to establish the statistical diagnosis model. The Noisy-Or and Noisy-And structure are employed to construct the framework of the model, where the 4-level Bayesian network makes the fault prediction with properly given parameters. In order to verify the performance of our proposed method, a typical power system component fault diagnosis problem is used for empirical case study, and the result demonstrates the effectiveness of the proposed method.

Keywords: *Power system; component fault diagnosis; Bayesian networks; parameters learning; particle swarm optimization*

1. Introduction

With the continuous expansion of the power system and the increasing complexity of its network structure, fault diagnosis has increasingly become one of the key issues of wide public concern. Power system fault diagnosis can find fault for the fault condition as soon as possible, restore and adjust the system operating mode, achieve the power system security and stable operation, with the aid of the alarm information sent by a variety of remote terminate units in the dispatch centre. Nowadays, new energy power systems, like wind power system and solar system, have bring more system stability and security problems than traditional ones, which makes fault diagnosis more important than it is before.

In current literature, the framework of a power system fault diagnosis system is mainly based on artificial intelligence classification techniques, including expert systems, neural networks, Bayesian networks, rough set methods, etc. Expert system is widely used in on-line and off-line fault diagnosis and control (FDC) of power system equipment [1]. Multi-BP expert system is one of the most popular expert systems used in fault diagnosis [2]. Literature [3] used neural networks and wavelet entropy to solve the power system fault diagnosis problem. The accurate and real time measurement of power disturbance is a key element of protection, control, fault diagnosis, power quality monitoring and power metering in electric power systems [4]. Artificial neural network is used in Fault diagnosis system for tapped power transmission lines [5]. Literature [6] employed a genetic algorithm on fault section estimation in power system. Literature [7] solved the power system fault diagnosis and alarm processing using the rough set theory. Literature [8] took a Bayesian network to solve the power system fault diagnosis.

Based on the former studies, a combination Bayesian network based on Noisy-Or and Noisy-And node, is established in this paper, where network parameters are learnt with a specifically designed particle swarm optimization (PSO) algorithm.

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* Manuscript received July 20, 2012; revised August 24, 2012.
Corresponding author. Tel.: +86-10-61772820; *E-mail address*: shi.ruifeng@126.com.

In the following of this paper, Section 2 gives the parameters learning issue in the Bayesian network model of power system fault diagnosis; Section 3 gives the method of the parameters learning with a particle swarm optimization; Section 4 analyze and verify the validity of the proposed method through a empirical case study; and finally, Section 5 draw a conclusion of this study.

2. Parameters Learning of Bayesian Network Model

Bayesian network parameters learning is a process where the conditional probability table for each node is learnt from a given network structure with independence assumptions. Researchers often use some simplified models to deal with this issue, like the Noisy-Or and Noisy-And models mentioned in reference [11].

2.1. Noisy-Or and Noisy-And models

A. Noisy-Or model

A Noisy-Or node in the Bayesian network is quite similar to a logic "or", but there are still differences between these two concepts. If N_i is the unique prerequisite for N_j to be true, then the probability of N_j to be true is $1–q_{ij}$. Based on the independence hypothesis, the probability of N_j to be true is monotonic function of the number n in the prerequisites which are true. The parameter $c_{ij}=1–q_{ij}$ is the degree of conditional probability from note N_i to note N_j. In the network that all the evidence nodes are the ancestors of the node N_j and the network is modelled as a pseudo Poly-tree, the conditional probability c_{ij} of each edge and the probability of a node N_j's parent node N_i to the true, we can calculate the state of N_j by

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

where N_j represents the *j-th* network Noisy-Or node; N_i is the *i-th* direct prerequisite for N_j, which is also known as the parent node; c_{ij} is the conditional probability from node N_i to node N_j. A typical Noisy-Or model can be illustrated as Fig. 1.

B. Noisy-And model

Noisy-And node is similar to logic "and" too, and the model works like that of Noisy-Or model. A typical Noisy-And model is shown in Fig. 2, where all the evidence nodes are the ancestors of the node N_j, and the conditional probability c_{ij} of each edge and the probability of a node N_j's parent node N_i to the true, we can calculate the states of N_j with formula (2).

$$P(N_j = x) = \begin{cases} 1 - \prod_i (1 - c_{ij} (1 - P(N_i = \text{True}))) & x = \text{False} \\ \prod_i (1 - c_{ij} (1 - P(N_i = \text{True}))) & x = \text{True} \end{cases} \tag{2}$$

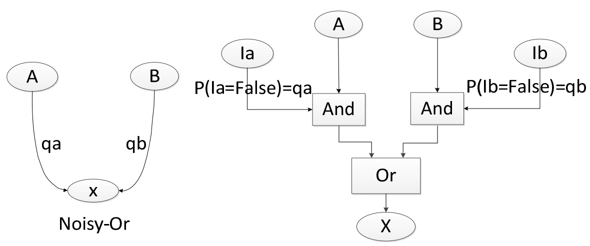

Fig. 1. Node graph of Noisy-Or

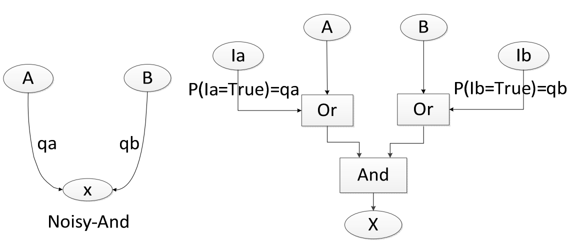

Fig. 2. Node graph of Noisy-And

2.2. Parameters learning in a power system component fault diagnosis Bayesian network

In general, the parameters number in a Bayesian network model is proportional to the number of directed edges in the network due to the independence assumption. Sowmya used a neural network to learn the Bayesian network parameters based on the Noisy-Or and Noisy-And [9], in which the main algorithm include the following steps:

Step 1: Initialization: randomly or using prior knowledge to initialize the parameters of the Bayesian network;

Step 2: The parameters adjustment process: for each sample data, proceed as follows:

1) Employing Bayesian network inference to obtain the calculated values of the target variables;

2) Obtaining the mean square deviation of the target variables with

$$E = \frac{1}{2}\sum_{iu}(\zeta(N_i = \text{True}) - P(N_i = \text{True}))^2 \tag{3}$$

where $\zeta(N_i = \text{True})$ represents the belief that the *i-th* target variable N_i takes the true desired value in the sample. $P(N_i\text{=True})$ is the node that takes the true value of the calculated one in the training sample set, and *u* is the *u-th* training sample in the training sample set.

Step 3: Repeat step 2 until the stop criterion is satisfied.

3. Bayesian Network Parameters Learning Based on Particle Swarm Optimization

3.1. Particle swarm optimization

PSO is a popular evolutionary optimizer during the past two decades, which is widely used in practical engineering optimization problems because of its easy to employ, high searching accuracy, fast convergence and other merits.

The main searching loop in PSO includes two steps: to update the velocity and the location of the particles continuously until the final convergence condition is satisfied.

The process of updating the velocity of one particle can be described as

$$v_{iu}^{k+1} = wv_{iu}^{k} + c_1\xi(p_{iu}^{k} - x_{iu}^{k}) + c_2\eta(p_{gu}^{k} - x_{iu}^{k}) \tag{4}$$

The process of updating the location of one particle is

$$x_{iu}^{k+1} = x_{iu}^{k} + \gamma v_{iu}^{k+1} \tag{5}$$

where w is the coefficient vector to keep the original speed as the inertia weight, c_1 is the weight coefficient that the particles track the best value of their own searching history, c_2 is the weight coefficient that the particles track the global best value of the whole population, ξ, η are two random noise factors uniformly generated within the interval [0,1], and γ is the constraint factor.

3.2. Parameters learning with PSO

The algorithm for parameters learning of Bayesian network with PSO can be described as follows.

1) Initialization of particle population. Set the population size, randomly generate the initial position and velocity for each particle.

2) Calculate the fitness of each particle. First, calculate the error $\zeta(N_i = \text{True}) - P(N_i = \text{True})$, with given $\zeta(N_i = \text{True})$ from the samples set; second, obtain the training result $P(N_i = \text{True})$ and the error $\zeta(N_i = \text{True}) - P(N_i = \text{True})$; finally, calculate the fitness of the particle according to the formula (2)-(3).

3) Elitism. Renew the individual optimal values and the global optimal value according to the fitness.

4) Update velocity and position. Update the velocity of each particle with formula (4), then update the position of each particle with formula (5).

5) If the stop criterion is not satisfied, turn to step 2) to continue the searching process, otherwise, give the global optimal solution as the final result and end the searching process.

The flow chart of a PSO based Bayesian network parameters learning process is given in Fig. 3.

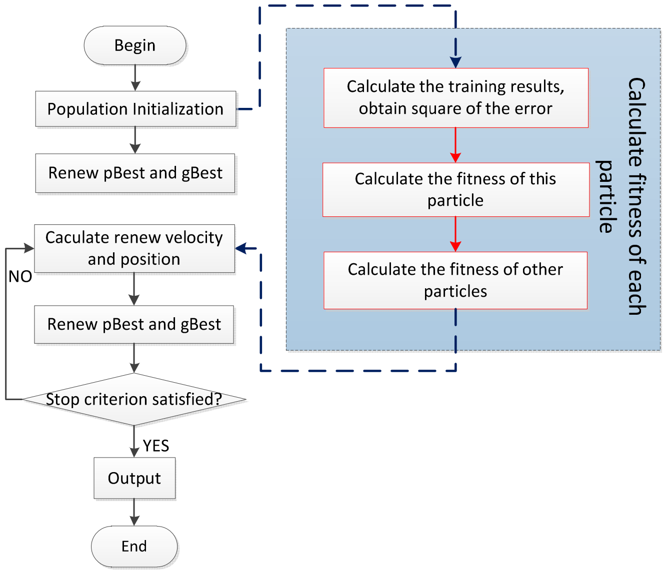

Fig. 3. Flow chart of Bayesian network parameters learning based on PSO

4. Case Study

In order to verify the effectiveness of the method proposed in this paper, a numerical example is taken for empirical case study.

4.1. Problem description

The example is originally introduced in reference [11], where an artificial fish-swarm algorithm was employed to solve the parameters learning in a Bayesian network diagnosis system. We use PSO to learn the parameters in this paper, where a three-stage (I, II, III of paragraph) protection of a power system transmission lines is taken into consideration [10]. Figure 4 shows tie lines of the example.

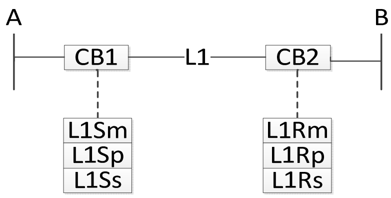

Fig. 4. Network system wiring diagram of power lines

The symbols in the figure, m represents the main protection (I segment); p represents the first backup protection (n segments); s represents the second backup protection (III segment); S represents the protection of export at the left of the line; R represents the protection of export at the right of the line.

The Bayesian network topology corresponds to the test example is shown as Fig. 5, and the learning samples set of network parameters are given as Table 1.

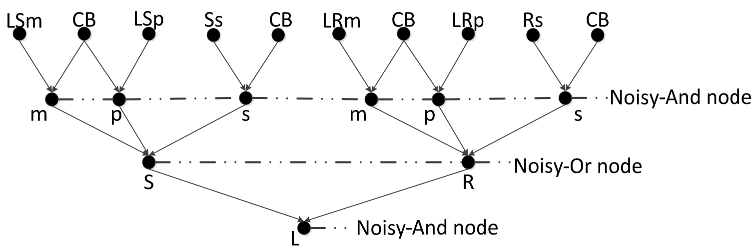

Fig. 5. Line fault diagnosis network topology based on Bayesian

Table 1 The training samples and the desired results of line fault diagnosis model

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

4.2. Simulation and parameters setting

Experimental Scenario: a PC with CPU of Intel Core i3 M-370 and 2GB memory.
The parameters of the PSO are set as following after experimental tests (Table 2):

Table 2 The training samples and the desired results of line fault diagnosis model

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

4.3. Analysis of results

After optimization with PSO, we get the result of the parameters for the Bayesian network as shown in Fig. 6. Comparison results of the PSO in this paper with that of AFA in reference [9] are shown in Table 2, where PSO outperforms AFA with a closer output to the desired one.

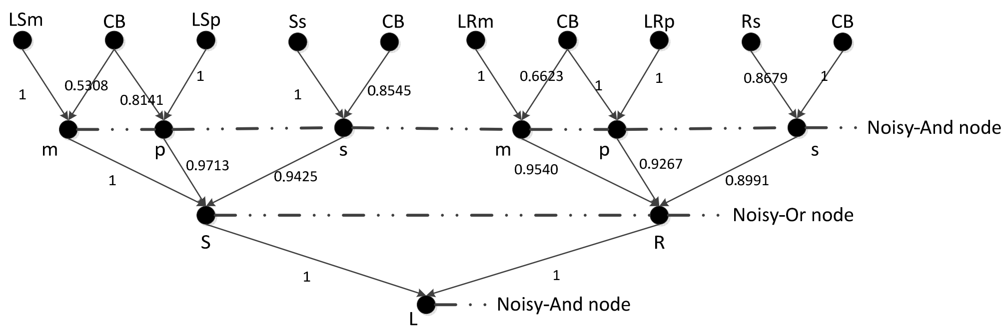

Fig. 5. Final results: the optimal Bayesian weights combination obtained with PSO

Table 2 Comparison of training results

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

5. Conclusion

A PSO based parameters learning algorithm for the Bayesian network of power system fault diagnosis model is proposed in this paper. The framework of the network and the algorithm process are introduced. An empirical numerical case study is employed to verify the effectiveness of the proposed algorithm, and simulation results revealed that our proposed PSO based algorithm outperforms the AFA algorithm in dealing with this issue.

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