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"Artificial intelligence based Fault Diagnosis of Power Transformer-A Probabilistic Neural Network and Interval Type-2 Support Vector Machine Approach"

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Abstract

Power transformers have an important role in electrical power transmission and its interruption has financial losses, thus its condition monitoring is essential and performance of this equipment is effective for power system reliability. In this paper, proposed method has advantages of both probabilistic neural network (PNN) and Interval Type-2 Fuzzy Support Vector Machine (IT2FSVM). Firstly, main feature is extracted from primary and secondary three phase currents and search coils differential voltage by wavelet transform and this information is used as probabilistic neural network inputs. AI techniques are applied to establish classification features for faults in the transformers based on the collected gas data. The features are applied as input data to PNN and IT2FSVM combination of classifiers for faults classification. The experimental data from NTPC Korba-India is used to evaluate the performance of proposed method. The results of the various DGA methods are classified using AI techniques. In comparison to the results obtained from the AI techniques, the PNN plus IT2SVM has been shown to possess the most excellent performance in identifying the transformer fault type. The test results indicate that the PNN plus IT2SVM approach can significantly improve the diagnosis accuracies for power transformer fault classification. In addition, the study aims to study the joint effect of PNN and IT2SVM on the classification performance when used together.

Key words: Probabilistic Neural Network (PNN), Interval Type-2 Fuzzy Logic, Support Vector Machines, Dissolved gas analysis, Transformer Fault Diagnosis.

1. Introduction

Power transformer has an important role in electrical network. This equipment is a main element in electrical power transmission, because of power source, transmission and distribution lines and consumer in different voltage levels are connected by transformer. Much kind of faults damage it. Most of them are short circuit winding faults and tab changer fault. Internal fault generates heat that causes deterioration insulation and decomposes oil and releases various gases such as hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2),carbon monoxide (CO),carbon dioxide(CO_2). Winding fault, overheating and partial discharge is detected through the dissolved gas analysis (DGA). Released gas ratio is used as a fault indicator. DGA results that are combined with probability neural network classifier are widely used for fault detection. Other signals - used for fault detection is electrical signals such as three phase currents and if search coils are installed, their voltages. Search coils differential voltages are used for early detection and location of internal winding of transformer. Wavelet results are as probabilistic neural network inputs in order to detect inrush current. Interval type-2 Fuzzy SVM classifier is used for fault detection. Key point for fault detection is the feature extraction from raw signals. The wide varieties of electrical and thermal stresses often age the transformers and subject them to incipient faults. If an incipient failure of a transformer is detected before it leads to a catastrophic failure, predictive maintenance can be deployed to minimize the risk of failures and further prevent loss of services. In industrial practice, dissolved gas analysis (DGA) is a very efficient tool for such purposes since it can warn about an impendent problem, provide an early diagnosis, and ensure transformers' maximum uptime. The DGA methods ana1yse and interpret the attributes acquired: ratios of specific dissolved gas concentrations, their generation rates and total combustible gases are used to conclude the fault situations. Recently, artificial intelligence techniques have been extensively used with the purpose of developing more accurate diagnostic tools based on DGA data. R. Naresh, et al (2008) presents a new and efficient integrated neural fuzzy approach for transformer fault diagnosis using dissolved gas analysis. The proposed approach formulates the modeling problem of higher dimensions into lower dimensions by using the input feature selection based on competitive learning and neural fuzzy model. Then, the fuzzy rule base for the identification of fault is designed by applying the subtractive clustering method which is efficient at handling the noisy input data. V.Miranda (2005) et al describes how mapping a neural network into a rule-based fuzzy inference system leads to knowledge extraction. This mapping makes explicit the knowledge implicitly captured by the neural network during the learning stage, by transforming it into a set of rules. This method is applied to transformer fault diagnosis using dissolved gas-in-oil analysis. A.Shintemirov (2009) et al presents an intelligent fault classification approach to power transformer dissolved gas analysis (DGA), dealing with highly versatile or noise-corrupted data. Bootstrap and genetic programming (GP) are implemented to improve the interpretation accuracy for DGA of power transformers. Bootstrap pre-processing is utilized to approximately equalize the sample numbers for different fault classes to improve subsequent fault classification with GP feature extraction. GP is applied to establish classification features for each class based on the collected gas data. The features extracted with GP are then used as the inputs to artificial neural network (ANN), support vector machine (SVM) and K-nearest neighbor (KNN) classifiers for fault classification. The aim of this paper is to present a new method for detection and classification of power transformers faults by using a dissolved gas analysis and an artificial intelligence technique for decision with a maximal classification rate. Here we use probabilistic neural network and interval type-2 fuzzy support vector machine for classification and detection of power transformer fault profile. This paper is organized as follows: Section 2 introduces the PNN architecture and theory of operation. Section 3 presents interval type-2 fuzzy support vector machine (IT2SVM) technique. Section 4 presents probabilistic neural network plus interval type-2 fuzzy SVM Fusion Model. Section 5 presents Simulation of Transformers Faults Classification. The simulation results are presented in Section 6. Finally, the conclusion is provided in Section 7.

2. PNN Architecture and Theory of Operation

The probabilistic Neural Network used in this paper is shown in Fig.1. The first (leftmost) layer contains one input node for each input attribute in an application. All connections in the network have a weight of 1, which means that the input vector is passed directly to each hidden node. In PNN, there is one hidden node for each training instance i in the training set. Each hidden node h_i has a center point y_i associated with it, which is the input vector of instance i. A hidden node also has a spread factor, s_i, which determines the size of its respective field. There are a variety of ways to set this parameter. s_i is equal to the fraction f of the distance to the nearest neighbor of each instance i. The value of f begins at 0.5 and a binary search is performed to fine tune this value. At each of five steps, the value of f that results in the highest average confidence of classification is chosen (HongYu et al. 2010). A hidden node receives an input vector x and outputs an activation given by the Gaussian function g, which returns a value of 1 if x and y_i are equal and drops to an insignificant value as the distance grows (HongYu et al. 2010):

$$g(x, y_i, s_i) = \exp(-D^2(x, y_i)/2s_i^2)$$

The distance function D determines how far apart the two vectors are. By far the most common distance function used in PNNs is Euclidean distance. However, in order to appropriately handle applications that have both linear and nominal attributes, a heterogeneous distance function HVDM is used to normalize Euclidean distance for linear attributes and the Value Difference Metric (VDM) for nominal attributes. It is defined as:

$$HDVM(x,y) = \sqrt{\sum_{i=1}^{m} d_a^2\,(x_a, y_a)}$$

Where m is the number of attributes. The function d_a (x, y) returns a distance between the two values x and y for attribute 'a' and is defined as:

$$d_a(x,y) = \begin{cases} 1, & if\ x\ or\ y\ is\ unknown \\ vdm_a & if\ a\ is\ normal \\ diff_a & if\ a\ is\ linear \end{cases}$$

The function d_a (x, y) uses the following function, based on the Value Difference Metric (VDM) for nominal (discrete, unordered) attributes:

$$Vdm_a(x,y) = \sqrt{\sum_{c=1}^{C} \left|\left(N_{a,x,c}/N_{a,x}\right) - \left(N_{a,y,c}/N_{a,y}\right)\right|^2}$$

Where $N_{a,x}$ is the number of times attribute a had value x; $N_{a,x,c}$ is the number of times attribute a had value x and the output class was c and C is the number of output classes. For linear attributes, the following function is used:

$$Diff_a(x,y) = |x-y|/4S_a$$

Where s_a is the sample standard deviation of the value occurring for attribute a in the training set. Each hidden node hi in the network is connected to a single class node. If the output class of instance i is j, then h_i is connected to class node C_j. Each class node C_j

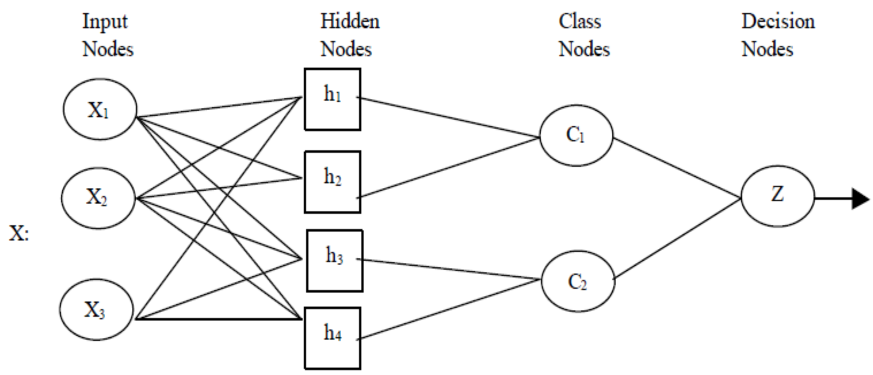


Fig.1 Probabilistic neural network architecture

Computes the sum of the activations of the hidden nodes that are connected to it (i.e., all the hidden nodes for a particular class) and passes this sum to a decision node. The decision node outputs the class with the highest summed activation. One of the greatest advantages of this network is that it doesn't require any iterative training and thus can learn quite quickly. The most directly way to reduce storage requirement and speed up execution is to reduce the number of nodes in the network. One common solution to this problem is to keep only a randomly selected subset of the original training data in building the network. However, arbitrary removing instances can reduce generalization accuracy. In addition, it is difficult to know how many nodes can be safely removed without a reasonable stopping criterion. Other subset selection algorithm exist in linear regression theory, including forward selection, in which the network starts with no nodes and nodes are added one at a time to the network. Another method that has been used is k-means clustering.

Classification Theory of PNN

The PNN is inspired from Bayesian classification and classical estimators for probability density functions (PDF). The basic operation performed by the PNN is an estimation of the probability density function (PDF) of features of each class from the provided training samples using Gaussian Kernel. These estimated densities are then used in a Bayes decision rule to perform the classification. If the probability density function (PDF) of each of the population is known, then an unknown x belong to class i if:

$$f_i(x) > f_j(x), \quad for\ all\ j \neq i$$

Where f_k is the PDF for class k. There are other parameters which may be included during the parameter calculations and these parameters are:-Prior probability (h) which represents the probability of an unknown sample is being drawn from a particular population and Misclassification cost (c) which expresses the cost of incorrectly classifying an unknown. According to the above definition of the PDF and the other parameters that should be included, the classification decision becomes:-

$$h_i c_i f_i > h_j c_j f_j, \quad for\ all\ j \neq i$$

This is defined as Bayes optimal decision rule. Estimating the PDF is done using the samples of the populations (the training set), accordingly: PDF for a single sample (in a population) is calculated from the following formula:

$$1/sW\left((x - x_k)/s\right)$$

Where: x: unknown (input), x_k: k^{th} sample, W: weighting function and s: smoothing parameter. So, the PDF for a single population is calculated from the following formula which is known as Parzen's PDF estimator:

$$1/n\sigma \sum_{k=1}^{n} w(x - x_k/\sigma)$$

Which is exactly expresses the average of the PDF's for the "n" samples in the population. The estimated PDF approaches the true PDF as training set size increases as long as the true PDF is smooth. With regards to the weighting function, we see that it provides a sphere of influence since there is:-large values of small distances between the unknown and the training samples and it rapidly decreases to zero as the distance increases. The weighting function commonly use Gaussian function since it behaves well and easily computed and also it isn't related to any assumption about a normal distribution. When the weighting function use Gaussian function, the estimated PDF is given by:

$$g(x) = 1/n\sigma \sum_{k=1}^{n} exp - (x - x_k)^2/\sigma^2$$

In case of inputting the network a vector, here the PDF for a single sample (in a population) will be given by the following formula:

$$1/\left(\prod 2\right)^{p/2} s^p\, exp(-|x - x_k|^2/2s^2)$$

Where x: unknown (input), x_k : k^{th} sample, s : sampling parameter, p : length of vector And in that case of inputting the network a vector, the PDF for a single population is expressed as:

$$g(x) = 1/\left(\prod 2\right)^{p/2} \sigma^p n, \sum_{k=1}^{n_i} exp\,(-\|x - x_k\|^2/2\sigma^2)$$

Which is the average of the PDF's for the n_i samples in the i^{th} population. The classification criteria in this case of multivariate input will be expressed as follows:

$$g_i(x) > g_j(x), for\ all\ j \neq i$$

$$g_i(x) = (1/n_i) \sum exp(-\|x - x_k\|^2/2\sigma^2)$$

This eliminates common factors and absorbs the '2' into s.

3. Interval Type-2 Fuzzy Support Vector Machine (IT2SVM)

SVM is a powerful and promising machine learning tool, support vector machines (SVMs) employ Structural Risk Minimization (SRM) principle to achieve better generalization ability than traditional machine learning algorithms, such as decision trees and neural networks. SVM classification aims to construct an optimal separating hyper plane in a higher transformed feature space by maximizing the margin between the separating hyper plane and classification data. The transformation of feature spaces from input spaces can be made through kernel trick, which allows every dot-product to be replaced simply by a kernel function. Kernel functions play an essential role in the SVM classification since they determine feature spaces in which data examples are classified and can directly affect SVM classification results and performances. A less time-consuming way is to randomly choose several SVMs with different kernels and construct an ensemble model to combine the different SVM classifiers and generate a hybrid classifier. This paper proposes an ensemble model to combine multiple SVM classifiers by applying the knowledge of interval type-2 fuzzy logic system (IT2FLS). Interval type-2 fuzzy sets and IT2FLS can better handle uncertainties and imprecision in classification data such as noise or outliers. Unlike type-1 FLS, MFs of type-2 fuzzy sets themselves are fuzzy such that membership grades of type-2 fuzzy sets are fuzzy sets in [0, 1]. This basic characteristic of type-2 fuzzy sets makes type-2 FLS especially useful to handle situations where shapes, positions or other parameters of MFs are uncertain. The proposed interval type-2 fuzzy ensemble model takes consideration of the classification results of data examples from different SVMs and generates outputs indicating whether data examples belong to positive or negative class. For a binary classification problem, assume there is a training data set $S:\{(x_i, y_i)\}_{i=1}^{N}$, where each input $mx_i \in R^m$ and output $y_i \in \{\pm 1\}$. The goal of SVMs is to map the input vector $\boldsymbol{x}$ into a feature space $Z = \emptyset(x)$ and find an optimal hyper plane $w.\ z + b = 0$ in the feature space to separate the training data into two classes with the maximum margin,

Where, $I_w = \sum_{i=1}^{N} \alpha_i y_i z_i$

α_i is a set of Lagrange multipliers to the following dual problem (J. Mendel et al. 2000)

$$Maximize\text{: } w(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=j=1}^{N} \alpha_i \alpha_j y_i y_j (z_i . z_j)$$

$$Subject\ to\text{: } C \geq \alpha_i \geq 0, \sum_{i=1}^{N} \alpha_i y_i = 0.$$

Where C is a user-defined regularization parameter, determining the tradeoff between maximizing margin and minimizing the number of misclassified data examples. It is useful to handle non-separable problems and outliers. The kernel trick of SVMs allows us to substitute the dot product of data points in (1) with just a kernel function:

$K(x_i . x_j) = z_i . z_j.$

The decision function is made by computing

$$f(x) = sign(w.z + b) = sign(\sum_{i=1}^{N} \alpha_i y_i K(x_i.x) + b)$$

Where $f(x)$ is the distance of a testing data x to the optimal hyper plane. If the distance is less than 0, the testing data belongs to the negative class. Otherwise, it is in the positive class. Several kernel functions have been used widely and successfully, such as, *polynomial kernel* with degree *d,*

$$K(x_i.x_j) = (1 + x_i.x_j)^d$$

Gaussian RBF kernel with tuning parameter σ,

$$K(x_i.x_j) = exp\left(-\|x_i - x_j\|^2/(2\sigma^2)\right)$$

and *sigmoid kernel* with parameter θ,

$$K(x_i.x_j) = \tanh(x_i.x_j - \theta).$$

Type-2 Fuzzy Sets and Interval Type-2 FLS

A. Type-2 Fuzzy Sets

A type-2 fuzzy set, denoted by $\tilde{A}$, is characterized by a type-2 MF $\mu_{\tilde{A}}(x,u)$, where $x \epsilon X$ and $u \epsilon J_x \subseteq [0,1]$, and can be expressed as (T. Joachims 1999):

$$\tilde{A} = \int_{x \varepsilon X} \int_{u \varepsilon J_x} \mu_{\tilde{A}}(x,u)/(x,u), \quad J_x \subseteq [0,1]$$

Where ∫∫ denotes union over all admissible x and u. $J_x \subseteq [0,1]$ is called ***primary membership*** of x. The union of all primary memberships is defined as the footprint of uncertainty (FOU), bounded by the maximum and minimum type-1 MF called ***upper*** MF $\overline{\mu}_{\tilde{A}}(x)$ and ***lower*** MF $\underline{\mu}_{\tilde{A}}(x)$. When the uncertainties of MFs disappear, type-2 fuzzy sets reduce to type-1 fuzzy sets whose MFs can be precisely determined. Corresponding to each primary membership, there is a ***secondary membership*** that defines the possibilities of the primary membership. General type-2 FLS is computationally intensive. However, when secondary MFs are ***interval* fuzzy *sets***, the computation of type-2 FLS can be simplified a lot. Therefore, in the paper, we only consider interval type-2 fuzzy sets and FLS. The secondary memberships of interval type-2 fuzzy sets are either zero or one $(f_x(u) = 1, \forall\ u\ \varepsilon\ J_x \subseteq [0,1])$. They reflect a uniform uncertainty at the primary memberships. A type-2 FLS, similar to a type-1 FLS, includes four components in general: fuzzifier, fuzzy rule base, fuzzy inference engine, and output processor. One significant difference between type-1 and type-2 FLS is that the output processor of type-2 FLS needs one additional step: ***type-reducer*** just before defuzzifier, which is used to reduce type-2 output fuzzy sets to type-1 output fuzzy sets. After the type reduction, defuzzifier further reduces type-1 output fuzzy sets into crisp values.

B. Fuzzy Inference of Interval Type-2 FLS

Fuzzy inference engine combines the fired fuzzy rules and maps crisp inputs into type-2 output fuzzy sets. In our interval type-2 FLS, we use the ***meet*** operation under ***product*** t-norm, so the firing strength is an interval type-1 set:

$$f^{i}(x) = \left[\underline{f}^{i}(x), \overline{f}^{i}(x)\right]$$

Where $\underline{f}^{i}(x)$ and $\overline{f}^{i}(x)$ can be written in (8b) and (8c), where * denotes the product operation:

$$\underline{f}^{i}(x) = \underline{\mu}_{\tilde{F}_1^i}(x_1) * \ldots\ldots * \underline{\mu}_{\tilde{F}_p^i}(x_p)$$

$$\overline{f}^{i}(x) = \overline{\mu}_{\tilde{F}_1^i}(x_1) * \ldots\ldots * \overline{\mu}_{\tilde{F}_p^i}(x_p)$$

C. Type Reduction of Interval Type-2 FLS

The outputs from the inference engine are type-2 fuzzy sets which must be reduced to type-1 fuzzy sets before defuzzifier can be applied to generate crisp outputs. In this study, ***center-of-sets*** type reducer is used since it requires reasonable computational complexity comparing with expensive centroid type reducer. Center-of-sets type reducer can be divided into two phases. The first phase is to calculate the centroids of all type-2 consequence fuzzy sets. The second phase is to calculate the reduced fuzzy sets.

● ***Computing the Centroids of Rule Consequences:***

Suppose the output of an interval type-2 FLS is represented by interval type-2 fuzzy sets $\tilde{G}^t$, where t = 1, … T, T is the number of output fuzzy sets. The centroid of i^{th} output fuzzy set $y^t = [y_l^t, y_r^t]$ is a type-1 interval set with leftmost point y_l^t and rightmost point y_r^t respectively. Karnik-Mendel iterative algorithm is used to compute the rightmost point y_r^t for each of T type-2 output fuzzy sets, where Z is the number of discretised points for each output fuzzy set, $J_{y_z} = [L_z, R_z]$, $h_z = (L_z + R_z)/2$ and $\Delta_z = (R_z + L_z)/2$, z = 1…..Z. Fig.2 shows how to calculate h_z , L_z , R_z and Δ_z needed by the algorithm. The leftmost point y_l^t can be calculated in the similar way, set $\theta_z = (h_z + \Delta_z)$ for $z \le e$ and $\theta_z = (h_z - \Delta_z)$for $z > e$+1. It has been proved that this iterative procedure can converge in at most Z iterations to find y_l^tor y_r^t.

●***Computing Reduced Type-1 Fuzzy Sets:***

To compute a type-reduced set, it is sufficient to compute its upper and lower bounds y_l and

y_r, which can be expressed as follows:

$$y_l = \frac{\sum_{i=1}^{M} f_l^i y_l^i}{\sum_{i=1}^{M} f_l^i}, \quad y_r = \frac{\sum_{i=1}^{M} f_r^i y_r^i}{\sum_{i=1}^{M} f_r^i}$$

where f_l^i and y_l^i are the firing strength and the centroid of the output fuzzy set of i^{th} rule (i = 1, …, M) associated with y_l; f_r^i and y_r^i are the firing strength and the centroid of the output fuzzy set of i^{th} rule (i = 1, …, M) associated with y_r. To compute y_r, we use the iterative procedure, y_l can be computed in the similar way by setting $f_r^i = \overline{f}^i$ for $i \le R$ and $f_r^i = \underline{f}^i$ for $i > R$. The iterative procedure is proved to converge in no more than M iterations to compute y_r and y_l respectively.

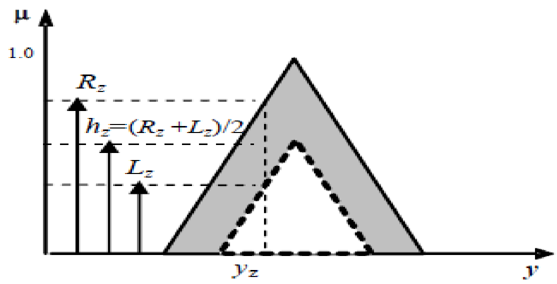


Fig.2 Calculation of the parameters needed by each y_z.

D. Defuzzification

The final output of type-2 FLS is set to the average of y_r and y_l:

$$y(x) = (y_l + y_r)/2$$

4. Probabilistic Neural Network plus Interval Type-2 Fuzzy SVM Fusion Model

A Probabilistic Neural Network plus Interval Type-2 Fuzzy SVM Fusion Model as shown in Fig.3 is constructed to combine classification results from multiple IT2SVMs. The system can be divided into two phases. In Phase I, different SVMs are trained and classified to obtain individual SVM accuracies,

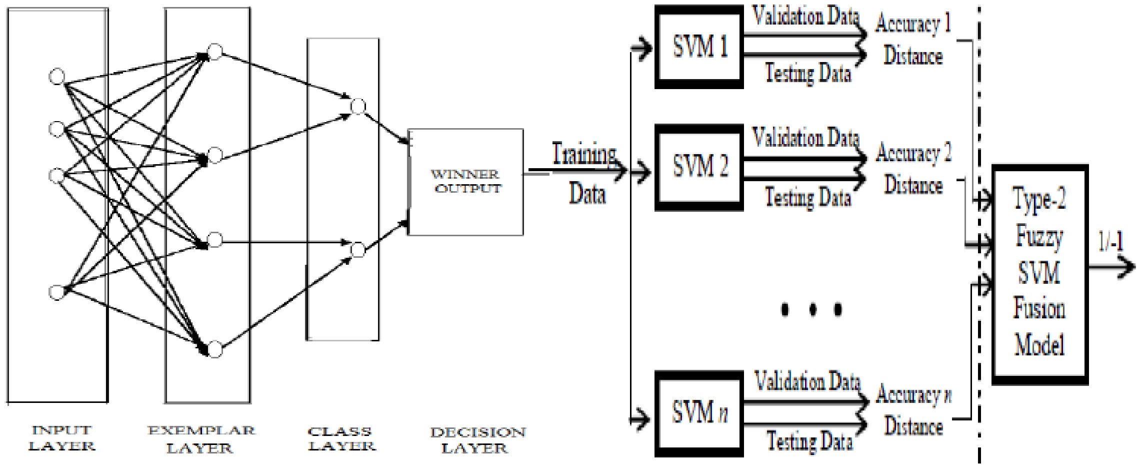
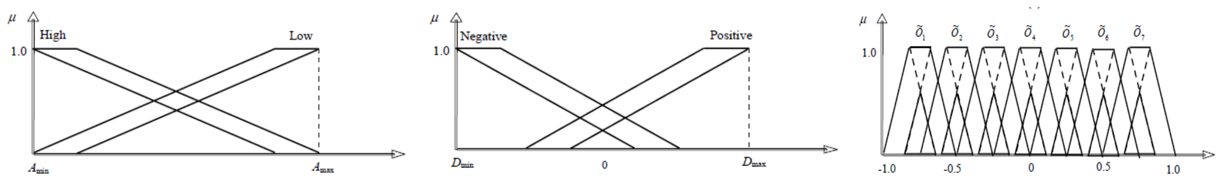


Fig.3 PNN plus Interval Type-2 fuzzy SVM fusion system.

and distances of data examples to SVM hyper planes. In Phase II, an interval type-2 FLS is constructed to combine classification results from multiple SVM classifiers. The type-2 FLS takes SVM accuracies and distances of data examples in Phase I as the system inputs and produces outputs to indicate whether data examples belong to positive or negative class. To explain the FLS in detail, in the following sections, we will take three IT2SVM classifiers as an example to demonstrate how to combine SVM classifiers using the type-2 FLS. This process can be easily extended to combine arbitrary number of SVM classifiers in general.

A. Input and Output Interval Type-2 Fuzzy MFs

The interval type-2 FLS has three accuracy inputs (one for each SVM classifier), three distance inputs (one from each SVM) and one output. All the inputs and the output are defined as interval type-2 fuzzy sets as shown in Fig.4. Each accuracy input is represented by two fuzzy sets: ***high*** and ***low***, and each distance input is described by two fuzzy sets: ***positive*** and ***negative***. The output is represented by seven fuzzy sets. The domain of the accuracy MFs is set to between the minimum and maximum accuracies.



a. **b.** **c.**

Fig.4. Input and output interval type-2 fuzzy MFs. (a). Accuracy,(b). Distance,(c). Output

The admissible ranges of the interval type-2 MFs for accuracy inputs are set to around 2%. Considering the SVM classification results, the domain of ***negative*** distance MF is set to between the minimum distance and 0.5 and the domain of ***positive*** distance MF is set to between -0.5 and the maximum distance. The admissible ranges of the interval type-2 MFs for distance inputs are set to 0.1~0.3. The admissible range of the type-2 MFs for the output is set to around 0.1.

B. Fuzzy Rule Base

Since the system has six inputs in total and each input contains two fuzzy sets, there are 2 ^ 6 = 64 fuzzy rules. The *i*th rule is defined as follows (i = 1...64):

$IF\ a_1\ is\ \tilde{A}_1^i\ and\ a_2\ is\ \tilde{A}_2^i\ and\ a_3\ is\ \tilde{A}_3^i\ and\ d_1\ is\ \tilde{D}_1^i\ and\ d_2\ is\ \tilde{D}_2^i and\ d_3\ is\ \tilde{D}_3^i.THEN\ g_i\ is\ \tilde{O}^i$

Where$\tilde{A}_1^i$, $\tilde{A}_2^i$ and $\tilde{A}_3^i$ in {low, high}, $\tilde{D}_1^i$, $\tilde{D}_2^i$ and $\tilde{D}_3^i$ in {negative, positive},and $\tilde{O}^i$ in $\{\tilde{O}_1, \ldots, \tilde{O}_7\}$.

We assign one of the seven output fuzzy sets to the consequence of each fuzzy rule by considering both the accuracy and distance information of three SVMs. For example, if all the accuracies of three SVM are ***high*** and they all classify one data example in ***positive*** class; the consequence of the corresponding rule is set to $\tilde{O}_7$, indicating the data example is more likely in the positive class. On the other hand, if all three accuracies are ***high*** and all three distances are ***negative***, the consequence of that rule is set to $\tilde{O}_1$, indicating the data example is more likely in the negative class.

C. Fuzzy Inference and Output Processing

In the inference engine of the type-2 fuzzy SVM fusion model, we use the ***meet*** under the ***product t-norm*** and the ***join*** under the ***maximum*** operation and the extended sup-star composition. **C*enter-of-sets*** type-reducer (Karnik-Mendel iterative procedure) is used to reduce the type-2 output fuzzy sets into the type-1 sets. The discrete level is set to 50 points (Z = 50). After the type-reduction, the reduced type-1 fuzzy sets will be defuzzified to produce a crisp value in [-1, 1]. If the crisp output is less than zero, we consider the data example is in the negative class. Otherwise, it belongs to the positive class.

5. Simulation of Transformers Faults Classification

Transformer Fault Types: IEC Publication 60599 provides a coded list of faults detectable by dissolved gas analysis (DGA):

• Partial discharge (PD): PD occurs in the gas phase of voids or gas bubbles. It is usually easily detectable by DGA, however, because it is produced over very long periods of time and within large volumes of paper insulation. It often generates large amounts of hydrogen.

• Low energy discharge (D1): D1 such as tracking, small arcs, and uninterrupted sparking discharges are usually easily detectable by DGA, because gas formation is large enough.

• High energy discharge (D2): D2 is evidenced by extensive carbonization, metal fusion and possible tripping of the equipment.

• Thermal faults T <300 ° C (T1): T1 evidenced by paper turned brownish.

• Thermal faults 300 <T< 700 ºC (T2): T2 evidenced when paper carbonizes.

• Thermal faults T > 700 ºC (T3): T3 evidenced by oil carbonization, metal coloration or fusion.

Diagnosis and Interpretation Methods:

The DGA methods have been widely used by the utilities to interpret the dissolved gas. According to the pattern of the gases composition, their types and quantities, the interpretation approaches below for dissolved gas are extensively followed: Key gas method; Ratios method; The graphical representation method. In this key gas method, we need five key gas concentrations H_2, CH_4, C_2H_2, C_2H_4 and C_2H_6 available for consistent interpretation of the fault. Table 1 shows the diagnostic interpretations applying various key gas concentrations. The results are mainly adjectives and provide a basis for further investigation.

Table1. Interpretation gas dissolved in the oil

Gas Detected	Interpretation
Oxygen (O_2)	Transformer seal fault
Oxide and Dioxide Carbon (CO and CO_2)	Cellulose decomposition
Hydrogen (H_2)	Electric discharge (corona effect, low partial discharge)
Acetylene (C_2H_2)	Electric fault (arc, spark)
Ethylene (C_2H_4)	Thermal fault (overheating local)
Ethane (C_2H_6)	Secondary indicator of thermal fault
Methane(CH_4)	Secondary indicator of an arc or serious overheating

Table.2. Concentration typical values observed in transformers

H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	CO	CO_2
60-150	40-110	50-90	60-280	3-50	540-900	5100-13000

The ppm concentration typical values range observed in power transformers according to IEC 60599 are given in Table 2. In Ratios method, we employ the relationships between gas contents. The key gas ppm values are used in these methods to generate the ratios between them. The IEC method uses gas ratios that are combinations of key-gas ratios C_2H_2/C_2H_4, CH_4/H_2 and C_2H_4/C_2H_6. Table 3 shows the IEC standard for interpreting fault types and gives the values for the three key-gas ratios corresponding to the suggested fault diagnosis. When key-gas ratios exceed specific limits, incipient faults can be expected in the transformer. The graphical representation method is used to visualize the different cases and facilitate their comparison. The coordinates and limits of the discharge and thermal fault zones of the Triangle are indicated in Fig.5. Zone DT in

Fig.5 corresponds to mixtures of thermal and electrical faults. The Triangle coordinates corresponding to DGA results in ppm can be calculated as follows: % C_2H_2 = 100 x / (x + y + z), % C_2H_4 = 100y / (x + y + z) and % CH_4=100z / (x + y + z), where x = (C_2H_2), y = (C_2H_4) and z = (CH_4). You can translate the previous figure in a painting that gives the limits of each fault which are summarized in Table 4.

Training and Testing Data

This study employs dissolved gas content data in power transformer oil from chemistry laboratory of the NTPC Korba-India and Gas (STEG). The data is divided into two data sets: the training data sets (97 samples) and the testing data sets (35 samples). The extracted DGA data contain not only the five concentrations of key gas, three relatives' percentages and three ratios but also the diagnosis results from on-site inspections. The training data sets have been evaluated using various methods DGA and the corresponding judgments related to seven classes have been provided: normal unit (51 samples), Partial Discharge (3 samples), low energy discharge (5 samples), high energy discharge (19 samples), low temperature overheating (7 samples), middle temperature overheating (11 samples) and high temperature overheating (18 samples).

Table.3. Diagnosis using the ratio method (IEC 599)

Fault type	C_2H_2 / C_2H_4	CH_4 / H_2	C_2H_4 / C_2H_6
PD	< 0.1	< 0.1	< 0.2
D1	> 1	0.1 – 0.5	> 1
D2	0.6 – 2.5	0.1 – 1	> 2
T1	< 0.1	> 1	< 1
T2	< 0.1	> 1	1 – 4
T3	< 0.1	> 1	> 4

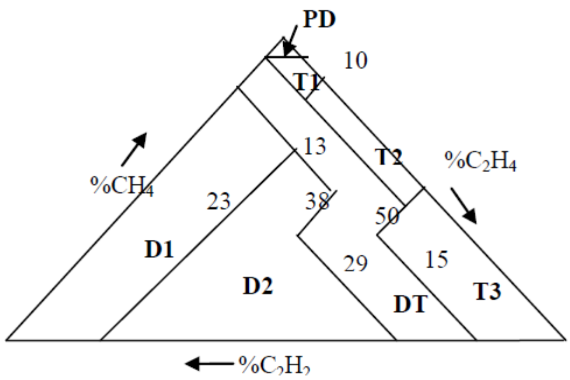


Fig.5 Coordinates and fault zones of the Triangle

Table 4. Graphical representation method zone limits

PD	98 % CH_4	100 % CH_4		
D1	23 % C_2H_4	13 % C_2H_2	100 % C_2H_2	
D2	23 % C_2H_4	13 % C_2H_2	38 % C_2H_4	29 % C_2H_2
T1	4 % C_2H_2	10 % C_2H_4		
T2	4 % C_2H_2	10 % C_2H_4		
T3	15 % C_2H_2	50 % C_2H_4	100 % C_2H_4	

Classification by Interval Type-2 Fuzzy Logic

For The fuzzy logic faults classification is performed using several DGA methods as gas signature.

Fuzzy key gas: Firstly, we will classify the faults using key gas as input data with: •5 linguistic variables are the 5 gas: H2, CH4, C2H2, C2H4 and C2H6; •3 linguistic values: small, medium and high; •5 sets of reference: U = [0, 650] for H2, U = [0, 550] for CH4, U = [0, 450] for C2H2, U = [0, 750] for C2H4 and U = [0, 370] for C2H6; •7 outputs, the reference sets are : U = [0, 1] for the non-fault, U = [0, 2] for the PD, U = [1, 3] for the D1, U = [2, 5] for the D2, U = [3, 6] pour for the T1, U = [4, 7] for the T2 and U = [5, 8] for the T3 ; •3 membership functions: triangular, trapezoidal and Gaussian; •35 = 251 fuzzy rules; •Defuzzification by the centroid method.

Classification by SVM

As shown in Fig.6, the diagnostic model includes six IT2FSVM classifiers which are used to identify the seven states: normal state and the six faults (PD, D1, D2, T1, T2 and T3). With all the training samples of the states, IT2FSVM1 is trained to separate the normal state from the fault state. When input of IT2FSVM1 is a sample representing the normal state, output of IT2FSVM1 is set to +1; otherwise -1. With the samples of single fault, IT2FSVM2 is trained to separate the discharge fault from the overheating fault. When the input of IT2FSVM2 is a sample representing discharge fault, the output of IT2FSVM2 is set to +1; otherwise-1. With the samples of discharge fault, IT2FSVM3 is trained to separate the high-energy discharge (D2) fault from the partial discharge (PD) and low energy discharge (D1) fault. When the input of IT2FSVM3 is a sample representing the D2 fault, the output of IT2FSVM3 is set to +1; otherwise -1. With the samples of overheating fault, IT2FSVM4 is trained to separate the high temperature overheating (T3) fault from the low and middle

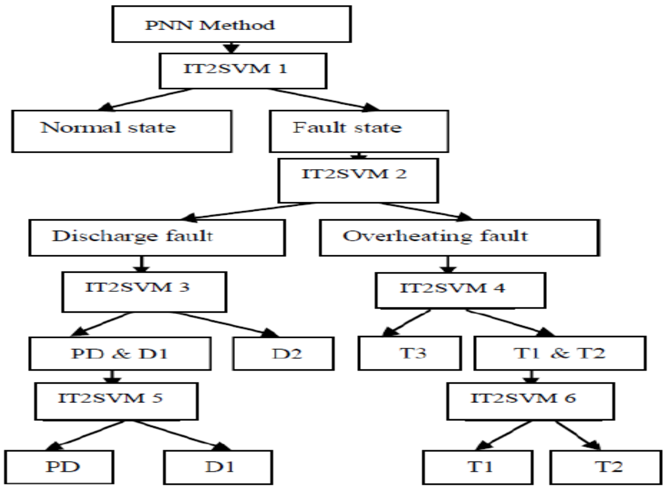


Fig.6 Diagnostic model of power transformer based on IT2FSVM classifier

Temperature overheating (T1 and T2) fault. When the input of IT2FSVM4 is a sample representing the T3 fault, the output of IT2FSVM5 is set to +1; otherwise -1. IT2FSVM5 is trained to separate the middle temperature overheating (T2) fault from the low temperature overheating (T1) fault. When the input of IT2FSVM5 is a sample representing the T2 fault, the output of IT2FSVM5 is set to +1; otherwise -1. IT2FSVM6 is trained to separate the partial discharge (PD) fault from the low energy discharge (D1) fault. When the input of IT2FSVM6 is a sample representing the D1 fault, the output of IT2FSVM6 is set to +1; otherwise -1.

The PNN provides a general solution to pattern classification problems based on Bayesian theory. It is chosen because of its ability to classify a new sample with the maximum probability of success given a large training set using prior knowledge. The PNN combines the simplicity, speed and transparency of traditional statistical classification models and the computational power and flexibility of back-propagated neural networks. On the other hand, IT2FSVM are expressed in the form of a hyper plane that discriminates between positive and negative instances. This is achieved by maximizing the distance between the two classes (positive and negative instances) and the hyper-plane. The IT2FSVM are applied in this study since they can avoid local minima and have superior generalization capability.

6. Simulation Results

The performance of key gas method is analyzed in terms false alarm rate and non-detection rate for triangular, trapezoidal and Gaussian membership functions as shown in Table 5. According to the results, we find that the triangular membership function is more efficient for system fault diagnosis, but this method does not give excellent results. So, we must propose an alternative method. All the six IT2FSVMs adopt polynomial and Gaussian as their kernel function. In IT2FSVM, the parameters σ and C of IT2FSVM model are optimized by the cross validation method. The adjusted parameters with maximal classification accuracy are selected as the most appropriate parameters. Then, the optimal parameters are utilized to train the IT2FSVM model. So the output codification is presented in Table 6.

Firstly, we will classify the faults by SVM with the polynomial kernel. To select more efficient kernel between the two cores used (polynomial and Gaussian), we compare the false alarm rate and non-detection rate given in Table 7. The results in Table 7 show that the Gaussian kernel gives the best performance for the test. This is aided by a proper choice of the kernel parameter σ by the cross validation method, because this parameter determines the hyper sphere radius which encloses the data in multidimensional space. So, for comparison with other classification techniques, we adopt the SVM with Gaussian kernel SVM as the most efficient.

Table.5.The key gas method classification performance

Membership function	False alarm rate (%)	Non-detection rate (%)
Gaussian	16.7 (5 / 30)	53.3 (16 / 30)
Trapezoid	6.7 (2 / 30)	26.7 (8 / 30)
Triangular	3.3 (1 / 30)	26.7 (8 / 30)

Table 6. Codification output of SVM

	svm1	svm2	svm3	svm4	svm5	svm6
No fault	+1					
PD	-1	+1	-1			-1
D1	-1	+1	-1			+1
D2	-1	+1	+1			
T1	-1	-1		-1	-1	
T2	-1	-1		-1	+1	
T3	-1	-1		+1		

Table.7. False alarm and non-detection rates of SVM for different kernels

Kernel type	False alarm rate (%)	Non-detection rate (%)
Polynomial	0	20 (6/30)
Gaussian	0	13.3 (4/30)

7. Conclusion

In this paper, the artificial intelligence techniques are implemented for the faults classification using the dissolved gas analysis for power transformers. The DGA methods studied are key gas, graphical representation and ratios method. The fault diagnosis models performance was analyzed with interval type-2 fuzzy logic (using Gaussian, trapezoidal and triangular membership functions), probabilistic neural network (PNN) and Support Vector Machine (with polynomial and Gaussian kernel functions). The real data sets are used to investigate the performance of the DGA methods in power transformer oil. In this paper, we propose an interval type-2 SVM fusion model to combine multiple individual SVM classifiers. The experimental results show that interval type-2 FLS is a suitable and feasible way to implement ensemble approaches in terms of performance and computational complexity. The proposed type-2 SVM fusion system demonstrates more stable and more robust generalization ability than individual SVMs. The experimental results show that the interval type-2 fuzzy logic classifier with triangular membership presents the best result in comparison with the other two membership functions. The classification accuracies of PNN are superior to RBF, MLP NN and the SVM with Gaussian kernel function has more excellent diagnostic performance than the SVM with polynomial kernel function. According to test results, it is found that the ratios method is more suitable as a gas signature. The IT2SVM with the Gaussian kernel function has a better performance than the other AI methods in diagnosis accuracy. The proposed method can be applied to online diagnosis of incipient faults in transformers. Proposed approach for fault classification is presented. IT2SVM combined with PNN has a good efficiency in transformer fault classification.

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