The Compare of Transformer Fault Diagnosis Based on Feature Selection and Parameter Optimization and Fuzzy Reasoning Spiking Neural P Systems

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Abstract

Nowadays, Due to existing complexity and changing organizations using accurate and modern tools is compulsory needed on performing the maintenance strategies. Human's improvements during last decades about gathering and storage the results and data cause the organizations have a huge dimension of data related to maintenance. Detection techniques based on dissolved gas analysis (DGA) have been developed to early fault detection in power transformers. Transformer, as one of the most important parts in power supply system, can put the reliability of power supply and the safe operation of electrical system in an entire electricity network into a great danger. Making decision on the strategy requires knowledge that matches reality maintenance organization. On the other hand, it requires a good knowledge and proper analysis of data used. So using data and information and applying them during the strategic follow-up implementation mainstream for Histological maintenance and repair are of great importance. The purpose of current paper is based on a review of 35 refereed article and dissertation that focused on transformer fault diagnosis based on feature selection.

Key words: Fault Diagnosis, Transformer, Parameter Optimization, Feature Selection

Introduction

Today the electric networks become larger and more complex with big data received from a lot of events in different sections, among which power transformer is one of the most important sections in power systems. Any fault in the transformer can cause a severe outage, which therefore necessitates continuous monitoring and diagnostics of its operation. In this sense, any faults caused in power transformers will produce a lot of alarms, some of which are uncertain, incomplete and misinformed, thus, it is necessary to develop a good method to help dispatchers evaluate where the faults are and which transformer fail. However transformer fault diagnosis decision-making based on dissolved and free gas analysis (DGA) diagnostic methods may give conflict analysis results and complicate the final decision making by operators. In fact, intelligent fault diagnosis systems are necessary to deal with changes in typology of power network to fast diagnose the fault stat and location of power transformers faults.

In recent years, artificial intelligence approaches have been proposed with high performance programs and in developing more smart diagnostic techniques for power transformers based on DGA methods, such as support vector machine(Lv,et al,2005), fuzzy logic(Liao,et al,2011), neural network(Naresh,et al,2008), grey clustering(Lin ,et al,2009), wavelet networks(Chen ,et al,2009). However, these approaches are using several techniques for detecting transformer faults based gases concentrations in the oil and DGA is recognized as the most informative method. This method involves sampling the oil and testing the sample to measure the concentration of the dissolved gases. The standards are associated with sampling, testing, and analyzing the results such as the standard IEC 60599.

Detection techniques based on dissolved gas analysis (DGA) have been developed to early fault detection in power transformers. Various methods based on DGA such as IEC, Roger, Orenburg, etc. However, these methods have been used in different problems with different standards there. Also, it is difficult to detect accurately by DGA without experts. Now we want detect transformer errors and prevent serious accidents by using data mining techniques and data from the test results of DGA transformers oil and clustering and classifier ensemble. With the development of industrial automation and increasing the number of physical machinery and equipment in the organizations, the investment in machinery and the physical capital witnesses a growing trend and subsequent maintenance costs also include a large amount of corporate expenditures. One of the basic costs includes maintenance and repairs which occupies from 15 to 70 percent of production costs based on the type of industry (Bevilacqua, M., Braglia, M, 2000). The amount of spending on maintenance and control of a selected group of companies in 1989 was 600 Billion dollars (Chan, F.T.S., Lau, H.C.W., Ip, R.W.L., Chan, H.K., Kong, S, 2005). The annual maintenance costs, in comparison with the first annual rotation in some European countries on the basis of research results in 1999 in the EFNMS was as follows: Belgium 4,8%, France 4%, Ireland 5.1%, Netherlands 5%, Italy 5.1%, Spain 3.6% and the UK 3.7% (European Federation of National Maintenance Societies .www.efnms.org). The increased maintenance costs and more attention on the management of their organizations on this issue made them seek profits and reduce costs in their maintenance.

Making decision on the strategy requires knowledge that matches reality maintenance organization. On the other hand, it requires a good knowledge and proper analysis of data used. So using data and information and applying them during the strategic follow-up implementation mainstream for Histological maintenance and repair are of great importance. In addition, IT development and the exceptionally fast access to information are increased. The advancement of technology has led to increased corporate accessing the vast resources; and the possibility of an investigation has provided numerous advantage, and on the other hand, this leads to many organizations be drowning in data. Lack of knowledge or lack of sufficient data and analysis makes strategic use of information in many cases impossible and it has changed to be one of the management challenges (Hand. D.J, 1998).

Transformer Fault Diagnosis

Nowadays, Due to existing complexity and changing organizations using accurate and modern tools is compulsory needed on performing the maintenance strategies. Human's improvements during last decades about gathering and storage the results and data cause the organizations have a huge dimension of data related to maintenance. The main note in such database is the information and knowledge that is discovered and the use of intelligent and structural methods are needed. Data mining is a new scientific field of recycling information from database. These techniques by recognizing effective factors on events would make analysis, programming, controlling and inspecting accessible. Transformer, as one of the most important parts in power supply system, can put the reliability of power supply and the safe operation of electrical system in an entire electricity network into a great danger. Dissolved Gas in Oil Analysis (DGA) is presently the easiest and simplest way for fault diagnosis of oil-immersed transformers. The method requires no understanding of transformers' complicated internal structure in depth. It is only needed to analyze the actual data of dissolved gas in oil of a transformer to obtain the current working status of the transformer. Therefore, the correct selection of features of dissolved gas data can improve efficiency of transformer fault diagnosis. Failure of transformer is very complex, dissolved Gas in Oil Analysis (DGA) is presently the easier and simpler way for fault diagnosis of oil-immersed transformers. The correct selection of features of dissolved gas data can improve efficiency of transformer fault diagnosis. SVM is more effective than traditional mathematic model to describe the type of fault of transformer. As for the problem of difficulty of determining parameters in SVM applications, genetic algorithm (GA) was used to select SVM parameters. The test results show that this GA-SVM model is effective to detect failure of transformer (Han Han, Wang Hou-jun, Dong xiucheng, 2011).

Transformer, as a most important part in power supply system, can put the reliability of power supply and the safe operation of electrical system in an entire electricity network into great danger. Dissolved Gas in Oil Analysis (DGA) is presently the easier and simpler way for fault diagnosis of oil-immersed transformers. The method requires no understanding of transformers' complicated internal structure in depth. It is only needed to analyze the actual data of dissolved gas in oil of a transformer to obtain the current working status of the transformer. Therefore, the correct selection of features of dissolved gas data can improve efficiency of transformer fault diagnosis. In recent years, many methods, like expert systems, artificial nerve network, and fuzzy inference, etc., have been applied in transformer fault diagnosis and achieved greatly. However, expert systems have difficult to gain complete knowledge and should improve explicit quality of system rules as well as system robustness; artificial nerve networks have the problem of slow convergence rate and are easy to fall into local extremum; fuzzy clustering analysis is hard to ensure the reasonability of its classification when analyzing DGA data with high dimension and strong de-centrality. Support Vector Machine (SVM) was proposed by Vapnik, etc (Vapnik, 2004). Based on the structural risk minimization in Statistic Learning Theory. In order to improve popularization capability of learning machine, searching for global optimal solution can achieve good performance. Supporting Vector Machine shows its unique advantages to solve small number of samples, non-linear and high dimensional pattern identification. There should be good perspective if SVM is applied to transformer fault diagnosis. As for the problem of difficulty of determining parameters in SVM applications, this paper uses genetic algorithm (GA) to select SVM parameters and proposes SVM transformer fault diagnosis based on parameter optimization.

Supporting Vector Machine Principle (SVMP)

The SVM theory for classification is illustrated in Figure 1, H refers to separating hyper plane, and the so-called optimal separating line means to realize the maximum margin on the premise of separating the two types correctly. When separation under current dimensional space is infeasible, you can map it to a high dimensional space and then calculate hyper plane H through kernel function.

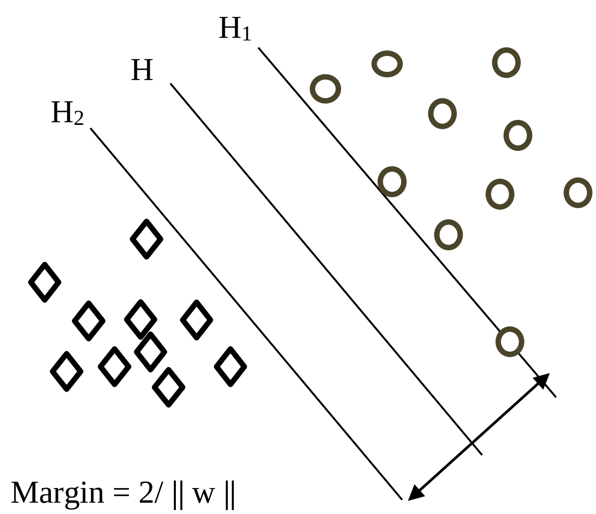

Figure.1 Optimal separating hyper plane

SVM Optimal Separating Hyper plane

If there is a sample set satisfying: $(x , y ,i) = 1,...,n$, $x \in R$, $y_d \in\{+1,-1\}$ When the optimal separating hyper plane cannot separate the two points completely while hoping to obtain a balance between empiric risk and generalization ability, a relaxation factor ε is introduced:

$$y_i [(\omega \cdot x_i) + b] -1+ \varepsilon\, i \geq 0,\ i = 1,... \qquad (1)$$

When $0 < \varepsilon_i < 1$, sample point x_i can be classified correctly; but when $\varepsilon_i \geq 1$, the classification of sample point *xi* has error, so an error classification penalty coefficient C is introduced. When the data is linearly inseparable, the input can be mapped into a high-dimensional space for

classification. According to the related functional theory, the dot product calculation in high-dimensional space can be transformed into a kernel function $K(x_i, x_i)$ in low-dimensional space on the premise of satisfying Mercer condition.
A Lagrange function (Lagrange multiplier: $a_i \geq 0$) is introduced:

$$L(\omega, b, a) = \frac{1}{2}\|\omega\|^2 - \sum_{i=1}^{n} a_i \left[y_i(\omega . x_i + b) - 1\right] \quad (2)$$

Solving the following quadratic programming problem:

$$\begin{cases} \max \sum_{i=1}^{n} a_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} a_i\, a_j y_i y_j k(x_i . x_j) \\ \text{S.t} \qquad C \geq a_i \geq 0 \quad i = 1, \dots, n \\ \sum_{i=1}^{n} a_i\, y_j = 0 \end{cases} \quad (3)$$

A Classification Function can Be obtained:

$$f(x) = sgn\{(\omega . x) + b\} = sgn\{\sum_{i=1}^{n} a_i^2 y_i k(x_i . x) + b^2\} \quad (4)$$

Where a_i^* refers to optimal solution, b_i^* refers to classification threshold and $k(x_i.x)$ is a kernel function.

SVM classification algorithm

1. One-to-many classification algorithm:

This method constructs *k* SVM classifiers for all *k* types of samples. Each classification has the data of one type as its positive type, and others as its negative type. Trial samples are put into *k* clusters to determine the type of the samples. Obviously one-to-many algorithm has data skew, that is, the data of the negative type is more than that of the positive type.

2. One-to-one classification algorithm:

This method constructs a SVM classifier by any two types of samples in the *k* types of samples, in total of $k(k-l)/2$ classifiers. Then, trial samples vote and the classifier having most votes is the winner, that is, the classification of the samples.

3. DAGSVM algorithm:

The algorithm combines SVM and a decision tree. The procedure is similar to one-to-one classification algorithm, which is to construct binary classifier. The difference is that binary acyclic digraph is used in the procedure.

4. Tree Supporting Vector Machine Multi-classification:

It is similar to construct a binary tree. From the root node, SVM classifies the node into two types, and then carries out classification for sub-types until only one type is left. The number of SVM used in the method is relatively small.

SVM Parameter Optimization

1. GA algorithm

GA is a global optimization based on natural selection and natural genetics, using three basic gene operations – reproduction, cross over and mutation – to calculate extremum for multi-variable functions. Genetic algorithm is to implement operations on individuals in a population. It does not directly deal with parameters in domain space, but processes individuals of chromosome (Gene chain encoding) instead. Simulating that organisms show different vitality depending on organisms' fitness, the fitness of chromosome is determined. The larger the fitness is; the higher possibility the chromosome is being selected so that a benign population can be reserved. The individuals in the population can be optimized generation by generation and gradually approach optimization. The Main genetic operators are: selection, cross over and mutation:

Selection: To select according to the value of fitness of each individual. The individual with higher fitness has bigger probability to be inherited by the population of next generation. The individual with lower fitness has smaller probability to be inherited by the population of next generation. So the fitness of individuals in the population can constantly get closer to optimization.
Cross-over also called regrouping: To select two individuals from the initial population and exchange the value of some locus of two individuals. Cross-over operator can generate a progeny and the progeny inherits basic features from its parent. And diversity is added to the progeny.
Mutation: To randomly change the locus values in an individual's encoding string with small Probability.

2. GA parameter selection

In GA, the running parameters needed to be determined include mainly the size of population, crossover probability, mutation probability, and termination algebra. These parameters have great impact on the running performance of GA and must be selected carefully. The initial size of the population – p size – is set to be 40 with the maximum algebra – maxgen - set to 50, crossover probability – pc –set to 0.8, and mutation probability – pm –set to 0.05.

Transformer fault diagnosis model

1. *Feature selection for Dissolved Gas in Oil in Transformer Diagnosis*

DGA is an easier and more effective method for oil-immersed transformer fault diagnosis. The main parameters include H2, CH_4 , C_2H_4 , C_2H_6 , C_2H_2 , etc. The common way is to directly map these feature values to classify domain for analysis. It lacks the analysis for closeness of association between each kind of gas and the types of fault, and has its blindness. It is because it is important for fault classification to find the parameters that can show distinct difference between different faults, not to focus on data integrity description. Therefore, it is necessary to extract representative features of faults from hose parameters to improve the accuracy of fault classification.

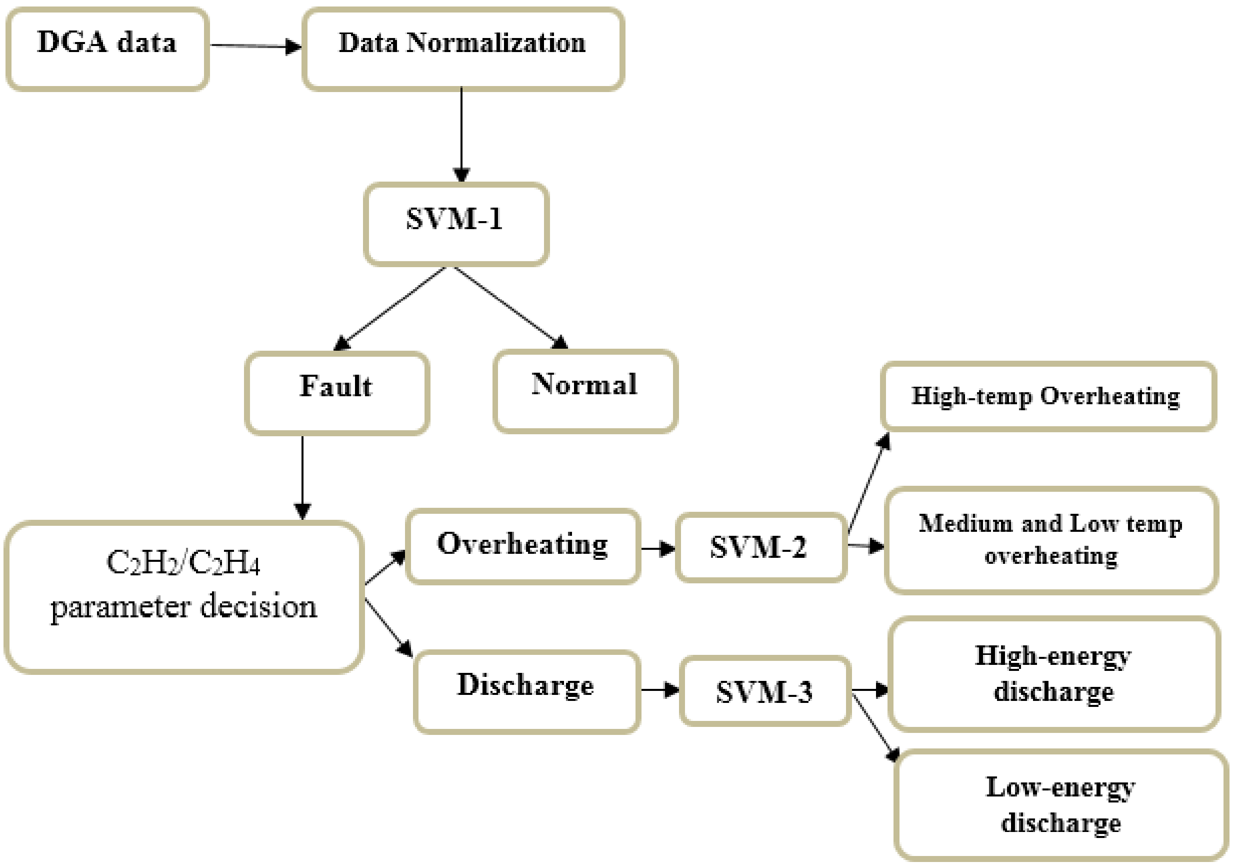

Figure 2: Transformer Fault Diagnosis Model

In the circumstance of distinguishing between normal and fault, the paper uses Preventive Test Code for Electric Power Equipment (Wu Xiaohui, Liu J iong, Liang Yongchun, Wang Xiaoming, Li Yanming, 2007) as its criteria. However, it is complicated to put in actual implementation. This paper starts from the value of dissolved gas in oil and then determines if there exists a fault or not. IEC Three-ratio encoding is more effective to detect latent faults in early stage in actual applications (Rogers R, 1978). The parameters of C_2H_2/ C_2H_4 overlaps in small range (ZHANG Rui, GUO Ruijun , LI Hua , YAN Zhang,2005), during the faults like discharging and overheating. Using this parameter to determine whether a transformer is over heated or has discharging fault can have the accuracy as high as 96%. The accuracy gets lower when other parameters are introduced. Therefore, this paper uses the parameters of C_2H_2/ C_2H_4 to diagnose discharging and overheating faults.

2. Diagnosis model generation

Using Tree SVM Multi-classification, there are 3 SVM classifiers for monitoring five working status: normal, high-energy discharge, low-energy discharge, high-temperature overheating, and medium and low temperature overheating? The diagnosis procedure is as following, DGA data is sent to SVM-1 after being normalized and then to be classified into normal status and fault status. The data classified as being fault is given C_2H_2/ C_2H_4 parameter decision. The parameter value is analyzed by using 0.1 as classification threshold recommended by Improved Three-ratio method which is more reasonable than using 0.5 as threshold in Rogers's Ratio. The C_2H_2/ C_2H_4 parameter lower than 0.1 is determined to have an overheating fault, and the data enters SVM-2 classifier to be classified into high temperature overheating and medium-and-low temperature overheating. And the C_2H_2/ C_2H_4 parameter higher than 0.1 is determined to have a discharge fault and the data enters SVM-3 classifier to be classified into high-energy discharge and low-energy discharge.

Simulation results

Essentially, This paper uses 193 of transformers' historic status data as samples, among which 21 are examples in normal status, 41 in medium and low temperature fault status, 33 in high-temperature overheating fault status, 36 in low-energy discharge fault status, and 62 in high-energy discharge fault status. The number of train and test data was shown in table. 1.

	Fault				
	Normal	High-temp Overheating	Medium and Low temp overheating	High-energy discharge	Low-energy discharge
Number of Train data	10	15	21	30	16
Number of Test data	11	18	20	32	20

Table 1: The training and checking sample sets of states

Under the running environment of MATLAB6.5, the average of parameter optimization is 7.92s with diagnosis total accuracy of the validation set as high as 92.0792%.The accuracy and best value of parameter c and g in SVM1-3 was shown in table 2.

	Best c value	**Best g value**	**accuracy**	**Total accuracy**
SVM1	3.4294	82.4201	97.0296%	92.0792%
SVM2	31.5890	7.3625	92.1053%	
SVM3	25.9668	0.3378	96.1538%	

Table 2: Optimal parameters of GA-SVM and Classification accuracy

Table 2.3 give the Comparison of diagnostic results among IEC three ratios, BPNN, GA-SVM.

	IEC three ratios	BPNN	GA-SVM
Accuracy rate%	79.2079	84.1584	92.0792

Table 3: Comparison of diagnostic results

Power Transformer Fault Diagnosis

Fuzzy Reasoning Spiking neural P systems (FRSN P systems) as a membrane computing with distributed parallel computing model is a powerful and suitable graphical approach model in fuzzy diagnosis knowledge. In a sense, this feature is required for establishing the power transformers faults identifications and capturing knowledge implicitly during the learning stage, using linguistic variables, membership functions with “low”, “medium”, and “high” descriptions for each gas signature, and inference rule base. Membership functions are used to translate judgments into numerical expression by fuzzy numbers. The performance method is analyzed in terms of four gas ratio (IEC 60599) signature as input data of FRSN P systems. Test case results evaluate that the proposals method for power transformer fault diagnosis can significantly improve the diagnosis accuracy power transformer (Yousif.et al, 2016).

As a newly attractive research field of computer science, fuzzy reasoning spiking neural P systems (FRSN P systems), formally introduced by Hong Peng 2013 (Peng.et al ,2013), which are a class of SN P systems with distributed and parallel computing models. In this paper, FRSN P systems are introduced as diagnostic technique to tackle the power transformer faults based on DGA, and can be viewed as a directed graph; reasoning steps and transmits pulses from input proposition neurons to the output proposition neurons under the control of firing/spiking mechanism of neurons (Wang,J,et al ,2013).

Furthermore, this method uses the IEC ratio gases as input signature to FRSN P systems diagnosis model to establish the fault reasoning results with confidence levels, based on confidence levels for different fault types of transformer can get decision which one faulty. In addition, fault diagnosis process is expressed by assume the initial parameters of FRSN P systems model with linguistic terms to give operators more accuracy to describe the degree of uncertainty fault information(Wang,T,et al,.2014). This paper is organized as follows. Section 2 provides the definitions of FRSN P systems. Section 3 presents power transformer DGA based on FRSN P systems and fault diagnosis model. Section 4 discusses the test results. Finally, conclusions and proposals for future work are given in Section 5.

FRSN P Systems Fault Diagnosis Based on DGA

Dissolved gas analysis (DGA) is powerful technique that has been used to identify the incipient power oil transformers faults. In this technique, the faults can be identified according to the gases concentrations dissolved in oil of transformer, hydrogen (H_2), (CH_4), (C_2H_6), (C_2H_4), (C_2H_2); various interpretative DGA methods have been established such as Gas key method, IEC ratio method, and the graphical representation method (Bacha,et al,2012). In this study, we propose adaptive IEC ratio (AIEC ratio) method as the first incipient diagnosis of the possible faults of oil transformer in order to identify the fault types based incipient possible faults diagnosed by IEC ratio method, we use the ratio of gases as input data to FRSN P systems diagnosis model and the output fuzzy reasoning results.

Adaptive IEC Ratio with Fuzzy Representation

In IEC ratio method, five gases, H_2, CH_4, C_2H_2, C_2H_4 and C_2H_6, as concentration gases in oil transformer, are used. From these gases, three ratios are produced; $R_1 = (C_2H_2/ C_2H_4)$, $R_2 = (CH_4/ H_2)$, $R_3 = (C_2H_4 /C_2H_6)$ Table 2.4 shows that the transformer DGA faults are classified to six types, low energy discharge, high energy discharge, partial discharge, low thermal, medium thermal and high thermal faults, which are widely used to interpret the DGA. From the operator expert knowledge, in real world fault diagnosis events, in this study linguistic terms are always used to express the fault types related to gas concentrations ratio, such as $(C_2H_2)/(C_2H_4)$ very low, low, medium, high and very high in the transformer oil.In this proposed method, we use the linguistic terms to describe a degree of gas concentrations ratio to become more capable to use fuzzy knowledge with fuzzy numbers. We can use adaptive IEC ratio (AIEC ratio) to deal with FRSN P systems and graphically represents with fault diagnosis model from input proposition neurons by reasoning steps to reach the final rezoning results after computation halts in output proposition neurons.

Table 4 shows the interpreting fault types of IEC 60599 standard with values of three gas ratios of R_1, R_2 ,R3 (Standard IEC 60599 ,2007).

R_1 **C_2H_2/C_2H_4**	**R_2** **CH_4/H_2**	**R_3** **C_2H_4/C_2H_6**	**Fault type**
$R_1 > 1.0$	$0.1 \leq R_2 \leq 0.5$	$R_3 > 1.0$	D1
$0.6 \leq R_1 \leq 2.5$	$0.1 \leq R_2 \leq 1.0$	$R_3 > 2.0$	D2
$R_1 < 1.0$	$R_2 < 0.1$	$R_3 < 0.2$	PD
$R_1 < 1.0$	$R_2 > 1.0$	$R_3 < 1.0$	T1
$R_1 < 1.0$	$R_2 > 1.0$	$1.0 \leq R_3 \leq 4.0$	T2
$R_1 < 1.0$	$R_2 > 1.0$	$R_3 > 4.0$	T3

Table 4. IEC60599 gas ratio limits.

2.3.6 FRSN P Systems Fault Diagnosis

FRSN P systems diagnostic model based DGA, we can constrict the graphical diagnosis model of FRSN P systems with reasoning steps to identify the fault type of oil transformer, see Figure 4. Three ratios of R_1,R_2 and R_3 , each ratio with five levels of very low(VL), low(L), medium(M), high(H) and very high(VH), respectively, serves as input proposition neuron with initial values and after reasoning steps , six fault types are identified by confidence levels to give us which one has more confidence with linguistic expression. This allowed us to diagnose the fault with more information and more correct decisions. From the historical database of transformer, we can use the confidence level of each fault dissolved gas to use in the matrix calculations of proposed method based on their experience operator and also we have to determine the certainty factor to represent the degree of confidence fault occurs. The rule neurons with synapse input neurons, the confidence (0.8) and other rule neurons (1.0) processing, rule-based reasoning, symbolic representation, and parallel computing. It makes transformer fault diagnosis based on DGA more accurate, fast and adaptive to system changes.

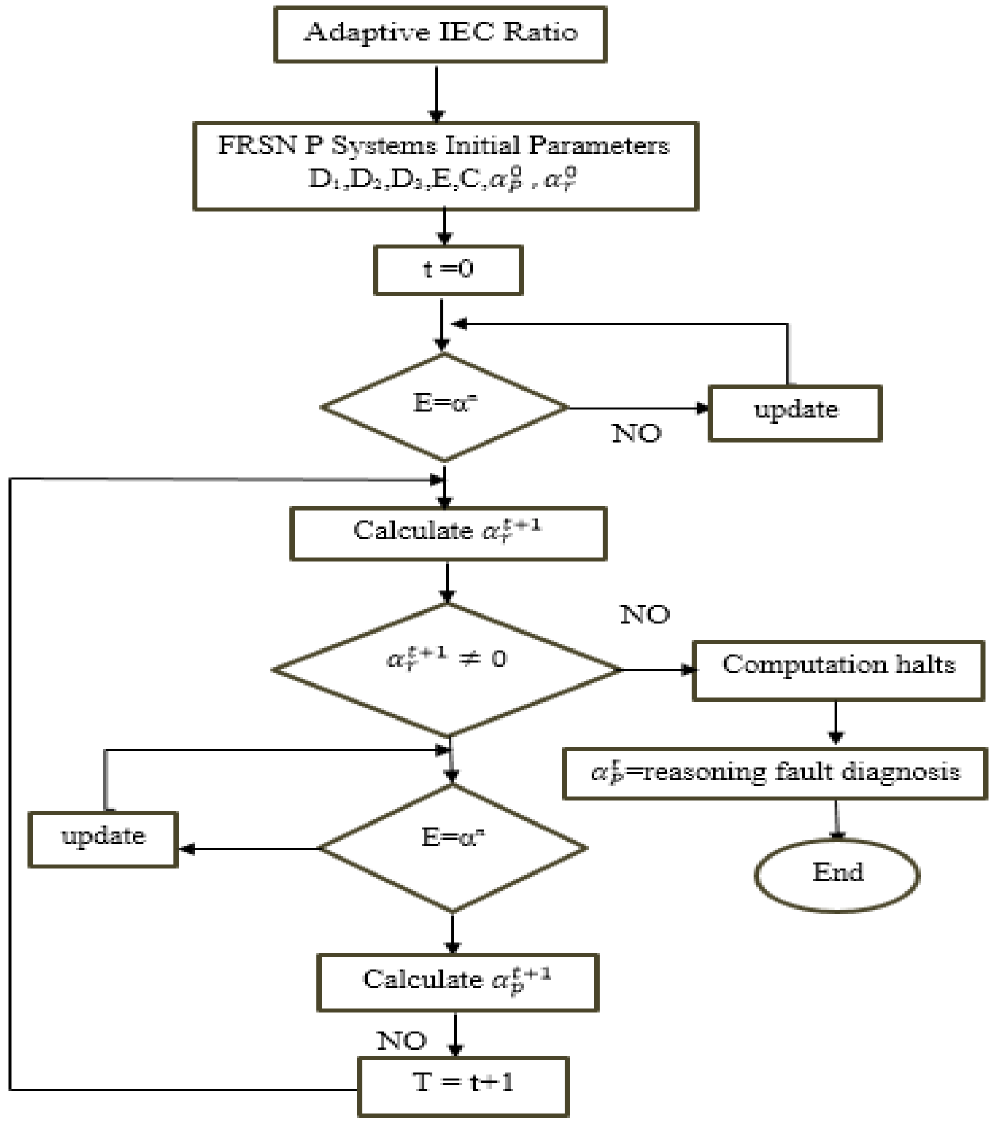

Figure 3. FRSN P systems transformer fault diagnosis flow chart.

In this graphical model, IEC ratio with fuzzy representation as linguistic terms can build the FRSN P systems diagnostic model as shown in Figure 3.

Discussion and Results

In these cases, comparative studies of FRSN P systems with ratio support vector machine method (SVMR) and graphical support vector machine (SVMG), considered the same cases fault situations, the status tested gas data of transformer for eight tested cases are shown in Table 4, and the FRSN P systems diagnosis results are shown in Table 2.4. From the case studies (1, 2, 3), the

fault type is Thermal faults T < 300◦C (T1) with confidence level (0.72), case studies (4, 5, 6) their isn't fault with confidence level (0.08), case (7) is High energy discharge (D2) and case (8) is Thermal faults 300 < T < 700◦C (T2) fault with confidence level (0.72). SVM can solve the problem of multi-classification for small number of samples and non-linear data in a fairly good way, applicable in transformer oil chromatography fault diagnosis. The paper uses GA to study transformer fault diagnosis after finding the optimized c and g parameters in SVM. GA adopts encoding mechanism to randomly generate initial population so as to quickly extend space for searching and stabilize individuals' diversity in the population. The method effectively improves global searching capability and convergence rate. The analysis result of experiments for transformer fault diagnosis shows that GA can effectively implement optimization selection for c and g parameters in SVM algorithm and improve accuracy of transformer fault diagnosis. In this study, the FRSN P systems technique has combined strength of uncertainty.
the FRSN P systems diagnosis results are shown in Table 5.

Cases	FRSN P systems Diagnosis Results		
	Fault type	**CF**	**Fault state**
1	D1, D2, PD, T2, T3	(0.08)	No
	T1	(0.72)	YES
2	D1, D2, PD, T2, T3	(0.08)	NO
	T1	(0.72)	YES
3	D1, D2, PD, T2, T3	(0.08)	NO
	T1	(0.72)	YES
4	D1, D2, PD,T1, T2, T3	(0.08)	NO
5	D1, D2, PD,T1, T2, T3	(0.08)	NO
6	D1, D2, PD,T1, T2, T3	(0.08)	NO
7	D1, PD,T1, T2, T3	(0.08)	NO
	D2	(0.72)	YES
8	D1, D2, PD,T1, T3	(0.08)	NO
	T2	(0.72)	YES

Table 5: Ratio gas data with linguistic terms.

Table 6 show us, the comparing results proposal method with SVMR and SVMG methods, according to test results in this table, the FRSN P systems is more suitable as dissolved gas signature and solved the problem of conflict between SVMR and SVMG.

Cases	SVM		FRSN P systems
	SVMR	**SVMG**	
1	T1	T2	T1
2	No fault	T1	T1

3	T1	T2	T1
4	No fault	D2	No fault
5	T2	No fault	No fault
6	No fault	T2	No fault
7	D1	D2	D2
8	T2	T3	T2

Table 6. Comparison FRSN P systems method with SVM method (SVMR/SVMG).

Processing, rule-based reasoning, symbolic representation, and parallel computing. It makes transformer fault diagnosis based on DGA more accurate, fast and adaptive to system changes. Especially, the reasoning process can be visualized in a form of graphical representation of FRSN P systems. The rule base and parameters are saved in matrix forms and the whole reasoning process is implemented by fuzzy matrix operations. The aim of this study is to apply adaptive IEC Ratio with fuzzy representation and construct FRSN P systems diagnosis model to deal with fault transformers based on (IEC 60599) DGA as signature. Thus, the diagnosis model can be represented by fuzzy production rules, dynamic reasoning algorithm and firing mechanism to diagnose six types of fault transformers. Moreover, the practical test cases of transformer fault diagnosis are used to evaluate the proposed method. This paper proposes FRSN P systems and tests its validity and feasibility in transformer fault diagnosis and compare results with support vector machine (SVMR/SVMG) methods for the same fault cases. Future work will focus on verifying the performance superiority of FRSN P systems, compared with other diagnosis methods; it can be integrated with other analysis applications comprehensive analysis.

Conclusion

SVM can solve the problem of multi-classification for small number of samples and non-linear data in a fairly good way, applicable in transformer oil chromatography fault diagnosis. The paper uses GA to study transformer fault diagnosis after finding the optimized c and g parameters in SVM. GA adopts encoding mechanism to randomly generate initial population so as to quickly extend space for searching and stabilize individuals' diversity in the population. The method effectively improves global searching capability and convergence rate. The analysis result of experiments for transformer fault diagnosis shows that GA can effectively implement optimization selection for c and g parameters in SVM algorithm and improve accuracy of transformer fault diagnosis. Clustering ensemble approach is suitable for increasing accuracy and stability via a combination of results of different clustering or one clustering with various input parameters.

According to the above description and the rapid advance of its entry into the field of data mining and power industry equipment repairs and maintenance have us believe that this project can, by data mining, reduce costs and increase industries power system reliability through timely diagnosis and prediction of power plant equipment errors in the most sensitive transformers, which is one of the most important and effective steps taken in electricity industry. And in this way, we need to harvest data about the number of transformers and analysis of dissolved gases in oil that after the receipt of the data, they should be classified by clustering groups available, and they are later analyzed in order to understand and predict transformer faults.

Table 6. Shows, the comparing results proposal method with SVMR and SVMG methods, according to test results in this table, the FRSN P systems is more suitable as dissolved gas signature and solved the problem of conflict between SVMR and SVMG.

Cases	**SVM**		**FRSN P systems**
	SVMR	**SVMG**	
1	T1	T2	T1
2	No fault	T1	T1
3	T1	T2	T1
4	No fault	D2	No fault
5	T2	No fault	No fault
6	No fault	T2	No fault
7	D1	D2	D2
8	T2	T3	T2

Table 6. Comparison FRSN P systems method with SVM method (SVMR/SVMG).

Processing, rule-based reasoning, symbolic representation, and parallel computing. It Makes transformer fault diagnosis based on DGA more accurate, fast and adaptive to System changes. Especially, the reasoning process can be visualized in a form of graphical representation of FRSN P systems. The rule base and parameters are saved in matrix forms and the whole reasoning process is implemented by fuzzy matrix operations.

The aim of this study is to compare of transformer fault diagnosis based on feature selection and parameter optimization and fuzzy reasoning spiking neural P systems. Thus, the diagnosis model can be represented by fuzzy production rules, dynamic reasoning algorithm and firing mechanism to diagnose six types of fault transformers. Moreover, the practical test cases of transformer fault diagnosis are used to evaluate the proposed method. This paper proposes FRSN P systems and tests its validity and feasibility in transformer fault diagnosis and compare results with support vector machine (SVMR/SVMG) methods for the same fault cases. Future work will focus on verifying the performance superiority of FRSN P systems, compared with other diagnosis methods; it can be integrated with other analysis applications comprehensive analysis.

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