Chapter 84
Advance in Neural Networks for Power Transformer Condition Assessment

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Abstract Artificial neural networks (ANN) have emerged as rapidly evolving and highly practical approaches for condition assessment of power transformers. This study reviewed different ANN approaches for assessing power transformer conditions by discussing historical developments and presenting state-of-the-art ANN methods. Relevant publications from international journals covering a broad range of ANN methods were reviewed. This paper concludes that no single ANN approach enables detection of all faults of power transformers; therefore, overall and reliable assessment of power transformer conditions is necessary. Moreover, the most effective condition assessment technique is to combine artificial intelligent approaches to form hybrid intelligence-based systems and to aggregate them into an overall evaluation. This paper is helpful in the academics, research and engineering community, which is working on condition assessment of transformer fault diagnosis using artificial intelligence.

Keywords Neural networks · Power transformers · Condition assessment

84.1 Introduction

Power transformer is an important apparatus in power systems and its failure may interrupt power supplies and diminish profits. Minimizing the risk of power outages entails detecting incipient faults inside power transformers immediately. Moreover, the conditions must be assessed routinely, as well as the apparatus reliability maintained. Therefore, accurately evaluating power transformer conditions is essential.

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Time-based and condition-based monitoring strategies have been developed for transformer fault identification and diagnosis. Time-based monitoring uses various off-line tests to schedule tests for incipient faults in transformers; however, this labor-intensive strategy is costly and sometimes ineffective in detecting faults that develop between regular intervals of examination. Condition-based monitoring applies advanced fault diagnosis techniques to identify on-line and off-line incipient faults and to provide real-time transformer conditions; thus, it can also optimize maintenance schedules.

Various condition assessment techniques of power transformer have been developed to reduce operating costs, enhance the reliability of operation, and improve power supply and service to customers. Advances in artificial neural networks (ANN) techniques have rapidly improved transformer condition monitoring and assessment tools in recent years. Many practical transformer operation problems have been solved by ANN-based condition monitoring and assessment systems. This study reviews various ANN techniques for evaluating power transformer conditions. A review of the accumulating literature on the practicability, reliability, and automation of intelligent condition assessment systems was performed to determine the state of the art in this important area.

84.2 Transformer Condition Assessment

Dissolved gas analysis (DGA) [1–8] is among the most common techniques used for on-line condition assessment of power transformers. The DGA requires routine oil sampling and modern technologies for on-line gas monitoring. The key step in using gas analysis for fault detecting is correctly diagnosing the fault that generated the gases. Abnormal electrical or thermal stresses cause insulation oil to break down and to release small quantities of gases.

These dissolved gases include hydrogen (H_2), methane (CH_4), ethylene (C_2H_4), ethane (C_2H_6), acetylene (C_2H_2), carbon monoxide (CO), and carbon dioxide (CO_2). Each fault type produces gases that are generally combustible. An increase in total combustible gases (TCG) that correlates with an increase in gas generating rates may indicate the existence of any one or a combination of thermal, electrical or corona faults. The composition of these gases depends on the fault type. Faults in oil-filled transformers can be identified according to the gases generated and the gases that are typical or predominant at various temperatures.

The DGA can provide the early diagnosis needed to increase the chance of finding an appropriate cure. Interpretation schemes are generally based on defined principles such as gas concentrations, key gases, key gas ratios, and graphical representations. Common schemes mentioned in IEEE Standard C57.104-2008 include Key Gas Analysis [1, 2], Dornenberg Ratio [3] and Rogers Ratio [4] Methods, Nomograph [5], IEC Ratio [5], Duval Triangle [6, 7], and CIGRE Method [8]. The DGA can distinguish faults such as partial discharge, overheating, and arcing in many different power transformers.

Various DGA methods have been used by organizations and utilities to assess transformer conditions. These DGA interpretation schemes are based on empirical assumptions and practical knowledge gathered by experts worldwide. Nevertheless, if these interpretation schemes are not applied cautiously, they may incorrectly identify faults because they only indicate possible faults. In some cases, DGA interpretation schemes may differ about identified faults, which is clearly unacceptable for a reliable fault diagnosis system.

Because the conventional DGA diagnosis results may be imprecise and even incomplete, a suitable information integration method is needed to process DGA data to overcome such uncertainties. Therefore, the integration of available transformer DGA-based diagnostic approaches to generate an overall condition assessment is very important for asset management in modern power system operation.

84.3 Artificial Intelligence Applications

An ANN acquires knowledge through training, which is a major advantage when the training set is often composed of actual observations of the physical world rather than being formed of the human opinions used for fuzzy (or expert) systems. However, the training set must adequately represent the domain of interest. Otherwise, the network must make decisions that are not based on experience. Diagnosis accuracy evaluations of the ANN-based transformer fault diagnosis systems have confirmed their effectiveness and reliability.

Many works on applications of ANN in condition assessment of transformers have been published; the proposed systems have been promising because the ANN can learn hidden relations among fault types and dissolved gas concentrations. Besides their learning capabilities, another advantage of ANN is their capability to acquire new information by incremental training from newly obtained samples. Doing so is usually impossible in systems based on fuzzy rules unless the implementations also rely on a back-propagation procedure to evolve parameters. After training, the diagnostic accuracies of the ANN were tested with a new set of DGA results and compared with those obtained by inspection and analysis.

A two-step ANN method [9] was used to detect transformer faults. The first ANN classified the fault as overheating, corona, or arcing; the second ANN determined if the cellulose was involved. The results of the two-step ANN approach were promising even with limited sample data; however, additional training data should be needed for the ANN to learn more complex relationships. Moreover, the accuracy of fault diagnosis can be improved choosing the proper value of learning rate, momentum factor and activation functions.

The ANN diagnostic method has proven very effective for diagnosing the insulating properties of an oil-insulated power apparatus [10]. A comparative study of ANNs in detecting incipient transformer faults was presented in [11], and the diagnosis accuracies obtained were about 87–100 %. An ANN trained with Levenberg–Marquardt learning algorithm demonstrated that the algorithm is apparently the fastest method for training a moderate-sized feedforward ANN [12].

Self-organizing polynomial modeling technique [13] was proposed to heuristically formulate the model using a hierarchical architecture with several layers of functional nodes using simple low-order polynomials. The networks can learn numerical, complicated, and uncertain relationships between dissolved gas content in transformers and fault conditions. A fuzzy-based vector quantization network was used to classify historical DGA data [14]. For each category of gas attributes, a learning vector quantization network was trained to classify potential faults caused by insulation deterioration. Remarkable classification accuracy has been achieved with substantially reduced training.

Evolutionary algorithms were used to automatically tune the network parameters (connection weights and bias terms) of the ANN to achieve the best model [15, 16]. The evolutionary algorithms based systems can identify complex relationships among the gases dissolved in transformer oil and corresponding fault types by combining the global search capabilities of evolutionary algorithms with the highly nonlinear mapping capabilities of the ANN.

Conventional ANN has difficulty determining the number of neurons in hidden layers, and training is time consuming. To overcome the drawbacks of traditional ANN, extension-based methods based on the matter-element model and extended relation functions have been used for diagnosing power transformer faults [17, 18]. A cerebellar model articulation controller neural network (CMACNN) method was presented for diagnosing power transformer faults [19]. The CMACNN fault diagnosis scheme functions like the human cerebellum and enables a powerful and efficient fault diagnosis. The results also confirm that multiple incipient faults can be detected simultaneously. An effective and flexible probabilistic neural network (PNN) overcomes the slow repeated iterative process and poor adaptation capability for structural data of the conventional ANN [20]; diagnostic results confirmed the effectiveness of the PNN approach.

Self-organizing map (SOM)-based approach to analyzing DGA data has demonstrated convincing performance in DGA for fault diagnosis [21]. The evolution of incipient faults can now be visualized by plotting DGA trajectories, and the incipient fault can thereby be monitored visually so that proper corrective actions can be taken at the right time. Studies have reported the use of wavelet networks (WN) and DGA samples for incipient fault detection in power transformers [22, 23]. A comparative study of evolving WN for incipient fault diagnosis in transformers indicated that the diagnostic accuracy and efficiency of five WN approaches are superior to those of conventional ANN and are suitable for fault diagnosis of power transformers [24].

The novel hybrid self-adaptive training approach-based radial basis function (RBF) neural network [25] showed several performance advantages over other ANN: better approximation capability, simpler network structure, and faster learning speed. The proposed method generated RBF neural network models based

Table 84.1 The advantages and disadvantages of artificial intelligence approaches

Method	Advantages	Disadvantages
ES	• Inference by specialized knowledge and experience	• Cannot obtain knowledge from new data samples by self-learning
	• Makes a decision similar to that made by human experts	• Relies heavily on knowledge engineers and domain experts
FLS	• Manages decisions that involve imprecise knowledge	• Requires identification of proper membership functions
	• Softens fault decision boundaries for solving uncertainty problems	• Cannot learn directly from data samples
ANN	• Accurately and efficiently captures input–output relations by training	• Accuracy depends on correct and complete training samples
	• Excellent interpolation and extrapolation capacity	• Difficulty in determining network structures and parameters

on fuzzy c-means and quantum-inspired particle swarm optimization (PSO), which can automatically configure network structures and automatically obtain model parameters.

84.4 Issuess for ANN Applications

Like expert system (ES), the ANN cannot directly handle fuzzy information. This limitation comes from the basic configuration of the network: knowledge is distributed over the entire pattern of weights, and the weights are involved in each decision. Moreover, operations of ANN are also obscured by nonlinearities. The ANN knowledge is discreetly distributed throughout the network according to the sample learning rather than stored in a knowledge base as in ES. When the difference between the training samples and the fault samples is very large, the reasoning used by ANN to reach a conclusion is not clear.

An ANN shares many similarities with a fuzzy logic system (FLS). They both use stored knowledge to make decisions about new inputs. Both can generalize; both produce correct responses despite minor variations in the inputs. Table 84.1 summarizes the advantages and disadvantages of artificial intelligence approaches for power transformer condition assessment. The performance of ES depends on the quantity and quality of the obtained knowledge. The FLS explicitly displays expert knowledge that is not extracted from the DGA data. The ANN performs in transformer fault diagnoses but the knowledge it captured remains hidden in the model. This paper suggests that hybrid intelligence-based systems, which combine an ES, FLS, ANN, and computational intelligence for diagnosing transformer faults, are the state-of-the-art condition assessment tools for power transformers.

84.5 Conclusions

This paper has reviewed literature on transformer fault diagnosis and the great progress made in recent decades. This review provides important information about research directions and trends in the field of transformer condition monitoring using ANN. Although condition assessment of ANN can offer early warning of insulation conditions, no single method can detect the full range of faults and reliably estimate remnant life. Each method has its own strengths and weaknesses. Moreover, a more useful method is to combine and integrate all the diagnosis results obtained from major DGA approaches to present an overall evaluation. Therefore, instead of using one diagnostic method, hybrid intelligent methods that combine the strengths of each method require further study to improve detection of incipient faults in power transformers.

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