Research of Bayesian Networks Application to Transformer Fault Diagnosis

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Abstract. The power transformer as the key equipment in electrical power systems, its operation reliability directly influences security of electrical power systems. Three-ratio method based on the Dissolved Gases Analysis is most widely used for transformer fault diagnosis currently. Considering the incomplete encoding and the over absolute faults classification zone of three-ratio method, this paper proposes no-code ratio method and Bayesian Network to diagnose the faults of transformer. The Bayesian Network diagnostic model is built by Bayesian Network Tool in MATLAB, and the simulation result shows the validity of this method.

Keywords: power transformer, fault diagnosis, Bayesian Network, no-code ratio.

1 Introduction

With complicated structure, high cost and wide distribution, power transformer is one of the key electrical equipments in power systems. The transformer works to convert voltage and transmit power, so its safe operation directly influences the stability and security of the entire power system. The faults diagnosis of transformer is very difficult due to its complicated structure and uncertain factors of faults, and three-ratio method (IEC standard) based on Dissolved Gases Analysis (DGA) is most convenient and effective method for transformer faults diagnosis currently in China [1]. However, this method has some drawbacks found in practical application, such as incomplete encoding, too absolute coding border, and so on. In order to overcome these drawbacks, some intelligent methods like artificial neural networks [2], wavelet analysis [3], gray clustering [4], Petri networks [5], are introduced into the transformer fault diagnosis and achieve better results.

The analysis of faults generation mechanism shows there is no definite function relationship between transformer faults and gas content in oil and it is difficult to speculate the distribution of gas content. In addition, the accuracy and quantity of data acquisition in field is very limit, thus prior knowledge is needed. Bayesian Network

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(BN) may be used to model a system that works with uncertainty, which can be caused by an imperfect or incomplete understanding of the problem [1], with its recent development of Bayesian Network inference theorem, many people are trying to apply it into practice. This paper proposes no-code ratio method and Bayesian Network to diagnose the faults of transformer, and builds Bayesian Network diagnostic model by Bayesian Network Tool (BNT) in MATLAB.

2 Bayesian Network

Bayesian Network is valid knowledge representation and probabilistic reasoning model for uncertain knowledge and which is a popular graphical tools for decision analysis [6].

The Bayesian Network of a variable set $X=\{x1, x2, \cdots, xn\}$ consists of two parts.

- Network structure *S*, representing the conditional dependence of variables in *X*.
- Local probability distribution *P*: Associated with each variable.

The combination of these two parts defines the joint probability distribution of *X*. Represented in a graphical form, as shown in Fig. 1, Bayesian Network is a directed acyclic graph, where each node corresponding with each variable in *X*, no arc connected between two nodes shows they are conditional independence. For any given network structure *S*, the joint probability distribution of *X* is represented in Eq.1.

$$p(x) = \prod_{i=1}^{n} p(x_i|Pa_i) \tag{1}$$

Where Pa_i is the father nodes set of x_i, the item *p* in the product, is the local probability, this can bring about the following benefits.

- The capacity of the joint distribution table can be exponentially decreased by the local probability distribution, because the interaction relationship between the variables is sparse in a multivariate Bayesian Network.
- There are many Bayesian inference algorithms for local distribution table.
- It helps to build knowledge engineering model by separating quantitative representation and qualitative representation of Bayesian Network.

Different from the general knowledge-based system, Bayesian Network deals with uncertain knowledge with powerful mathematical tool and interprets it in a simple and intuitive way. In addition, Bayesian Network combines graphical representation method and numerical representation method, which is different from the general probability analysis tools too.

Since Bayesian Network *BN=<S,P>* is composed by two parts, the network topology *S* and the set of local probability distribution *P*, so the learning of Bayesian Networks can be divided into two steps.

- Structural learning, that is directed acyclic graph learning.
- Parameter learning, that is the learning of local conditional probability distribution of each variable in the network.

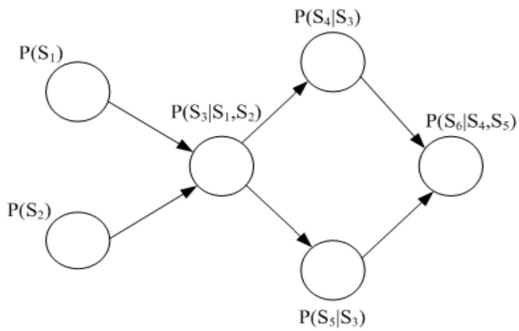

Fig. 1. Bayesian Network

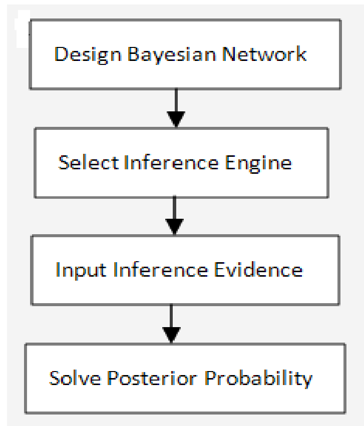

Fig. 2. Inference procedures

3 Introduction of Bayesian Network Toolbox

BNT is software package for Bayesian Network learning based on MATLAB, and developed by Kevin P. Murphy, which provides many underlying basic functions library for Bayesian learning, and supports multiple types of nodes (probability distribution), exact inference & approximate inference, parameter learning & structural learning, static model & dynamic model. BNT software package is free, source code open and easy to be expanded.

BNT offers the following two parameter learning methods.

- For complete data, there are Maximum likelihood estimation (*learn params()*) and Bayesian Network method (*bayes update params ()*).
- For incomplete data, if network topology is known, Expectation Maximization (EM) is used to calculate parameters, if network topology is unknown, SEM (Structural EM) (*learn struct EM()*) can be used.

In order to improve calculating speed and effective application of various inference algorithm, BNT adopts engine mechanism, and different engine completes the transformation, refinement and solving of model by different algorithms. Fig. 2 shows the inference procedures.

4 Transformer Fault Diagnosis Based on No-code Ratio Method and Bayesian Network

4.1 Determination of Attribute Variables, Fault Types, and the Training Sample Set

In order to construct a faults diagnosis Bayesian Network with correct and expansible decision-making, we must firstly collect enough samples for learning. The faults of transformer are diverse; the symptoms of one fault for transformers of different models and different voltage levels are different. When the transformer fault happens, it is usually caused by excessive level of a certain gas or several certain gases, and when it is caused by excessive level of several certain gases, maybe only one or a few are dominant for the fault. Through transformer fault occurrences collecting in Chinese cities more than ten years and analysis of simulated faults chromatographic data from other nations, Chinese power workers no-code ratio method to analyze and diagnose transformer faults. The ratios for this method are CH4/H2, C2H2/C2H4, C2H4/C2H6, C2H2/total(%) , H2/total(%) , C2H4/total(%), CH4/total(%), C2H6/total(%) , (CH4+C2H4)/total(%), where total means total hydrocarbon. This method determines one fault directly by the ratio itself, no ratio coding. Comparing with the traditional three-ratio method, no-code ratio method saves the procedures of coding first and then querying the faults type by code, thus simplifies the analytical decision methods and improves the operability. However, no-code ratio method is not suitable for excessive level of pure hydrogen, H2, C2H2, and total hydrocarbons (total) as three characteristic gases are added to the attribute set to overcome the drawback. Thus the faults due to excessive level of some single gas and due to excessive rate of some gas in the total hydrocarbons or in the total gas are both considered. Table 1 shows the selection of the attribute set, and Table 2 shows the fault types according to IEC standards and DL/T 722-2000 guidelines.

Table 1. Attribute set

No.	*Attribute*	*No.*	*Attribute*
M1	H_2	M7	C_2H_2/total（%）
M2	C_2H_2	M8	H_2/total（%）
M3	total	M9	C_2H_4/total（%）
M4	CH_4/H_2	M10	CH_4/total（%）
M5	C_2H_2/C_2H_4	M11	C_2H_6/total（%）
M6	C_2H_4/C_2H_6	M12	（$CH_4+C_2H_4$）/total（%）

The number of samples employed in this paper are 302, 176 of which are training samples and 126 are testing samples, as shown in Table 4.

Table 2. Fault types

Fault types	*Fault description*	*Fault types*	*Fault description*
C	Normal	*PD*	Partial discharge(PD)
T1	Low temperature and overheat(LO)	*D1*	Low energy discharge(LD)
T2	Medium temperature and overheat(MO)	D2	High energy discharge(HD)
T3	High temperature and overheat(HO)		

Table 3. Discretization of fault types

Attribute No.	*Code Rules*			
	0	1	2	3
M1	[0,1]	[10,130]	[130,180]	[180,∞]
M2	0	[0,1]	[1,5]	[5,∞]
M3	[0,20]	[20,140]	[140,200]	[200,∞]
M4	[0,0.1]	[0.1,1]	[1,∞]	–
M5	[0,0.1]	[0.1,3]	[3,∞]	–
M6	[0,1]	[1,3]	[3,∞]	–
M7~M12	[0,15]	[15,50]	[50,80]	[80,∞]

Table 4. Samples allocation

Samples type	*Normal C*	*LO T1*	*MO T2*	*HO T3*	*PD PD*	*LD D1*	*HD D2*	*TOTAL*
Training samples	25	18	27	28	25	25	28	176
Testing samples	19	13	17	20	18	19	20	126
total	44	31	44	48	43	44	48	302

4.2 Bayesian Network Modeling for Transformer Fault Diagnosis by BNT

The Bayesian Network is firstly determined and defined it in MATLAB according to Fig. 2. Secondly, parameter learning is executed and the conditional probability (CPT) of each variable in the Bayesian Network is calculated. Finally, the testing samples are input and inferred. The attribute values in Table 1 are discretized by Table 3 as input of the Bayesian Network. The network output is fault type, which is $[1\ 0\ 0\ 0\ 0\ 0\ 0\ ]^T$ when the transformer state is normal. If there is some certain fault happened, the output of *C* is 0, and the output of that certain fault is 1, other outputs of faults are all 0. For example, if the *T1* fault happens, the output of the Bayesian Network is $[0\ 1\ 0\ 0\ 0\ 0\ 0\ ]^T$.

4.3 Fault Testing and Analysis of Application Example

Four groups of transformer DGA faults diagnosis data recognized by maintenance are selected for testing, as shown in Table 5. And these four groups of data are not included in the training samples of Bayesian Network model. The diagnostic results of Bayesian Network in Table 6 shows the diagnostic results completely match the practical fault types, and the transformer faults diagnosis system designed in this paper is valid and effective.

In order to verify the validity of the method presented in this paper, 126 samples are analyzed, and the results are compared with those of three-ratio method, as shown in Table 7.

Table 5. Example faults

μL/L

No.	*equipment*	*H_2*	*CH_4*	*C_2H_6*	*C_2H_4*	*C_2H_2*	*Diagnosis result*	*Check result*
1	220kv main transformer	980	570	37	480	54	Arc discharge	Inter-turn short-circuited and burn
2	110kv main transformer	73	520	140	1230	7	High temperature and overheat	Core pallets and core short-circuited and melting point
3	110kv main transformer	259	863	393	994	6	Medium temperature and overheat	Low-pressure casing, conducting rod and screw nut overheat, and obvious overheat signs
4	110kv main transformer	80	20	6	20	62	Spark discharge	Bare conductive wires discharge to casing conducting pipe

Table 6. Output of Bayesian Network faults diagnosis model

No.	*Output*	*Faults*
1	0 0 0 0 0 0 1	Arc discharge D2
2	0 0 0 1 0 0 0	HO T3
3	0 0 1 0 0 0 0	MO T2
4	0 0 0 1 0 0 0	Spark discharge D1

Table 7. Comparison of two methods

	Three-ratio method	*No-code ratio and Bayesian Network model*
Testing samples	126	126
Correct diagnosis	96	117
Wrong diagnosis	19	7
Unable to diagnose	11	2
Correct rate（%）	76.2%	92.8%

The comparison results in Table 7 illustrates that the combination of no-code ratio and Bayesian Network can be used for transformer faults diagnosis, and which has higher correct diagnosis rate than the popular used three-ratio method.

5 Conclusions

This paper combines no-code ratio method and Bayesian Network to build Bayesian Network faults diagnosis model by BNT in MATLAB, which no only overcomes drawbacks of three-ratio method such as implement code, over absolute coding border, but also well utilize the causal reasoning of Bayesian Network to achieve probabilistic reasoning, thus the transformer faults can be quickly determined. Examples illustrates this combined method is valid and feasible, and can be used for uncertainty reasoning. The diagnostic results show the effectiveness of the method.

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