

Research on Transformer Fault Diagnosis based on Multi-source Information Fusion

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Abstract

DGA (Dissolved Gas Analysis) is the traditional transformer fault diagnosis method, but it mainly depends on the experience of operators. In order to solve the limitations of traditional method, this paper introduces intelligent method for fault diagnosis of transformer. The intelligent method made fusion of various data, including SCADA data, oil dissolved gas sensor data, related electrical test data, operation maintenance records, and so on, employed space-time weighting fusion method based on BP neural network, and put forward the model of transformer fault diagnosis based on multi-source information fusion, which improved the accuracy of the transformer fault diagnosis dramatically.

Keywords: *multi-source information fusion, transformer fault diagnosis, BP neural network, Space-time weighted fusion*

1. Introduction

In general, process of transformer fault diagnosis is divided into two steps: examining whether the failure existing and determining the fault type. There are some traditional methods of transformer fault diagnosis, such as preventive electrical test, impact voltage waveform test [1], neutral current method [2], oil dissolved gas analysis (DGA) [3], transfer function method. These methods have the characteristics of intuitive and convenient, but they have limitations in some respects, the diagnosis accuracy rate is low, and they can't make detection and analysis of transformer latent fault timely and accurately.

In order to solve the limitations of traditional diagnostic methods, scholars have launched a lot of research on intelligent methods. The result shows that intelligent diagnosis methods have a remarkable effect and a high accuracy rate. Intelligent fault diagnosis [4] uses flexible strategies to make the right judgments and decision for running state and fault of transformer by obtaining diagnostic information to simulate human experts, which takes the information processing and cognitive process of the human mind as the theoretical basis. At present, transformer intelligent diagnosis methods mainly include neural network, expert system and genetic algorithm, rough set, fuzzy rules, probability reasoning, data mining, statistical theory and support vector machine (SVM) [5-7], and so on.

Both traditional methods and intelligent methods, fault diagnosis processes are all characteristics of data collection, analysis and processing. Due to the complexity of transformer internal structure and the external environment, transformer fault diagnosis needs to rely on multiple characteristics of information sources and long experience to judge the type of fault is a complicated procedure. Multi-source information fusion technology has powerful capabilities of data collection, processing and decision-making, and it makes fusion diagnosis of real-time dissolved gas-in-oil data from transformer, then, determine the transformer current status and fault type accurately and efficiently, finally it provides guidance and advice that can be used in transformer repair work.

Multi-source information fusion technology in equipment condition monitoring and fault diagnosis is mainly reflected in this four aspects of model established, feature extraction, state estimation and diagnosis decision-making. Du proposes the thoughts and implements method of multilayer distributed reasoning mechanism of transformer fault diagnosis expert system based on information fusion. The method conducts comprehensive diagnosis combining preventive test, oil test and other test projects, then it determine the general location of fault [8]. Literature [9] takes oil chromatographic analysis, electrical Test and other multi-source information as fusion objects, transformer fault diagnosis model based on D-S evidence reasoning is proposed in this literature. Literature [10] comes up with the method of transformer fault diagnosis using information fusion algorithm based on least squares support vector machine combining DGA, which significantly improve the classification precision of the transformer fault diagnosis.

2. Related Works

2.1. Multi-source information fusion model

The key problem of information fusion research is to propose a theory and method of processing multi-source information that of similar or different characteristic patterns, and finally form the decision information. The emphasis of the research is feature recognition and fusion algorithms which lead to complementary integration of multi-source information and improves the information processing in the uncertainty environment and then solves vague and contradictory problem. Basic model of multi-source information fusion can be divided into functional model, structure model and hierarchical model.

2.1.1. Functional model

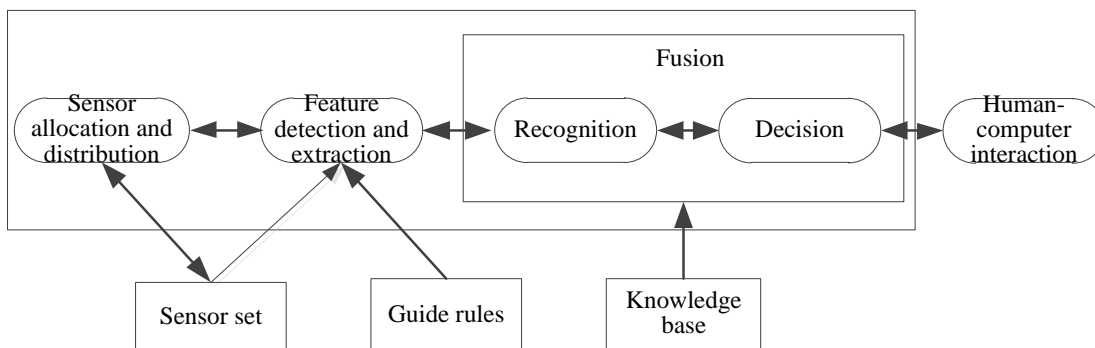


Figure 1. Fusion function model of multi-source information

Functional model of multi-source information fusion is shown in Figure 1, which includes four parts: fusion subject, sensor set, knowledge base and guide rules, and human-computer interaction module. It is a whole application system made up of hardware and software, data flow and control flow. In the figure, the fusion subject is in the solid line frame, sensor allocation and distribution module is responsible for the control and management of each sensor that distributed in the network; Feature detection and extraction module is mainly to preprocess the data on the sensor and accomplish the feature extraction; After feature extraction, data, the data is Passed into fusion module, which make recognition of the characteristic data and decision accordingly with the integration knowledge in knowledge base; human-computer interaction module put the final decision results to users. In the figure, unidirectional arrows represent data flow, forward transmission of double sided arrows stand for data flow and backward transmission of that stand for control flow, the control flow is mainly to modify configuration of command module.

2.1.2. Structure model

Generally, structure model of multi-source information fusion is the center type model, that is to say there is only one fusion subject unit in the model. Structural model can be divided into centralized, distributed and mixed types according to the position.

Centralized structure model: As shown in the left part of Figure 2, it has the advantage of simple structure, high precision, using fewer sensors, reducing the power and the cost of the system. But it makes information fusion only after receiving the information from all sensors. The disadvantage is that the system communicates with heavy burden and the speed of fusion is slow.

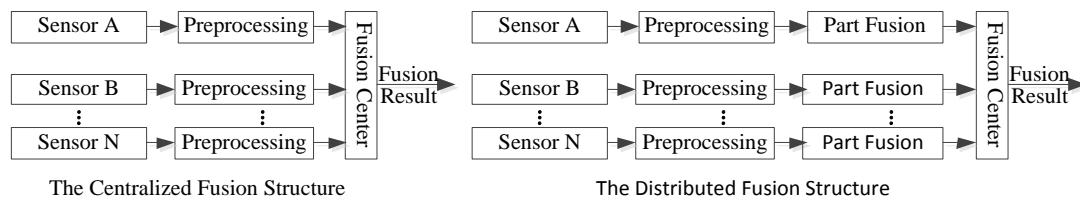


Figure 2. Structure model of multi-source information fusion

Distributed structure model: As shown in the right part of Figure 2, differed from the centralized structure model, in distributed structure, the part fusion results are put into fusion center after individual part fusion instead of putting direct into fusion center data after preprocessing of sensor data. Distributed structure model have the advantage of each node with its own processing unit, convergence speed and lighter communication burden; the disadvantage is that it misses some information, and its fusion precision is lower than centralized fusion precision.

Mixed structure model: It is a mixture of centralized and distributed models, the advantage is with maximum flexibility, the model is commonly used in very large system; Defect is that it increases the complexity of the data processing, and requires faster transfer rate.

2.1.3. Hierarchical model

According to the levels of data abstraction processing, Fusion hierarchy model can be divided into data layer fusion, feature layer fusion, decision layer fusion. The fusion layers determine which process should be applied to sensor information vary from stage to stage. It

relates to the abstraction of information, processing, accuracy of decision-making and fault tolerance of the system.

Data layer fusion directly mixes the raw collected data, and then extracts feature vector from the result of the fusion, finally it determines the recognition, due to the object of integration is raw data from the sensors, the data layer integration is the lowest level of fusion.

Feature layer fusion makes feature extraction of the original sensor information in the first place, and then gives fusion processing of the feature information get after extraction. Finally it makes recognition of fusion results and obtains policy. From the perspective of the location of fusion, it belongs to intermediate level. Feature layer fusion model is shown in Figure 3.

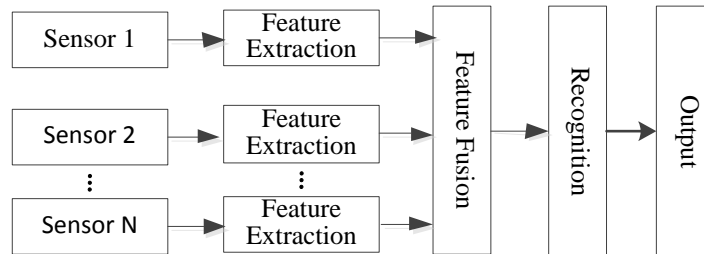


Figure 3. Feature layer fusion model

Fusion unit finishes the fusion of identify results and get fusion results after decision-making layer making feature extraction and recognition of original sensor data. Decision-making layer fusion is a kind of high level fusion. The object of information fusion is the decision results that after feature processing and recognition, fusions are just the comprehensive analysis of various decision results, and getting the conformance resolution of decision results. The feature layer integration is the compromise of fusion model in terms of accuracy and cost.

2.2. Transformer fault diagnosis method

Currently, Oil-immersed transformer is the most widely used type of transformer, because of transformer oil with excellent insulation and heat dissipation ability, large capacity and low price. Oil-immersed transformer is mainly composed of iron-core, winding, oil tank, oil pillow, insulating casing, tap-changer and gas relay, *etc.* The common faults of oil-immersed transformer are divided into internal faults and external faults. The internal faults refer to the faults of transformer's internal components, such as insulation fault, core fault, tap-changer, fault, etc. In nature, the internal faults of transformer contain hot fault and electrical fault. Hot fault refers to the internal transformer temperature rising and local overheating. Hot failure can also be divided into oil overheating, oil and solid insulation heat, serious overheating. In accordance with the severity of the thermal fault, it can be divided into three conditions: low temperature overheating (150 to 300 °C), middle temperature overheating (300 to 700 °C) and high temperature overheating (700 °C). Under the effect of a high strength electric field, decline of transformer inner insulation performance or degradation failure is known as the electric failure. According to the density of discharge energy, electrical fault is divided into partial discharge, spark discharge, and high energy arc discharge. Oil-immersed transformer fault classification model is shown in Figure 4.

When there is a latent fault of transformer, the transformer oil is decomposed into various kinds of low molecular hydrocarbons, CO, CO₂ gas on the effect of heat and high electric field. Then the concentration of these gases and gas production rate increase rapidly, air bubbles created by these gases in the transformer oil constantly dissolved into the oil through

convection and diffusion, these gases are known as characteristic gases, including seven kinds of gases: hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon monoxide (CO) and carbon dioxide (CO_2). There is a complicated nonlinear relationship between component concentration of characteristics gases and the fault type and fault severity, the composition of characteristics gases differ from the fault type, fault severity and the insulation materials adopted by transformer.

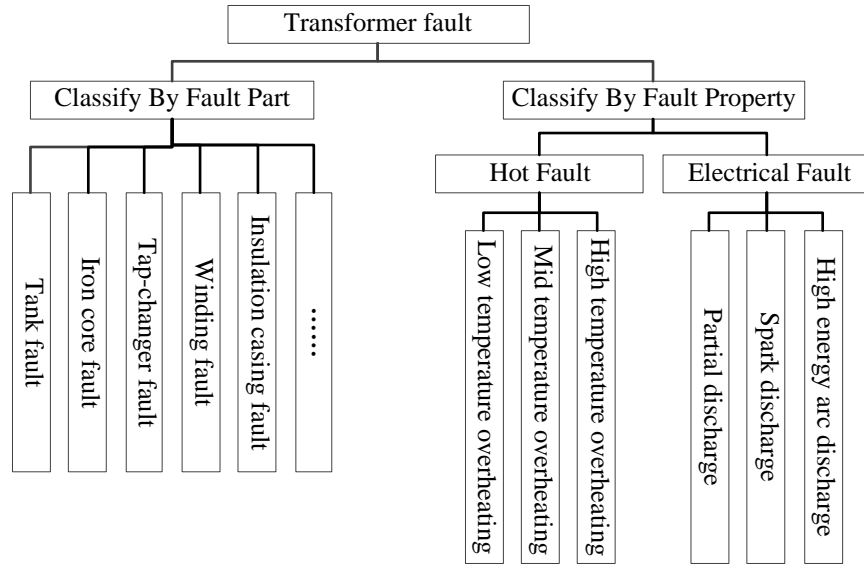


Figure 4. Oil-immersed transformer fault classification model

DGA (Dissolved Gas Analysis) method does not need power outage during data collection, it also has the low cost and the high accuracy rate, so it is the most common and effective method of transformer condition monitoring and fault diagnosis from now on, the DGA fault diagnosis method is divided into traditional method and intelligent method.

Traditional method is the crystallization of human production experience; it processes information of characteristic gases by using simple ratio calculation and intuitive judgment of fault type, including the characteristic gases method, three ratio method, and graphic method.

Characteristic gas method is according to the combination of characteristic gases to judge the fault type. The gas composition and content is different vary from fault type to fault type. The primary and secondary composition of characteristic gases when failure occurs is shown in Table 1. The table shows that according to the content proportion of H_2 and C_2H_2 , we can distinguish between thermal fault and electrical fault, electrical fault occurs when H_2 and C_2H_2 content are higher, hot fault occurs when lower.

Table 1. Relationship between fault type and ratio of gas content

FAULT TYPE	MAIN CHARACTERISTICS GAS	SECONDARY CHARACTERISTICS GAS
oil overheating	CH_4, C_2H_4	C_2H_2
serious overheating	H_2	C_2H_4, CH_4
oil & solid insulation overheating	CH_4, C_2H_4, CO, CO_2	C_2H_2
partial discharge	H_2, CH_4	C_2H_2
spark discharge	H_2, C_2H_2	C_2H_4, CO, CO_2
arc discharge	C_2H_2, H_2, CO, CO_2	C_2H_4

Three ratio method first takes three ratio of specific gases, then gets the coded combination according to the encoding rules (as shown in Table 2), and finally determines the fault type according to the CRT of fault type and encoding(as shown in Table 3).

Table 2. Encoding rules of three ratio method

RANGE OF GAS RATIO	ENCODING OF RATIO RANGE		
	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6
<0.1	0	1	0
$\geq 0.1 \sim < 1$	1	0	0
$\geq 1 \sim < 3$	1	2	1
≥ 3	2	2	2

Table 3. Map of three ratio encoding and fault type

CODING COMBINATION			JUDGE FAULT TYPE	FAILURE INSTANCE
0	0	1	low temperature overheating (under 150°C)	Insulated wires overheating, note CO, CO ₂ and CO ₂ / CO
	2	0	low temperature overheating (150°C~300°C)	Tap-changer poor contact, lead clip screw loosening or bad joint welding, Eddy current caused by copper overheating, iron core magnetic leakage, partial short-circuit, defective insulation between the layers, core multipoint pick and so on
	2	1	mid temperature overheating (300°C~700°C)	
	0,1,2	2	high temperature overheating (higher than 700 °C)	
	1	0	partial discharge	High humidity, partial discharge of low energy density caused by high air content
1	0,1	0,1,2	low energy discharge	Continuous spark discharge between lead and fixed components, shunting tap and oil gap flashover, Spark discharge in oil Between different potentials or spark discharge between the floating potentials
	2	0,1,2	low energy discharge and overheating	
2	0,1	0,1,2	arc discharge	Short circuit between the layers of coils, interphase flashover, oil clearance flashover between tap leads, lead discharge to tank shell, coil fuse, tap arcing, arc caused by loop current, lead discharge to other groundings and so on
	2	0,1,2	arc discharge and overheating	

The main cause of low diagnosis accuracy is that conventional DGA fault diagnosis method has many limitations. Only looking for new intelligent diagnosis methods can we break these limitations, thus to improve the accuracy of diagnostic results.

3. Transformer Fault Diagnosis Based on Multi-source Information Fusion

3.1. Model of transformer fault diagnosis based on Multi-source information fusion

The main task for transformer fault diagnosis is starting from located transformer fault, predicating the location, type and property of transformer fault according to various fault information, and providing fault interpretation and processing opinion. The main information

that transformer fault diagnosis uses including: SCADA data, special sensor information, related electrical test data, operation and repair records of equipment, etc. The fundamental structure of transformer fault diagnosis based on Information fusion is shown in Figure 5.

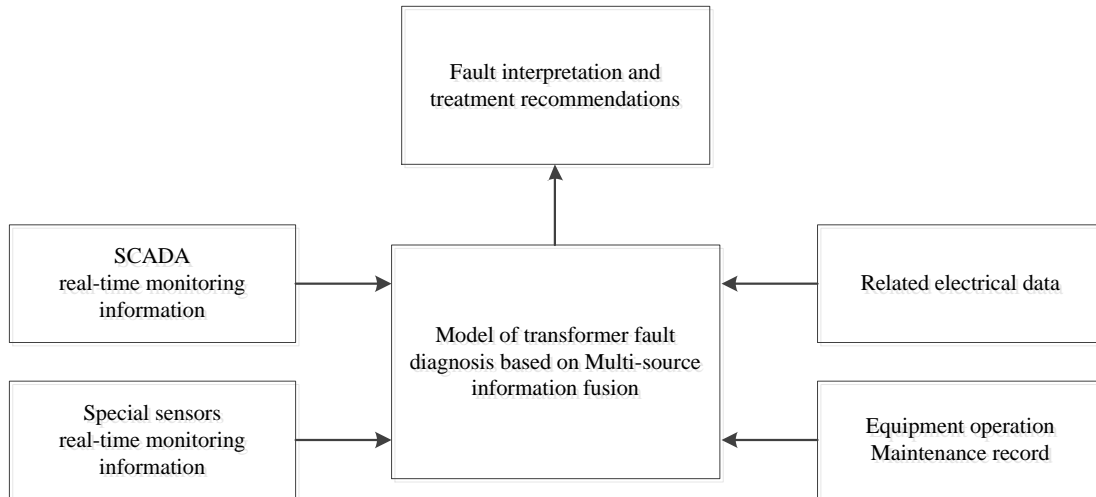


Figure 5. Structure of transformer fault diagnosis

Transformer fault diagnosis model includes four important units, they are data preprocessing unit, feature extraction unit, information fusion unit and result processing unit. These four units are conducted step by step and executed in sequence. The data source of one unit is its prior unit. The arrow in Figure 6 represents both processing order and data flow, this figure is also shows the procedure of transformer fault information fusion.

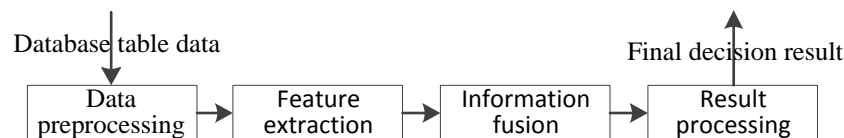


Figure 6. Data fusion model for fault diagnosis

Data preprocessing unit: it organizes the DGA information from database into matrix form. Then, it obtains the type of current transformer and converts the type into a constant value the system defining.

Feature extraction unit: it extracts data columns the matrix needed and generates feature information matrix.

Information fusion unit: According to the comparison analysis of a few fusion structures and algorithms in previous chapter, the structure this fusion model adopting is centralized feature fusion structure, and the fusion algorithm is BP neural network. This unit mainly responses for adding the feature information matrix the container (feature fusion conducted in neural network) that transformer type constant value corresponds to.

Result processing unit: after the process of feature data neural network fusion, the unit determines fault type, and furnishes what processing operation should be taken according to whether there is a fault. It produces corresponding maintenance advice on the basis of fault type and failure case library when the fault existing.

3.2 Space-time fusion of multi-sensor based on BP neural network

Traditional multi-sensor data fusion operations almost all think only data fusion of different space position of sensors at the same time, without considering the connections between information in one sensor but at different times, which is very important to fault diagnosis. Traditional methods separate the timeliness of data fusion from the spatiality, which have certain limitation, this paper proposes a space-time weighted information fusion model.

The fusion has two steps: First step, take the first one loop of sensors to the first I loops and information at the moment K to do time-domain weighting fusion, the fusion method uses BP neural network algorithm; Second step, take the accumulated information distributed on each sensor in different positions at the moment K and monitoring information form SCADA system to do space-domain weighting fusion, the result is shown if Figure 7.

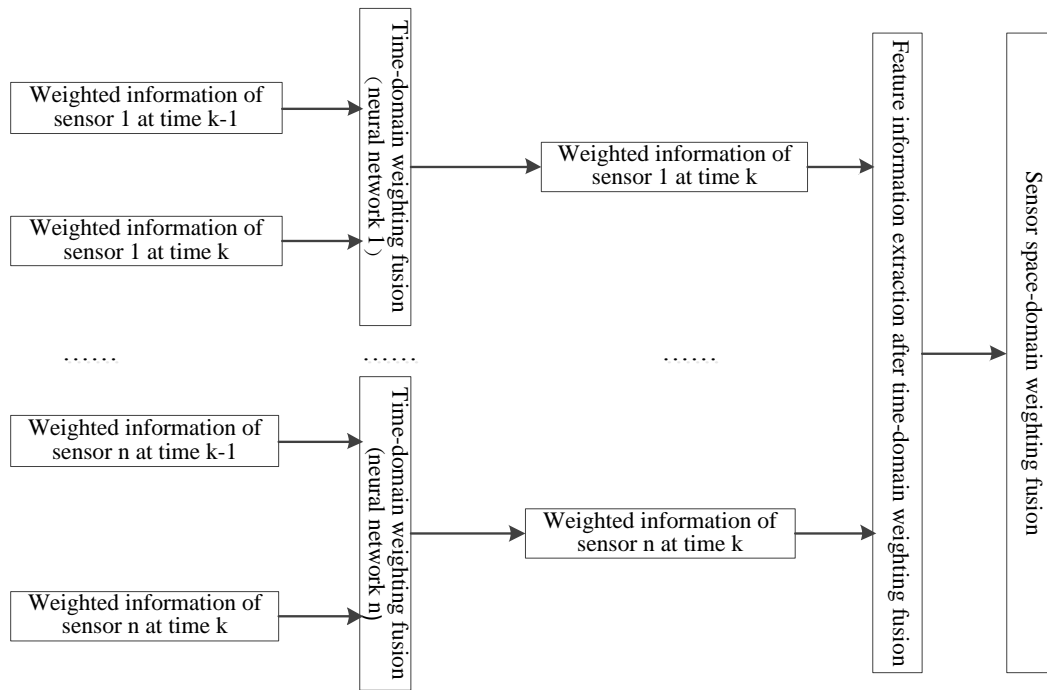


Figure 7. Multi-sensor space-time fusion model

3.3 Procedure of transformer fault diagnosis based on BP neural network

The procedure of transformer fault diagnosis based on BP neural network marches in a sequential execution mode, as is shown in Figure 8. First read pretreatment transformer oil and gas real-time data to the trained neural network in the form of a matrix, the network is

generated by using the sample data related to the input transformer type. If the network diagnosis results indicate no fault, the results will be directly presented on the system interface; otherwise the system will identify the type of fault corresponding to fault case in database, and the fault diagnosis result will be stored in the fault history list for the use of statistics and analysis.

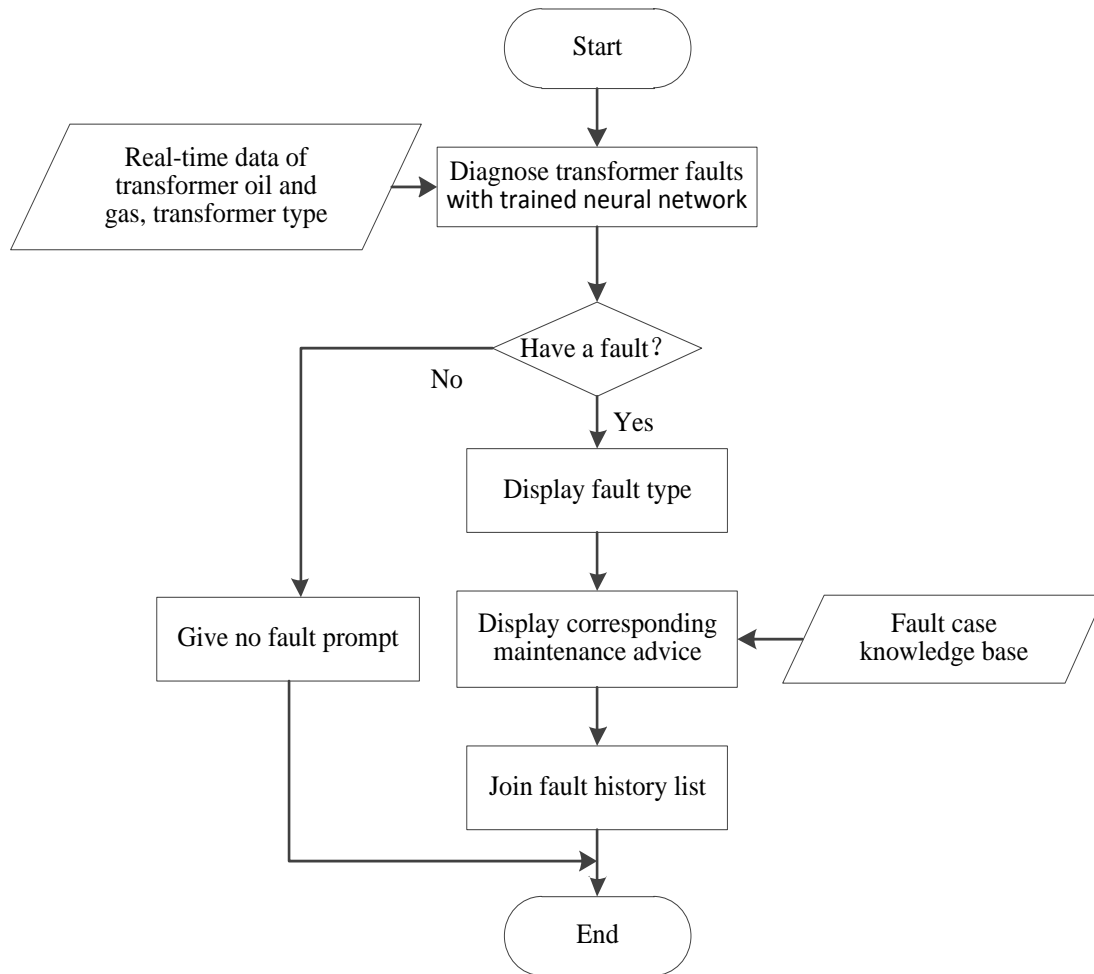


Figure 8. Flow chart of transformer fault diagnosis

4. Comparison of Transformer Fault Diagnosis Result

Results of transformer fault diagnosis based on BP neural network fusion model are accurate up to 93%, the diagnostic results of the BP neural network fusion model and that of the ratio method on some transformer DGA data are shown in Table 4.

Table 4. Results of two kinds of transformer fault diagnosis method of some tables

H2	CH4	C2H6	C2H4	C2H2	CO	Physical fault	Three ratio method	Fusion algorithm
2000	8850	1500	9400	200	800	high temperature overheating	high temperature overheating	high temperature overheating
330	43	14	106	220	369	overheating and high-energy discharge	low-energy discharge	overheating and high-energy discharge
5.5	9.2	7.7	2	0	236.3	low temperature overheating	low temperature overheating	low temperature overheating
97.81	15.87	2.71	8.1	24.36	1220.97	low-energy discharge	arc discharge	low-energy discharge
673.6	423.5	77.5	988.9	344.4	4	high-energy discharge	low temperature overheating	high-energy discharge
160	130	33	96	0	0	mid & low temperature overheating	low temperature overheating	mid&low temperature overheating
14.64	3.68	10.54	2.71	0.2	0.03	trouble-free	low-energy discharge	trouble-free
1000	200	30	400	1000	1700	high-energy discharge	low-energy discharge	high-energy discharge
33	93.1	28	90.5	0	362	high temperature overheating	high temperature overheating	high temperature overheating
207	363	87	516	13	101	high temperature overheating	high temperature overheating	high temperature overheating

5. Conclusion

At first, this paper deeply studied the multi-source information fusion and fault diagnosis method of power transformer, and then put forward the model of transformer fault diagnosis based-on information fusion technology. The model that adopts space-time weighted model and BP neural network fusion algorithm can take full advantage of fusion technique to dispose real-time transformer DGA data, SCADA data and Electrical test data, etc. At last, we get a Comparison between diagnosis of transformer fault diagnosis based on multi-source and that of traditional three-ratio method. For some of the problems of the research process, the following future research directions should be proposed.

(1) Data acquisition: How to manage the sensor is a critical issue. Optimal configurations of sensor, Determination of sensor priority, failure handling, registration deviation, spatial and temporal registration methods and so on are all need further investigation.

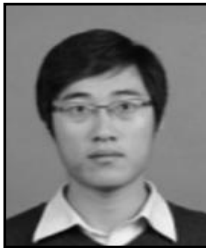
(2) Fusion algorithm: With the change of the fusion model structure, DGA data, feature data from the local environment and other feature data can be the data sources at the same time. So a new data fusion method with veracity and high efficiency is needed in order to deal with huge amounts of data and intelligence requirements.

References

- [1] Y. Yong, Z. Xudong and F. Yuancheng, "Research on Fault Diagnosis Method of Power Transformer Impact Test", North China Electric Power, vol. 10, (2006), pp. 1-4.
- [2] Y. Qin, "A Novel Method of Power Transformer Fault Diagnosis", Electrical Engineering, vol. 12, (2008), pp. 39-41.
- [3] K. Spurgeon, W. H. Tang and Q. H. Wu, "Dissolved Gas Analysis using Evidential Reasoning", Science, Measurement and Technology, IEEE, vol. 152, no. 3, (2005), pp. 110- 117.
- [4] Z. Jian, "Research on Transformer Fault Diagnosis Technology", Public Communication Science And Technology, vol. 17, no. 19, (2011).

- [5] Y. -D. Hou, X. -J. Wang and C. -L. Wen, "Transformer Fault Diagnosis based on the Improved D-S Evidence Theory", 2009 International Conference on Machine Learning and Cybernetics, IEEE, vol. 6, (2009), pp. 3413-3417.
- [6] Y. Li, S. Yong and Z. Yuefeng, "Transformer Comprehensive Fault Diagnosis Model Based on Probabilistic Inference and Fuzzy Mathematical", Proceedings of the CSEE, vol. 07, (2000), pp. 20-24.
- [7] X. Yancai, C. Xiuhai and Z. Hengjun, "Application of Genetic Support Vector Machine in Power Transformer Fault Diagnosis", Journal of Shanghai Jiaotong University, vol. 11, (2007), pp. 1878-1881.
- [8] D. Jianguang, "Transformer Fault Diagnosis Expert System", North China Electric Power University (Beijing), (2003).
- [9] G.Yishan and Z. Bo, "The Fault Diagnosis Model of Transformer Which Based on the Technology of Information Fusion", Ninth International Conference on Hybrid Intelligent Systems, IEEE, (2009), pp. 184-187.
- [10] T. Wenhui, S. Almas and Q. H. Wu, "Transformer Dissolved Gas Analysis using Least Square Support Vector Machine and Bootstrap", Control Conference, IEEE, (2007), pp. 482-486.

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