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Fault Diagnosis of Power Transformers Using Computational Intelligence: A Review

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Abstract

This study reviews computational intelligence (CI) approaches for oil-immersed power transformer maintenance by discussing historical developments and by presenting state-of-the-art fault diagnosis methods. The CI-based approaches have emerged as rapidly evolving but highly effective approaches for using dissolved gas analysis (DGA) data for diagnosing power transformer faults. This study reviews the various CI-based methods reported in international journals, including fuzzy logic, neural networks, and evolutionary optimization-based approaches.

Keywords: Fault Diagnosis; Power Transformers; Computational Intelligence

1. Introduction

Computational intelligence (CI) techniques attempt to emulate human and biological reasoning, decision-making, learning and optimization by applying computing techniques that mimic adaptive evolution in living beings. The CI techniques can be either used individually or in combination with other techniques to form complex hybrid methodologies for achieving systems with enhanced capabilities, *e.g.*, a single system can make decisions under uncertainty by using fuzzy logic, learn and adapt by using neural networks, and undergo evolutionary optimization by using genetic algorithms. Most successful attempts to combine techniques confirm that fault diagnosis can greatly benefit from CI techniques. Fuzzy logic (FL) not only improves diagnostic decision-making under the uncertainty inherent in diagnostic information such as vague symptoms and ambiguous mapping of symptoms to their causes, it can also capture gradual system degradation. Artificial neural networks (ANN) identify faults by matching models and by learning new symptoms. Evolutionary algorithms (EA) can optimize diagnostic models as well as the diagnostic process itself by using various methods of tracking changes, which are sometimes gradual, in the diagnosed system.

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By calculating the maximum practicable operating efficiency and optimum life of power transformers, fault diagnostic systems that apply CI techniques minimize the risks of premature failures and generate optimal system maintenance strategies. Because condition-based monitoring uses advanced fault diagnostic techniques to identify on-line and off-line incipient faults and to provide real-time transformer conditions, it can also optimize maintenance schedules. Advances in computational hardware facilities and software data analysis techniques now enable the in-depth understanding of various phenomena affecting transformer operations. Advanced CI techniques enable system operators to interpret various fault phenomena and to detect incipient faults. The CI techniques enable researchers to analyze fault phenomena and to use the correlations in data for analyzing faults and for diagnosing transformer faults with high accuracy.

This study surveys the many CI techniques applied in evaluating oil-immersed power transformer conditions in attempts to reduce operating costs, to enhance operational reliability, and to improve power supply and service to customers. This paper first introduces various methods of transformer fault diagnosis by CI techniques. Proposed CI methods for monitoring and diagnosing oil-immersed power transformers are then reviewed and compared.

2. Fault Diagnosis Using Computational Intelligence

Recent studies have applied CI in transformer fault diagnosis. Decision making under the uncertainty inherent in diagnostic data has been successfully characterized by using CI methodologies such as FL, ANN, and EA. The FL is a remarkably simple way of drawing definite conclusions from vague, ambiguous or imprecise information. In a sense, FL resembles human decision making in its capability to obtain precise solutions based on approximate data. Of the many ways that FL can implemented in system diagnosis, the most common is constructing a rule set from which conclusions and actions can be drawn.

The expert system (ES) and FL approaches involve human expertise and have many useful applications. However, the major challenge is transforming the experience acquired by experts into decision rules and membership functions. Diagnosis results also depend largely on the complete and accurate representation of accumulated human experience or knowledge. The FL provides a remarkably simple way to draw definite conclusions from vague, ambiguous or imprecise information. In a sense, FL resembles human decision making in its capability to find precise solutions based on approximate data. The FL can be used in several different ways to implement a diagnosis system, and the most common one is to construct a set of rules from which conclusions and actions can be drawn.

Although many fuzzy expert systems (FES) have been developed in recent years [1-6], none can learn from previous diagnostic results because their membership functions and diagnostic rules are determined by practical experience or by trial and error methods. The evolutionary programming (EP)-based fuzzy logic systems (FLS) for identifying incipient faults in power transformers has been developed [3-4]. Based on the cumulative data obtained in dissolved gas tests and the actual fault types identified, the proposed EP-based FLS automatically modifies the fuzzy if-then rules and simultaneously adjusts the corresponding membership functions. An FLS that can diagnose multiple faults in a transformer and quantitatively indicate the likelihood/severity of each fault was proposed in [5]. Tests in numerous transformers confirm that critical conditions can be reliably identified in transformers by monitoring insulation deterioration at each fault location. A novel FL-based DGA diagnostic tool [6] used a medical-style fuzzy pattern recognition technique for interpreting results. This approach enables highly reliable assessments of the relative severity of multiple faults.

The mechanism of a fault diagnosis by ANN differs from that by ES. Unlike ES, which stores knowledge in a knowledge base, ANN knowledge is discreetly distributed throughout the network according to sample learning. Although an ANN is highly capable of acquiring knowledge, it also has many drawbacks. For example, when the difference between the training samples and the fault samples is very large, the reasoning used by ANN to reach a conclusion is questionable. In [7], a two-step ANN

method was used to detect faults with or without cellulose involvement. The first ANN classified the fault as overheating, corona, or arcing while the second ANN determined whether cellulose was involved. The results of the two-ANN approach were promising even with limited sample data. However, additional training data were needed for the ANN to learn more complex relationships such as classes of specific faults. The use of ANN in existing diagnostic methods has proven very effective for diagnosing the insulating properties of an oil-insulated power apparatus [8]. A comparative study of the efficiency of ANNs in detecting incipient transformer faults was presented in [9]. The rate of successful diagnosis obtained by an ANN trained using five diagnostic criteria commonly used in DGA was dependant on the criterion under consideration, with values in the range of 87–100%. In [10], an ANN was trained by Levenberg-Marquardt learning algorithm, which is reportedly the fastest method for training a moderate-sized feedforward ANN. Both ES and ANN have weaknesses. The best way to overcome the shortcomings is by combing ES with ANN as a whole. A combined ANN and ES tool for transformer fault diagnosis was presented in [11].

Two EA-based ANNs for assessing power transformer condition were presented in [12-13]. The proposed EAs automatically tune the network parameters (connection weights and bias terms) of the ANN to achieve the best model. The systems presented in these studies effectively identify complex relationships among the gases dissolved in transformer oil and corresponding fault types by combining the global search capabilities of EAs with the highly nonlinear mapping capabilities of the ANN. By directly acquiring experience from training data, an ANN avoids several limitations of ES. However, conventional ANN has limited effectiveness for 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 power transformer fault diagnosis [14-15]. Such methods identify incipient faults by the degree of relation.

A new self-organizing polynomial network was proposed in [16] for providing intelligent decision support in transformer fault diagnosis. The technique heuristically formulates the model using a hierarchical architecture with several layers of functional nodes of simple low-order polynomials. The networks can learn complex and uncertain numerical relationships between dissolved gas content in transformers and fault conditions. A fuzzy-based vector quantization network can classify historical DGA data according to gas attributes [17]. For each category of gas attributes, a learning vector quantization network is trained to classify potential faults resulting from deteriorated insulation. Remarkably high classification accuracy can be achieved with substantially reduced training.

Because of its powerful visualization capability, fast and efficient learning process, and comparatively light use of computing resources, the self-organizing map (SOM)-based data mining approach to analyzing DGA data has convincingly demonstrated good performance in fault diagnosis by DGA [18]. Because the SOM diagnoses all DGA records, it eliminates the uncertainty and ambiguity observed in most conventional DGA interpretation schemes. The evolution of incipient faults can now be visualized by plotting DGA trajectories, and the incipient fault can thereby be monitored visually so that corrective action can be taken at the proper time.

A cerebellar model articulation controller neural network [19] functions like the human cerebellum in its use of IEC standard 599 to generate training data and in its self-learning characteristics and generalization, which enable a powerful and efficient fault diagnosis. Because the performance of ANN applications is limited by their slow and repetitive iterative processes and by their poor adaptation to structural data limits, an alternative diagnostic system based on probabilistic neural network (PNN) was proposed in [20]. The effective and flexible PNN avoids the drawbacks of conventional ANN.

Wavelet networks (WN) developed in recent years can efficiently model nonlinear signal processing, and some studies have reported the successful use of WN and DGA samples for incipient fault detection in power transformers [21-22]. Although WNs trained by binary encoding genetic algorithms (GA) have demonstrated good diagnostic capability, unsolved problems include the need for manually setting the network structure and parameters. A comparative study of evolving WN for incipient fault diagnosis in

power transformers was presented in [23]. Comparisons of diagnostic accuracy and efficiency showed that the five WN approaches proposed in that study are superior to those of conventional ANN and are suitable for fault diagnosis of power transformers.

Clustering techniques are also widely used to enhance fault diagnosis accuracy by using DGA data to enhance fault classification. The grey theory combines clustering analysis, relational analysis, prediction, and grey system decision making. The grey clustering analysis can process numerical data without adjusting parameters [24]. Grey prediction–clustering analysis [25] has proven effective for fault diagnosis by DGA in oil-immersed transformers. Because decomposing overall key gases and monitoring conditions is highly time consuming when using DGA procedure, the grey prediction GM(1,2) model uses variant hydrogen data to forecast trends in both combustible and non-combustible gases and uses grey clustering analysis to diagnose internal faults.

The hybrid self-adaptive training approach-based radial basis function neural network proposed in [26] showed several performance advantages over other ANNs, including better approximation capability, simpler network structure, and faster learning speed. The proposed method automatically configures network structures and automatically obtains model parameters. Bootstrap and genetic programming (GP) were implemented to improve the accuracy of DGA in identifying power transformer faults [27]. The features extracted by GP were then used as the inputs to ANN, support vector machine (SVM) and K-nearest neighbor (KNN) classifiers used for fault classification. The classification accuracies of the combined GP-ANN, GP-SVM, and GP-KNN classifiers were compared with those derived from ANN, SVM, and KNN classifiers, respectively. The test results confirmed that Bootstrap and GP preprocessing improved the accuracy of fault diagnosis.

The multi-layer SVM classifier used for diagnosing power transformer faults in [28-29] was trained with samples extracted by data processing. In the SVM with GA (SVMGA) developed for fault diagnosis of a power transformer in [30-31], the GA selects appropriate free parameters of SVM. The experimental results indicate that the SVMGA method achieves higher diagnostic accuracy compared to three-ratio IEC, normal SVM classifier and ANN. In [32-34], a particle swarm optimization (PSO)-based encoding technique improved classification accuracy by removing redundant input features that confuse the classifier while simultaneously optimizing the kernel parameters and used PSO algorithm to improve ANN and SVM performance. An innovative method based on ANN and multi-layer SVM was proposed, and a clonal selection algorithm-based encoding technique was applied to improve classification accuracy. For accurately forecasting faults based on DGA of oil-immersed transformers, a fuzzy information granulated PSO-SVM regression model was proposed in [35]. By transforming the original gas data into a sequence of granules, the implemented fuzzy information granulation approach provides a good overview because only the most dominant component data are retained in the original temporal series.

An artificial immune network classification algorithm (AINC), inspired by the capability of the natural immune system to respond to an almost unlimited multitude of foreign pathogens is proposed in [36]. The AINC responds to transformer fault samples by mimicking these adaptive learning and defense mechanisms of the immune system. Test results showed that using a limited number of antibodies to represent structures and features in all fault samples enhances the dynamic classification accuracy of the AINC.

Transformer fault diagnosis can be considered a multiple-attribute decision-making problem. An evidential reasoning algorithm [37-38] produces an overall diagnosis regarding transformer condition assessment by aggregating judgments obtained by conventional DGA methods. An integrated model based upon the fuzzy approach and evidential reasoning decision-making approach to condition assessment of power transformers was presented in [39]. The model uses an index system to consider the results of DGA, electrical testing, and oil testing in the final transformer condition assessment. The two levels of the model are a fuzzy model and an evidential reasoning model. The decision-making procedure based on the proposed integrated model enables accurate assessment of transformer condition.

3. Conclusions

This overview of computational intelligence applications in DGA of power transformer faults can be helpful to academics, researchers and engineers when designing or maintaining power transformers. Notably, not all the combinations of gas ratios proposed in a fault can be mapped to a fault type as described by the diagnostic criteria. Different transformer DGA diagnostic methods may give varied analysis results, and excessive data may complicate the final decision making by engineers. Another issue is that not all DGA approaches can accurately identity transformer faults in borderline cases. Therefore, integrating available transformer DGA data in a balanced overall diagnosis is essential. Additionally, although accurate transformer diagnosis depends on the experience of human experts in addition to standard diagnostic techniques, many researchers have attempts to standardize the decision processes used to guide DGA for evaluating transformers conditions. Such attempts include fuzzy expert systems and data analysis using fuzzy logic systems or artificial neural networks, which have limited capability to represent a DGA interpretation as a classification or pattern recognition problem.

Most interpretations of DGA data are based solely on the experience of human experts and their application of standard techniques. The options and criteria for generating diagnosis reports may differ among organizations and utilities. Determining the relationships between gas types and faults is a perplexing task because complex gas combination patterns may result from different faults. For these reasons, this study reviewed various computational intelligence techniques for reliably assessing transformer conditions and for solving complex decision making problems. A decision maker faces many uncertainties when diagnosing transformer faults. In the case of DGA, uncertainties may arise from vague, imprecise and incomplete diagnoses derived by conventional DGA methods. As discussed above, different transformer diagnosis techniques may give different analysis results, which can complicate the overall assessment by engineers. Therefore, combining available transformer diagnoses in a balanced overall condition assessment is a highly complex problem, and a suitable methodology is needed to handle various diagnostic information. In traditional DGA, however, fault diagnosis using crisp decision boundaries results in fault probabilities of either zero or one, which do not reveal the trends in faults or their severity. Moreover, not all combinations of gas ratios presented in a fault can be mapped to a fault type using conventional diagnostic criteria. Therefore, accurately interpreting such missing combinations of gas ratios, which are not reported in the IEEE and IEC DGA standards for DGA result interpretations, requires further study.

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