Deep Primary and Secondary Fusion Transformer Based on Internet of Things Technology

Xiaohua Zhang[1]*, Yuping Wu[2], Jianjun Chen[3], Jie Dong[4], Yu Yue[5]
State Grid Jibei Electric Power Company Limited, Beijing, China[1, 2]
State Grid Qinhuangdao Electric Power Supply Company, Qinhuangdao, Hebei, China[3, 5]
State Grid Jibei Electric Power Company Limited, Smart Distribution Network Center, Beijing, China[4]

***Abstract*—As one of the core equipment of power system, power transformer has great fault influence and complex fault causes. In order to ensure the safe and stable operation of power system, its operation state must be monitored and judged. With the increasing maturity of the Internet industry and the continuous development of sensor technology, the emergence of smart grid has contributed to the realization of intelligent transformer on-line monitoring, condition evaluation and fault diagnosis. This paper studies the deep primary and secondary fusion transformer based on the Internet of Things technology, summarizes the development status of intelligent transformer and its existing problems on the basis of relevant literature, and proposes the optimization technology of deep primary and secondary fusion transformer based on the Internet of Things technology to solve its existing problems, and conducts related experiments and fault detection research on the proposed technology. The experimental results show that this optimization technology has good feasibility, good self-state evaluation and fault diagnosis functions. The deep primary and secondary fusion based on the Internet of Things technology proposed in this study can increase the reliability monitoring of intelligent transformer operation, provide a strong technical guarantee for the normal operation of distribution network, and also provide important technical support for the next research of distribution network technology.**

Keywords*—Internet of things technology; primary and secondary integration; smart transformer; fault detection

I. Introduction

In recent years, the rapid growth of China's national economy has driven the rapid growth of energy industry, the main industry of economic growth [1, 2]. In order to meet the needs of national economic development, China Power Grid Corporation has successively put forward the construction objectives of "building a strong intelligent network" and "developing UHV technology", and strive to build a "3 / 5" structure with international scale and a network system to realize efficient power supply [3, 4]. In such a "large power grid", the power transformer as the power supply infrastructure of node substation is more important, which directly affects the safety and reliability of network power supply system [5, 6]. In addition to a large number of more functional relay protection and operation control equipment, modern power transformers also require that they can operate continuously in the power grid for a longer and longer time. Therefore, the accidents caused by the failure of transformer parts are completely unavoidable [7, 8]. In case of failure or major accident, even if there is an emergency plan in place in advance, it will not ensure that the power failure does not affect residents' daily life and commercial operation. Therefore, due to the particularity and complexity of transformer operation, it is of great practical significance to effectively monitor the transformer from multiple directions and angles, diagnose whether it is in an abnormal state, whether there is the possibility of error, and how to analyze, judge and use it [9, 10].

*Corresponding Author.

Regarding the research on intelligent evaluation and early warning of substation equipment status, some researchers have proposed that the comprehensive evaluation method in China is mainly based on the equipment status evaluation guidelines issued by the State Grid Corporation comprehensive evaluation method. The state quantities used in the method are relatively comprehensive, including family defects, maintenance records, inspection information, online monitoring, live detection and preventive test data, etc., which basically cover all relevant information of the equipment, including a large number of non-stop power supplies. The detection status quantity and the power failure detection status quantity, therefore, the workload of data acquisition in actual operation is relatively large. In addition, the introduction of various artificial intelligence methods into equipment condition evaluation has become a hot topic at home and abroad. The most widely used intelligent evaluation method is the fuzzy comprehensive evaluation method. The core of the fuzzy comprehensive evaluation method is the determination of the membership function and the determination of the weight. In addition, the gray theory, matter element analysis, evidence theory, Bayesian network, support vector machine and other intelligence analytical methods are also widely used in equipment condition evaluation [11]. Some researchers have proposed that the basic condition for power transformer maintenance is accurate, reasonable and efficient power transformer maintenance, and the reliability of evaluation directly affects the reliability of maintenance decision-making. At this stage, the latest research results are mainly focused on the use of intelligent algorithms to analyze DGA data and part of the electric quantity. These are the lack of overall representation of the transformer status. How to simplify system evaluation, maximize the collection of collectible information, and fully reflect the condition of the transformer is a very important step in the process of transformer maintenance. Nowadays, users have higher and higher requirements for reliability, and it is developing dynamically [12]. In summary, there are many research results on power transformers, but there are few research results on deep primary and secondary fusion transformers based on the Internet of Things technology.

This article studies the deep primary and secondary fusion transformer based on the Internet of Things technology. After a general understanding of the relevant theories on the basis of relevant literature data, the realization of deep primary and secondary fusion is analyzed, and then conduct experiments on the transformer with deep primary and secondary fusion. This experiment uses the DGA data and electrical test data of the selected transformer as the input feature vector of the diagnosis model,according to the existing research literature, the five characteristic gases are used as the input vector of the multi-parameter information fusion transformer fault diagnosis model. The transformer automatic fault diagnosis model is modeled based on Adaboost_rbf and dsmt，the sample data set is preprocessed by normalization method. Taking the relative volume fractions of the five characteristic gases in the DGA as the input feature vector, the three models of BP neural network, M-RVM, AdaBoost_RBF1 and PSO-IGWO optimized hybrid KELM are used to diagnose transformer faults.It is concluded that the diagnostic accuracy of transformers based on deep primary and secondary fusion is higher than that of transformers based on DGA.

II. Deep Primary and Secondary Fusion Transformer Research

A. Problems with Smart Transformers

1) Integrated design of overall structure: The integrated design of sensors and transformers needs to fully consider issues such as insulation, energy acquisition, communication, interference, heat dissipation, and maintenance. It also needs to meet the conditions of outdoor operation, and complete the research and design of high protection level structures according to actual use scenarios. In addition, it is more difficult to combine control methods such as capacity adjustment, voltage adjustment, three-phase power adjustment, and automatic load switching with the transformer itself.

2) Self-diagnosis and control system mechanism research and development: The intelligent fusion terminal needs to collect information for self-evaluation and self-diagnosis of the transformer, accurately reflect the operating status of the equipment, the appearance of the equipment, and the environmental operation and maintenance status to the platform, and can realize the corresponding automatic adjustment after being approved by the equipment owner or superior management unit as well as autonomous system actions with other equipment (such as distribution transformer clusters, low-voltage switches, etc), reasonable and accurate judgment algorithms and control mechanisms are essential for this project.

3) Wireless communication: In the data transmission part, the collected information includes analog signals and digital signals, and the types of information sources are different. This requires better compatibility of the communication module, and in this project, the data collected by the sensor is mainly collected through wireless communication. Transmitted to the remote monitoring terminal, this poses a challenge to data transmission. First, the transmission distance must be large enough, and secondly, the transmission delay must be small enough. Foreign countries usually use a combination of multiple communication technology methods, and integrate the best communication methods according to the actual needs of condition monitoring.

B. The Realization of Deep One-two Fusion Optimize the Layout of Transformer Structure

1) Transformer monitoring unit: The transformer online monitoring unit has a variety of communication interfaces, which can communicate with the transformer's environmental sensors, noise sensors, power quality management modules, oil chromatographic analysis modules, etc. It also has the ability to interact with the intelligent terminal of the station and the master station. The online monitoring device can also directly control the voltage and capacity adjustment switches of the transformer through the built-in APP capacity and voltage adjustment strategy, and through the built-in algorithm, cut off some unimportant branches when the transformer is overloaded to ensure the safe operation of the transformer.

2) Communication structure: The online monitoring platform communicates with the master station through wireless, optical fiber and other methods, interacts with data through 104 or MQTT, accepts the APP download of the master station, parameter settings, container management, cluster control; and can be integrated with the station area through the terminal 104 or MQTT interactive data; the environment and noise of the transformer are mainly collected through 485, wireless and other methods for data analysis; the component collection of the oil chromatogram is mainly carried out through 485; the communication with the power quality management module is mainly through the 485 method, Fig. 1.

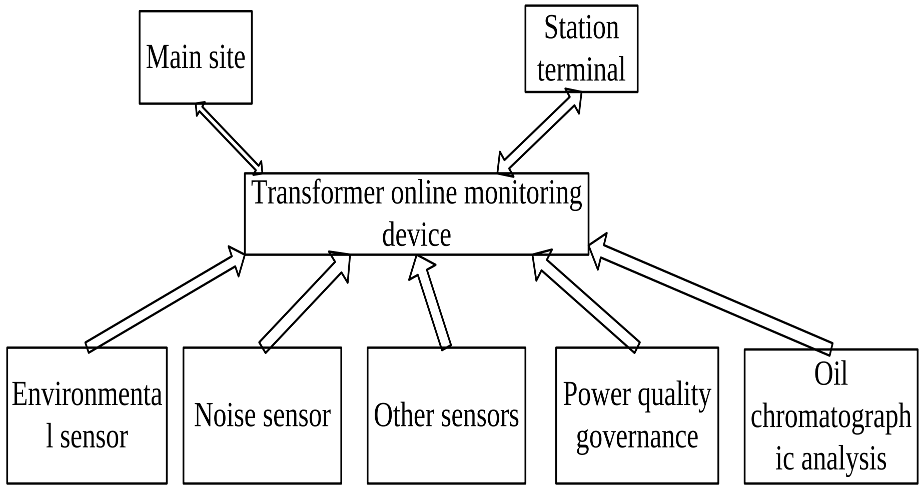

Fig. 1. Communication architecture.

C. Fault Diagnosis

1) Comprehensive application of artificial neural network (ANN) and evidence theory and other methods to construct a multi-information fusion comprehensive state assessment model for transformers. First, the data preprocessing module processes the operating data, constructs the parameter subspace and the fault subspace, selects training samples from the actual operating data, and constructs and trains the sub-network. Based on the evidence theory, construct the identification framework of the diagnosis system, determine the basic probability distribution function of each evidence, and seek to effectively fuse multiple preliminary diagnosis results, including models and methods that can quickly fuse feature-level diagnosis results based on multiple methods. Finally, the evidence is synthesized and diagnosed, so that it can identify the fault correctly and efficiently.

2) Through the creation of state test scenarios, a comprehensive simulation of the various states of the transformer, and the creation of a test data information database. Find the mutual influence relationship between the amount of information sensed by the distribution transformer, establish the transformer condition monitoring system and fault diagnosis model, complete the interactive algorithm between the computing unit and the ontology perception, environmental perception, historical state extraction, interconnection of similar equipment, etc, and realize the status communication and exchange between the equipment owner and the superior management unit, establish the transformer load capacity evaluation parameter system, and evaluate and predict the transformer load capacity. Incorporating systematic data such as transformer body structure, internal faults, technical parameters, cooling methods, power grid operating environment, geographical and meteorological environment, and using principal component analysis algorithm to establish a transformer state evaluation model to obtain a transformer health status score.

D. Panorama Detection

1) Distribution line image monitoring system is suitable for visual monitoring and patrolling of distribution lines. It is a lightweight and convenient installation image monitoring device designed for the visualization of distribution lines. This device can pass 3G/4G/0PGW, optical fiber network, etc, will transmit pictures to the monitoring center regularly, and line maintenance personnel can realize remote picture browsing through computer clients and WeChat clients. The realized functions mainly include: picture capture; timed picture upload; when there is no network or poor signal, the current picture is temporarily stored, and the picture will be resumed after the network is normal; remote manual wake-up capture/small video recording; supporting mobile client, anytime grasp the line status anywhere, and effectively solve the problem of high cost of line channel visualization.

2) Configure high/low voltage current and voltage transformer (built-in), pressure sensor, low oil level / pressure release sensor, temperature sensor, vibration sensor, configure oil chromatography online monitoring device, partial discharge detection device, camera (support picture with 4G / 5G way to upload to the station area).

E. Application of Iot Technology in Deep Primary and Secondary Integration Transformers

1) Global positioning system: Applying the timing characteristics of the GPS to the power system is more important and more extensive than the general positioning characteristics [13]. The power system includes monitoring and protection systems, such as automated microcomputers and safety systems, dispatch automation systems, monitoring systems, fault recorders and accident recorders. All of the above require an accurate time standard to achieve accurate synchronization. In addition, with the development and expansion of the power system, especially the expansion of the power grid, higher requirements are put forward for the convenience and accuracy of the time standard.

2) Radio frequency technology: Radio frequency technology mainly identifies tags. The label usually represents the data information on the device, which is set when the device leaves the factory. The information contained in the label usually refers to data parameters that may have a significant impact [14]. The label and the measured object have a binding relationship. The device information reflected on the label usually includes parameters that have a significant impact on the device, rated voltage, and operating current.

F. Fusion Algorithm

1) The RBF neural network is based on how to manipulate multiple variables and is a three-level network suitable for solving classification problems. A general RBF neural network structure composed of input layer, hidden layer and output layer [15].

The node output returned by the hidden layer of the RBF network can be expressed as:

$$r = \exp(-\frac{1}{2\sigma^2}\|R-T\|^2) \tag{1}$$

Among them, n is the output of the final hidden layer node normalized in the hidden layer, r is the return input vector n, t is the normalized center vector of the return function of the final hidden layer node, and σ is the normalization of the final hidden layer node the output, the normalized linear combination formula of the final hidden layer node is as follows:

$$y = \sum_{k=1}^{h} \varpi r - \theta_j \tag{2}$$

Where r is the output returned by the hidden layer from the node, y is the output of the hidden layer from node j, a is the threshold for returning from the hidden layer to the output plane, and θ is the input threshold for outputting node j from the hidden layer.

2) The structure of DBN is to iterate multiple restricted Boltzmann machines (RBMs), each layer is composed of multiple RBMs, and form a multi-layer deep learning structure by stacking multiple RBMs. These restricted Boltzmann machines can complete bottom-up unsupervised learning. According to the sensing data characteristics of substation equipment, a BP network is set at the top layer as the top-down supervised learning in deep learning [16]. This structure can better obtain the excellent feature expression of data, that is, more abstract and effective high-level features are extracted on the basis of multiple fusion features. In order to realize the evaluation of equipment status, on the basis of feature extraction, a supervised classifier needs to be added at the top of the network to predict and classify the equipment status, so as to determine the early warning and diagnosis information according to the classification results [17]. The basic structure of equipment condition assessment network is shown in Fig. 2.

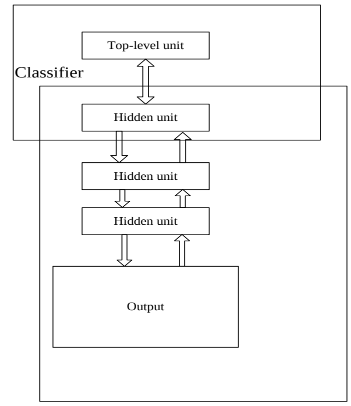

Fig. 2. Basic structure of equipment condition assessment network.

III. Deep Primary and Secondary Fusion Transformer Experiment Based on Internet of Things Technology

A. The Purpose of the Experiment

This article conducts experiments on the deep primary and secondary fusion transformers based on the Internet of Things technology, mainly to test the fault detection of the proposed deep primary and secondary fusion transformers.

B. Experimental Data

The transformer is a complex system, and its fault factors are so complicated that selecting a single DGA data cannot completely and accurately reflect the operating status of the transformer. Different characteristic signals of different levels must be used to synthesize for diagnostic purposes. In order to improve the accuracy of transformer fault diagnosis and more accurately determine the operating status of the transformer, this paper uses the DGA data and electrical test data of the selected transformer as the input feature vector of the diagnosis model [18]. At the same time, according to the existing research literature, the five characteristic gases (CH4, C2H2, C2H4, C2H6, H2), EC 3 ratio (C2H2/CH4, CH4/H2, C2H4/C2H6), Rogers ratio (C2H2/C2H4, CH4 /H2, CzH4/CzH6, C2H6/CH4), Donenberg ratio (C2H2/ C2H4, CH4)/H2, CzH2/CH4, CHs/C2H2) are used as the input vector of the multi-parameter information fusion transformer fault diagnosis model.

C. Failure Model Construction

In the fault diagnosis of power transformer, various state parameters and test characteristic parameters can reflect the fault type and fault location of transformer. It is important to select reliable and effective characteristic parameters to improve the accuracy of transformer fault diagnosis. The selection of characteristic parameters for fault diagnosis should not only meet the practicability of information, but also meet the independence of detection and collection, that is, the characteristic parameters should be independent of each other and reflect the fault characteristics of the transformer as a whole. According to the selection principle of the above characteristic parameters, the transformer fault characteristic parameters are classified into three parts: dissolved gas content in oil (unit: μL /L), electrical test and insulating oil test information, and gas production rate.

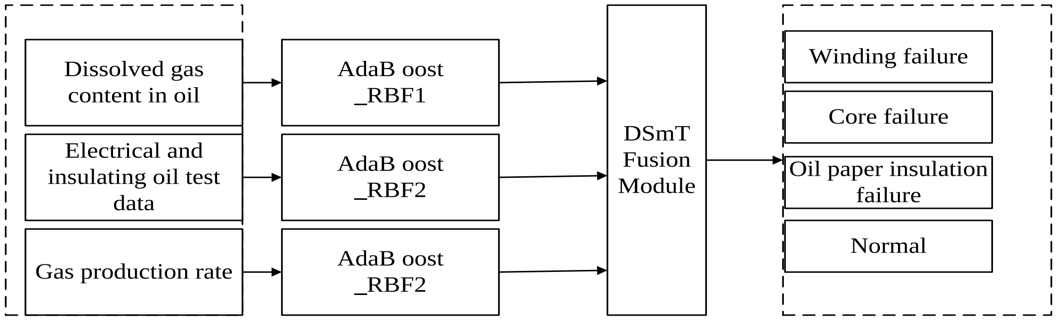

Fig. 3. Transformer fault diagnosis model.

The automatic fault diagnosis model of the transformer is based on Adaboost_rbf and dsmt, and the resulting block diagram after modeling is shown in Fig. 3. In this model, the reference unit of the average volume and fraction of each gas contained in the gas that can be dissolved in the oil is i1. As the core internal current, the oil breakdown trend and the data of the insulating oil test are the diagnostic information unit i2, which contains c2h2, h2 and their total hydrocarbons. The information unit of the absolute value of the gas production rate is the information unit of i3 to diagnose the gas production rate [19]. Combine a classified diagnostic module, use h1, h2, h3 as the input of Adaboost_rbf, and connect each AdaBoost_RBF module in parallel as a first-level diagnostic model system.

The output nodes are diagnostic information modules AdaBoost-RBF1, AdaBoost-RBF2 and AdaBoost-RBF3 corresponding to the basic reliability assignment of the identification framework. In the DSmT fusion module, each reliability assignment is fused to obtain the fused reliability assignment. The final transformer fault diagnosis results are obtained based on the decision rules of maximum reliability allocation.

D. Sample Preprocessing

Due to the large data differences and measurement errors between the transformer oil chromatographic data, the number of samples used only for fault state estimation will affect the final classification performance. In addition, due to different transformer models and peripherals, there are some differences in data [20]. Therefore, in order to effectively eliminate the impact of data differences on fault determination, this article introduces the following normalization methods for preprocessing sample data sets.

$$x_{mew} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{3}$$

Where is the value after normalization of the sample; x is the initial sample value.

IV. Analysis of Experimental Results

A. Accuracy of Diagnosis Results

This paper conducts algorithm training on the 110kV transformer operation test data collected from the official website of the Power Grid Research Institute. Among the collected samples, there are 50 groups of positive samples and 300 groups of negative samples [21]. Negative samples are classified according to the location where the fault occurs, and are also called winding faults, core performance faults, and petroleum paper electrode performance faults. Finally, the data information of the case sample and the label of the error type of the case sample together constitute a data set of three information modules [22]. Including 320 sets of dga test data, 156 sets of inspection result data and 187 sets of gas rate test data; among them, 320 sets of training sets and 100 sets of dga data tests; 100 sets of training sets and 20 sets of test data. In the air data, there are 100 training sets and 20 total tests.

Set the number of iterations T = 16, the neural network spread factor RBF spread = 0.06, and set the decision limit to ε = 0.3. Table 1 shows the AdaBoost RBF1 training results of the DGA information module. Here, the correct sample rate is the correct test rate of the correct 320 data set diagnostic index and the model's DGA training set.

It can be seen from Fig. 4 that the diagnostic accuracy of AdaBoost_RBF1 is better than that of BF neural network. The diagnostic accuracy of AdaBoost_RBF1 has been increasing and is infinitely close to 100%, while BF neural network has increased at the beginning, but then began to decline.

The electrical test/oil test information module AdaBoost_RBF2 and the gas production rate information module AdaBoost_RBF3 were trained respectively. The iteration parameter T=16 was set, and the spread was 1 and 0.1, respectively. The test sample accuracy of the three AdaBoost_RBF modules, RBF test sample accuracy and SVM test sample accuracy are compared in Table II. It can be seen that the performance of AdaBoost_RBF algorithm is obviously better than RBF and SVM.

TABLE I. Accuracy of Diagnosis Results

	RBF neural network	**AdaBoost_ RBF1**
1	80%	80%
2	81%	81%
4	78%	90%
6	71%	91%
8	70%	93%
10	68%	95%
12	67%	96%
14	60%	98%
16	71%	99%

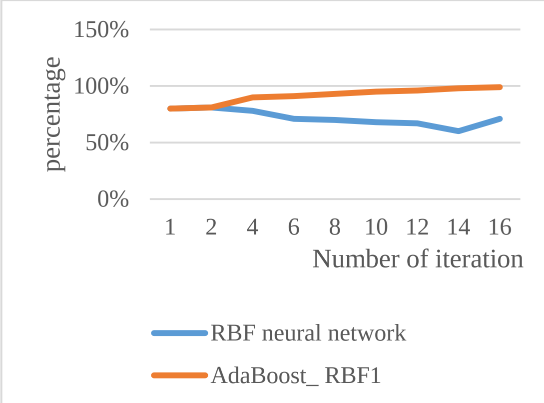

Fig. 4. Accuracy of diagnosis results.

TABLE II. TEST SAMPLE RECOGNITION ACCURACY

The accuracy of test samples under different algorithms	Module class		
	DGA	Electrical test and oil test	Gas production rate
AdaBoost_RBF	78.33%	93.33%	76.59%
RBF	66.67%	76.67%	51.06%
SVM	63.33%	83.33%	53.19%

B. Comprehensive Diagnosis

Taking the relative volume fractions of the five characteristic gases in the DGA as the input feature vector, the three models of BP neural network, M-RVM, AdaBoost_RBF1 and PSO-IGWO optimized hybrid KELM are used to diagnose transformer faults. The diagnosis results are shown in Table III.

It can be seen from Fig. 5 that the diagnostic accuracy of transformers based on deep primary and secondary fusion is higher than that of transformers based on DGA, which increases the accuracy by about 3%.

According to the above experimental results, the diagnostic accuracy of AdaBoost_RBF1 is better than that of BF neural network. The diagnostic accuracy of transformer based on depth primary and secondary fusion is higher than that of transformer based on DGA. It can be concluded that the diagnostic accuracy of the depth-based primary and secondary fusion transformer is high, the performance of fault detection is good, the accuracy of information detection is improved, the range of data observation is expanded, and the working test performance of the primary and secondary fusion transformer is improved.

TABLE III. COMPREHENSIVE DIAGNOSIS RESULT

	Deep primary and secondary fusion transformer	DGA transformer
BP neural network	76.1%	72.1%
M-RVM	83.5%	81.4%
AdaBoost_ RBF1	89.8%	87.3%
PSO-IGWO optimized hybrid KELM	87.8%	86.3%

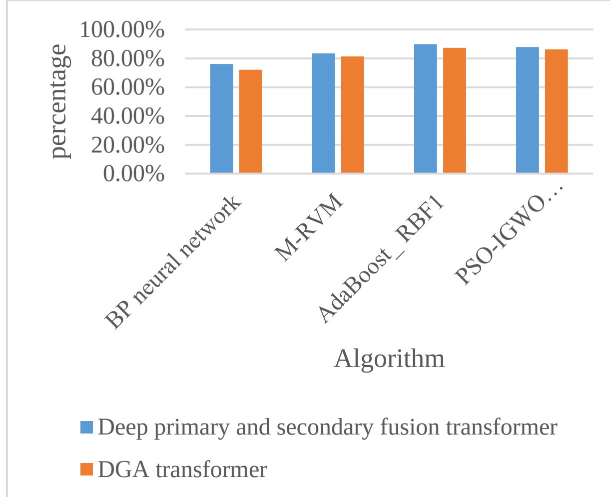

Fig. 5. Comprehensive diagnosis result.

The structure of the model has a direct impact on the effect of diagnosis: (1) Deep learning should fully consider the depth of the model, model parameters and other information. (2) Ensemble learning should not only select homogeneous base classifiers, but also combine different base classifiers to fully synthesize the advantages of each model. (3) Combine the advantages of various intelligent algorithms. Expert system, fuzzy theory, neural network, intelligent optimization computing and other intelligent methods should complement each other, enhance strengths and avoid weaknesses, so as to develop models with superior performance. (4) Model selection and training methods should consider the characteristics of data. To solve the problems of data imbalance and data redundancy with appropriate models and training methods will be more conducive to improving the accuracy of transformer fault diagnosis and guiding the production operation.

V. CONCLUSION

This paper focuses on the research of the deep primary and secondary fusion transformer based on the Internet of Things technology, through optimizing the transformer structure layout and neural network intelligent algorithm realizes the physical fusion and information fusion of primary and secondary equipment. So that it has the ability of panoramic perception of self-state, and realizes the holographic transparent operation of transformers, intelligent research and judgment of situation, active decision-making of hidden dangers, and dynamic autonomous adjustment. This paper verifies the feasibility and effectiveness of fault detection and fusion technology of deep primary and secondary fusion transformer based on Internet of Things technology through theory and experiment, which provides a reference for the subsequent development of intelligent transformers with higher fusion degree. The development of primary and secondary fusion equipment solves a series of complex management problems of the original primary and secondary equipment, but there are also shortcomings in some aspects. Future technology needs to further solve the safety, reliability and efficient fusion problems of primary and secondary fusion equipment. It needs to be further studied in the later period.

ACKNOWLEDGMENT

Research and application of local discharge detection of distribution network switchgear based on electric pulse technology (52053018000M).

REFERENCES

[1] W. U. Zhao, “Research on the Application of Internet of Things Technology to Digital Museum Construction,” Acta Geoscientica Sinica, Vol. 38, No. 2, pp. 293-298, 2017.

[2] S. Liu, “Research on the application of internet of things technology in digital sports and community fitness,” Boletin Tecnico / Technical Bulletin, Vol. 55, No. 4, pp. 139-145, 2017.

[3] Z. P. Fang, L. Yang, S. Yang, et al. “Transformer-Less Unified Power-Flow Controller Using the Cascade Multilevel Inverter,” IEEE Transactions on Power Electronics, Vol. 31, No. 8, pp. 5461-5472, 2016.

[4] K. H. Kim, E. Y. Lee, Energies, et al. “Simultaneous Production of Transformer Insulating Oil and Value-Added Glycerol Carbonates from Soybean Oil by Lipase-Catalyzed Transesterification in Dimethyl Carbonate,” Nano Letters, Vol. 2, No. 12, pp. 1349-1352, 2017.

[5] M. Liserre, G. Buticchi, M. Andresen, et al. “The Smart Transformer: Impact on the Electric Grid and Technology Challenges,” IEEE Industrial Electronics Magazine, Vol. 10, No. 2, pp. 46-58, 2016.

[6] M. Iwakuma, K. Funaki, H. Kanetaka, et al. “Quench analysis in a 72 kVA superconducting four-winding power transformer,” Cryogenics, Vol. 29, No. 11, pp. 1055-1062, 2016.

[7] J. Jiang, G. M. Ma, H. T. Song, et al. “Tracing Acetylene Dissolved in Transformer Oil by Tunable Diode Laser Absorption Spectrum,” IEEE Transactions on Dielectrics & Electrical Insulation, Vol. 7, No. 6, pp. 3435-3442, 2017.

[8] J. Li, Q. Zhang, W. Ke, et al. “Optimal dissolved gas ratios selected by genetic algorithm for power transformer fault diagnosis based on support vector machine,” IEEE Transactions on Dielectrics & Electrical Insulation, Vol. 23, No. 2, pp. 1198-1206, 2016.

[9] S. Dutta, S. Hazra, S. Bhattacharya, “A Digital Predictive Current-Mode Controller for a Single-Phase High-Frequency Transformer-Isolated Dual-Active Bridge DC-to-DC Converter,” IEEE Transactions on Industrial Electronics, Vol. 63, No. 9, pp. 5943-5952, 2016.

[10] V. F. Pires, J. F. Martins, D. Foito, et al. “A Grid Connected Photovoltaic System With a Multilevel Inverter and a Le-Blanc Transformer,” International Journal of Renewable Energy Research, Vol. 2, No. 1, pp. 84-91, 2016.

[11] X. Xi, R. Sioshansi, “A dynamic programming model of energy storage and transformer deployments to relieve distribution constraints,” Computational Management Science, Vol. 13, No. 1, pp. 119-146, 2016.

[12] N. Hashemnia, A. Abu-Siada, S. Islam, “Detection of power transformer bushing faults and oil degradation using frequency response analysis,” IEEE Transactions on Dielectrics and Electrical Insulation, Vol. 23, No. 1, pp. 222-229, 2016.

[13] Y. Chen, X. Liu, Y. Cui, et al. “A MultiWinding Transformer Cell-to-Cell Active Equalization Method for Lithium-Ion Batteries with Reduced Number of Driving Circuits,” IEEE Transactions on Power Electronics, Vol. 31, No. 7, pp. 4916-4929, 2016.

[14] Y. Kim, G. Jung, H. Kim, et al. “Wheel Transformer: A Wheel-Leg Hybrid Robot with Passive Transformable Wheels,” IEEE Transactions on Robotics, Vol. 30, No. 6, pp. 1487-1498, 2017.

[15] Y. Shi, T. Wu, M. Cai, et al. “Energy conversion characteristics of a hydropneumatic transformer in a sustainable-energy vehicle,” Applied Energy, Vol. 171(Jun.1), pp. 77-85, 2016.

[16] Zou X . The Application of Internet of Things Technology in Building Integration System Design[J]. Computer & Telecommunication, 2015.

[17] Zhang K , Amp I , Company T . Application and Practice of Internet of Things Technology in the Business Integration and Information Connection of the Life Cycle of Power Grid Assets.

[18] dos, Santos, Gustavo, et al. Thermography and artificial intelligence in transformer fault detection[J]. Electrical Engineering, 2018.

[19] Samet H , Marvasti F D . Fault detection in the secondary side of electric arc furnace transformer using the primary side data[J]. European transactions on electrical power, 2014.

[20] Jadhav R V, Lokhande S S , Gohokar V N . Monitoring of transformer parameters using Internet of Things in Smart Grid[C]// International Conference on Computing Communication Control & Automation. IEEE, 2017.

[21] Bai D , Yang Y , Li C . Research on Low Power Sensor Networking Technology of Transformer Equipment Based on Node Energy[J]. Journal of Physics Conference Series, 2019, 1346:012043.

[22] Dong X , Chang Y , Wang Y , et al. Understanding usage of Internet of Things (IOT) systems in China: Cognitive experience and affect experience as moderator[J]. Information Technology & People, 2017, 30(1):117-138.