Transformer winding faults classification based on transfer function analysis by support vector machine

M. Bigdeli1  M. Vakilian2  E. Rahimpour2

1Department of Electrical Engineering, Zanjan Branch, Islamic Azad University, Zanjan, Iran
2Department of Electrical Engineering, Sharif University of Technology, Tehran, Iran
3Power Products Division, Transformers, ABB AG, Bad Honnef, Germany
E-mail: bigdeli.mehdi@gmail.com

Abstract: This study presents an intelligent fault classification method for identification of transformer winding fault through transfer function (TF) analysis. For this analysis support vector machine (SVM) is used. The required data for training and testing of SVM are obtained by measurement on two groups of transformers (one is a classic 20 kV transformer and the other is a model transformer) under intact condition and under different fault conditions (axial displacement, radial deformation, disc space variation and short circuit of winding). Two different features extracted from the measured TFs are then used as the inputs to SVM classifier for fault classification. The accuracy of proposed method is compared with the accuracy of past well-known works. This comparison indicates that the proposed method can be used as a reliable method for transformer winding fault recognition.

1 Introduction

Power transformer is one of the most important and expensive equipments in the electrical power transmission and distribution systems. Their failure will impose high costs on electric power provider companies and will mitigate the power system reliability. Owing to the existence of a strong competition in the electrical power supply industry, the importance of the transformer monitoring systems application has increased over the time. To identify causes of transformer failure, different types of transformer faults are investigated in the literatures. Among these defects, the winding faults are a major cause of power transformers failures [1]. A survey of pertinent literature reveals that most publications on this topic can be classified in two main groups. Ozgonenel et al. [2], Subramanian et al. [3] and Ozgonenel and Onbilgin [4] presented a method to distinguish the inrush current from internal fault currents in order to differentiate protection of power transformer. Some of the related studies [5–8], employing the transmission line method, have presented a transformer model for identification of incipient and internal faults [such as turn-to-turn short circuit (SC) faults]. The other types of faults are related to the mechanical conditions of transformer windings which can be identified by employing a method based on comparison of transfer function (TF) measurements, in different time intervals [9–11]. The results of these studies help the operator to apply the required preventive measures or to accomplish the required maintenance [9–11] at the right time. The present paper focuses on the second topic.

The past researches [9–11] show that TF analysis is an effective diagnosis technique for winding fault detection in power transformers. TF method is a comparative method; in this method the results of a new measurement are compared with the referential measurement. If significant deviations were detected, the transformer is faulty and appropriate investigations should be undertaken to detect the type of fault, its location and the level of its severity.

The important winding faults, which are most likely detected by TF analysis, are classified as follows:

1. axial displacement (AD) [12–14],
2. radial deformation (RD) [14–16],
3. disc space variation (DSV) [17] and
4. SC [18–20].

The SC fault is not a mechanical fault per se, however it usually stems from them. It also can be detected by using TF method [18–20].

The faults mentioned before have been studied analytically and experimentally in [12, 14, 17, 20]. These works have presented the sensitivity of TFs in relation to the mentioned faults separately.

The analysis of DSV has been explained in [17] and those of RD and AD are elaborated in [12–16] using a high-frequency equivalent circuit of windings. They explain which parameters of the electric circuit of winding will change because of a specified fault and have not explained for an occurred winding fault, how it can be found out and whether the fault is one RD, AD. Faridi et al. [18] and Firoozí et al. [19] have detected only the location of SC and do not study the type and level of the fault either. A pattern-based method has been suggested in [20] for classification of SC faults in a distribution transformer using
the graphical information of its winding TF. Its conclusions, however, emphasise the necessity for further investigations to classify other winding faults such as AD and RD. In [21, 22], Ryder concludes that different types of faults dominate the frequency response at different ranges. Moreover, some mathematical indices have been introduced in [23] to evaluate the fault level.

In [24], a method based on application of mathematical indices is introduced for comparison of TFs to detect the fault type of transformer winding. This method is proposed to distinguish only the AD, RD and DSV faults (SC is not included). Therefore if changes occur in TFs because of SC, this method fails. The investigation carried out in [25] introduces a new index to specify the fault type. However, the proposed method was not verified.

Although these studies gave important results, such results are not efficient to detect the type of winding fault in transformers without performing additional investigations. To address these shortcomings, an intelligent-based method of TF analysis is proposed for winding fault detection.

Some important contributions of this work, if compared with the past well-known works can be listed as follows:

1. SC fault is studied in this work as a complement for the AD, RD and DSV faults to cover all of the most important winding faults that can be detected using TF analysis. Thus, determining these four types of faults in a winding it will be a more reasonable method for fault detection.
2. Two well-known algorithms are presented to compare the TFs for a proper extraction of winding fault features. Moreover, these methods are compared with each other.
3. An intelligent method is introduced to distinguish among these four fault types and to classify them under one of the AD, RD, DSV or SC types. For this purpose support vector machine (SVM) is used, which is very popular classification method.
4. The results of the proposed method are verified against the results of past works by application of transformers of different sizes. The results of this validation show that the proposed method is more reliable than the methods presented in the past works.

2 Problem definition

In this analysis the TF of concern is compared with a reference TF. In general, there are many comparative algorithms introduced in the literature. These methods can be classified into four main categories as follows.

2.1 Algorithms based on exact calculations

These algorithms employ a number of mathematical and statistical indices for comparison of the TFs. Indices such as the index of frequency ratio (IFR), index of amplitude ratio (IAR), correlation coefficient and so on belongs to this category. Some researchers [21–24, 26] have used these algorithms to evaluate the fault type, its level and location.

2.2 Algorithms based on electric circuit models

Investigations on evaluation of winding faults’ level and location through TFs analysis by application of an equivalent electric circuit model are presented in the literature [27–29]. The parameters of this equivalent circuit model are determined through application of transformer design information [13–16] or estimated by the transformer terminal measurements [27–29].

2.3 Algorithms based on estimation methods

TFs of transformers can be approximated by rational functions consisting of two polynomials with real coefficients. To estimate the poles and zeros of the TFs (in frequency domain), efficient methods are introduced [27, 30]. One of these is the vector fitting (VF) method. It is exact and effective method for estimating the TFs of transformers [30]. In [13, 15] based on detected poles using VF method, a new index is introduced for comparison of TFs. The obtained results showed that the proposed index can evaluate the fault level. Another work that belongs to this group [25] describes an algorithm based on estimated coefficients of rational function, which is able to detect the type, level and location of faults.

2.4 Algorithms based on artificial intelligence methods

The smart methods such as artificial neural networks (ANN), genetic algorithm, fuzzy logic and SVM and so on can be included in this group. Some researchers [18, 19, 31, 32] have used some of these methods to locate the winding faults.

Among these intelligent methods, SVM is known as one of the best methods for solving the classification problems. Its ability for detection of electrical faults in transformer [33–35] is proved. Another valuable use of SVM is for discrimination of transformer inrush current from internal fault currents [3].

As a result, in this paper SVM is used for classification of winding faults. The most important factor required for a successful SVM-based fault recognition is the proper features selection, as input. To extract the proper features for training and testing of SVM, both the calculation algorithm and the estimation algorithm are used. Since the method based on electric circuit model is not applicable to SVM as an input, therefore this method is not used.

At the first step, the required measurements are carried out on the two groups of transformers, under the intact and the faulted conditions. In these measurements, different degrees of AD, RD, DSV and SC are applied on the winding. In the next step, using mathematical-based algorithms (IFR, IAR) and estimation-based algorithms (VF method), appropriate indices are extracted with the required accuracy. The features extracted through IFR-, IAR- and VF-based algorithms are used as inputs of the SVM classifier to classify the fault in one of the multi-category fault classes.

Group 1 transformers include four model transformers of equal size. On each of them one of the four fault types is applied. The measured data obtained from this group of transformers is used in SVM training process. Group 2 transformers include four equal size windings of a real transformer on each of them one of the four fault types is applied and their measured data are employed for testing and accuracy evaluation of the SVM. Comparison of this classification accuracy against the past well-known methods is discussed next, in detail.

3 Background of methods employed

In this study, a combination of mathematical indices (IFR, IAR) beside VF and SVM are employed to detect the fault
In principle, a TF approximation (of a given order) can be found by fitting it with a function that is made of the ratio of the two polynomials as shown in

\[ f(s) = \frac{a_m s^m + \cdots + a_1 s + a_0}{b_n s^n + \cdots + b_1 s + b_0} \]  

(1)

where \( m \) and \( n \) are the number of numerator and denominator coefficients, and \( a_i \) and \( b_i \) are the values of \( i \)th coefficient for the numerator and denominator, respectively.

However, generally the TF of a passive system can be approximated by a rational function \( f(s) \) in the form shown by

\[ f(s) = \frac{N(s)}{D(s)} = \sum_{i=1}^{n} \frac{r_i}{s - p_i} + ds + e \]  

(2)

where \( r_i \) and \( p_i \) are residues and poles of \( f(s) \), respectively. Terms \( d \) and \( e \) are optional unknown coefficients, which may be zero, depending on the high-frequency asymptotic properties of the system. The \( r_i \) and \( p_i \) are either real quantities or appear in complex conjugate pairs, whereas \( d \) and \( e \) are real. The problem at hand is to estimate all of the coefficients in (2), so that a least squares approximation of \( f(s) \) is obtained over a given frequency interval. It should be noted that (2) represents a non-linear problem in terms of the unknowns, because the unknowns \( p_i \) appear in the denominator.

VF solves the problem of (2), sequentially as a linear problem in two stages, as has been shown in \([30]\). After achieving a good approximation of \( f(s) \) in (2), coefficients of \( a_i \) and \( b_i \) in (1) can be calculated using \( r_i \), \( p_i \), \( d \) and \( e \) \([25]\).

### 3.2 Mathematical indices

When faults occur in the winding, the most important changes observed in TF characteristics are in peak and trough points (this is shown in Figs. 3 and 4 and has been confirmed in past studies \([14, 27]\)). Thus, the frequency and amplitude variations in these points can be used as reliable indices to train the SVM. The variation of the \( i \)th frequency in peak and trough points, also referred to as the \( i \)th IFR, is defined as follows

\[ \text{IFR}_{ti} = \frac{f_k, ti}{f_o, ti}, \quad \text{IFR}_{pi} = \frac{f_k, pi}{f_o, pi} \]  

(3)

where \( f_k, ti \) and \( f_o, ti \) represent the \( i \)th frequency in trough points and \( f_k, pi \) and \( f_o, pi \) are the \( i \)th frequency in peak points (\( k \) indicates the fault condition and \( o \) represents the intact condition).

Similarly, the variation of amplitude in the peak and trough points is represented through the IAR as follows

\[ \text{IAR}_{ti} = \frac{A_k, ti}{A_o, ti}, \quad \text{IAR}_{pi} = \frac{A_k, pi}{A_o, pi} \]  

(4)

where \( A_k, ti \) and \( A_o, ti \) represent the amplitude of TF at the \( i \)th trough point, and \( A_k, pi \) and \( A_o, pi \) are the amplitude of TF at the \( i \)th peak point, respectively.
3.3 Support vector machine

The SVM introduced by Vapnik [36] was firstly proposed for classification problems of two classes but was found to be useful to deal with non-linearly separable cases too. The training of SVM is carried out in a pace that the dimension of the classified vectors does not have a distinct influence on the performance of SVM. Therefore SVM has the required potential to handle very large feature spaces. That is why it is known to be efficient especially in large classification problems. This property will also be beneficial in fault classification, because the number of features to be the basis of fault diagnosis do not have to be limited. Also, SVM-based classifiers are claimed to have good generalisation properties compared with conventional classifiers, because in training the SVM classifier, the so-called structural misclassification risk is to be minimised, whereas traditional classifiers are usually trained so that the empirical risk is minimised [3].

SVM is recognised as one of the standard tools for machine learning and data mining, which is based on advances in statistical learning theory. Originally developed to solve binary classification problems, SVM determines a number of support vectors from training samples and converts them into a feature space using various kernel functions, among which the most commonly used are radial basis function (RBF), polynomial basis function and sigmoid function. Hence, by solving a quadratic optimisation problem, the optimal separating hyper-plane with a maximal margin between two classes is defined [37].

For the purpose of multi-category classification, various different binary classification methods are implemented, such as ‘one-against-all’, ‘one-against-one’, ‘binary tree’ etc [38]. The SVM used in this work is a ‘one-against-one’ having been approved as one of the appropriate binary methods for multi-category classification [38] with a RBF kernel employed and defined by the following equation

\[ K(x, y) = \exp \left( -\frac{(x-y)^2}{2\sigma^2} \right) \]  

where \( x \) and \( y \) denote support vectors and \( \sigma \) is a RBF kernel parameter to be determined. In order to control the SVM generalisation capability a misclassification parameter \( C \) should also be defined [34]. In other words, the parameter \( C \) controls the trade-off between the margin and the size of the slack variables. If its magnitude is too large, a high
penalty exists for the non-separable points and many support vectors may be stored and employed to perform the over-fit process. And if its magnitude is too small, an under-fit process may be involved. It should be noted that selection of SVM parameters ($\alpha$ and $C$) has an important influence on the classification accuracy and both parameters are chosen by the user.

4 Test objects and measurements

Two groups of test objects are employed in this study. The structure of these transformers is shown in Fig. 1. However, some important data of test objects are given in Table 1. All measurements were executed in the time domain, then using fast Fourier transform (FFT) the frequency response of TF is obtained [14].

4.1 Group 1 of test objects

Four model transformers are employed in this study and several tests are performed on them. These tests are discussed in the following.

4.1.1 Study of AD: The test object for study of AD is a high-voltage winding which has 31 double inverted discs (there are six turns in each disc), beside a low-voltage winding in form of a four-layer concentric winding (there are 99 turns in each layer). These particular windings were manufactured for the special experimental purposes. Its specific construction permits a gradual axial movement of the internal layer winding with respect to the outer winding. Since the test object is 82.7 cm high, therefore a 1 cm AD deformation was around 7% of the disc radius in this winding equivalent to 1.2% displacement.

4.1.2 Study of RD: As a test object for the study of RD a high-voltage winding with 30 double inverted discs, where 11 turns exists in each disc and a one-layer low-voltage winding, having 23 turns are used. The deformation has occurred on the double disc winding in 4 degrees, as shown in Table 2.

4.1.3 Study of DSV: For studying DSV the same winding that is used in previous subsection experimented. For this purpose another intact winding, in which the space between its discs is 5 mm, is employed. To study the effect of DSV on TFs, the space between adjacent discs were changed to 7.5, 10, 15, 20 and 25 mm, subsequently the TF is measured in each step. For a proper study the following states are experimented:

State 1 of DSV: Space between disc 2 and disc 3 is varied.
State 2 of DSV: Space between disc 4 and disc 5 is varied.
State 3 of DSV: Space between disc 8 and disc 9 is varied.
State 4 of DSV: Space between disc 12 and disc 13 is varied.
State 5 of DSV: Space between disc 16 and disc 17 is varied.

Although some of the DSV faults given in the above states seem to be an exaggeration and those are impossible to occur on real transformers, they have been executed in order to accumulate more data about DSV and to obtain precise information on TF variations. Additionally, since the higher distances implemented between discs are compensable with smaller winding circumferences covered with the DSV, consequently the DSVs carried out in this work could be very similar to real faults that occur in transformers.

4.1.4 Study of SC: To study the winding’s SC, a high-voltage winding with 30 double inverted discs, where nine turns exists in each disc is used. All discs of the test winding are provided with a tap, whereby the recording of the impulse voltage distribution is enabled along the winding. The input terminal of the winding is subjected to the impulse voltage, the earth current at a selected tap along the winding recorded as the response signals. To experimentally determine the effect of SCs and their spatial arrangement on the TF, an SC is applied between two discs (in different places along the winding). For each individual position of the SC the TF is measured.

4.1.4 Study of SC: To study the sensitivity of TF measurements, for AD, RD, DSV and SC, different terminal conditions have been studied, as shown in Fig. 2.

<table>
<thead>
<tr>
<th>Test objects</th>
<th>Rated power, MVA</th>
<th>Rated voltage, kV</th>
<th>Rated current, A</th>
<th>Geometric dimensions defined in Fig. 1, mm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LV</td>
<td>HV</td>
<td>LV</td>
<td>r₆</td>
</tr>
<tr>
<td>Group 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AD</td>
<td>1.3</td>
<td>–</td>
<td>10</td>
<td>–</td>
</tr>
<tr>
<td>RD and DSV</td>
<td>1.2</td>
<td>0.4</td>
<td>10</td>
<td>1730</td>
</tr>
<tr>
<td>SC</td>
<td>1.2</td>
<td>–</td>
<td>10</td>
<td>–</td>
</tr>
<tr>
<td>Group 2</td>
<td>6.5</td>
<td>6.3</td>
<td>20</td>
<td>590</td>
</tr>
</tbody>
</table>

State 1 of DSV: Space between disc 2 and disc 3 is varied.
State 2 of DSV: Space between disc 4 and disc 5 is varied.
State 3 of DSV: Space between disc 8 and disc 9 is varied.
State 4 of DSV: Space between disc 12 and disc 13 is varied.
State 5 of DSV: Space between disc 16 and disc 17 is varied.

To investigate the sensitivity of TF measurements, for AD, RD, DSV and SC, different terminal conditions have been studied, as shown in Fig. 2.

Table 2 Degrees of RD

<table>
<thead>
<tr>
<th>Degree of RD</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>degree 1</td>
<td>the sixth up to the 54th discs were all radially deformed on one side. Deformation was around 7% of the disc radius</td>
</tr>
<tr>
<td>degree 2</td>
<td>the sixth up to the 54th discs were all radially deformed on two opposite sides. Deformation was around 7% of the disc radius</td>
</tr>
<tr>
<td>degree 3</td>
<td>the sixth up to the 54th discs were all radially deformed on three sides with 90° with respect to each another. Deformation was around 7% of the disc radius</td>
</tr>
<tr>
<td>degree 4</td>
<td>the sixth up to the 54th discs were all radially deformed on four sides with 90° with respect to each another. Deformation was around 7% of the disc radius</td>
</tr>
</tbody>
</table>
The measured results show that the winding faults (AD, RD, DSV and SC) affect the TFs and modify them, differently. For example, the measured $TF_{AD}$ is shown in Fig. 3.

### 4.2 Group 2 of test objects

In order to evaluate and validate the proposed method, another test object of similar type (layer-disc winding) with a different rating (see Table 1) is examined. Specifications of this test object are:

- High-voltage winding with 60 inverted discs, where 13 turns are present in each disc;
- Low-voltage winding with four layer concentric, where 35 turns are present in each layer.

To study the effect of AD, RD, DSV and SC similar terminal connections (Fig. 1) have been experimented. Experiments carried out to study different degrees of AD and RD are closely similar to experiments done on group 1. However, to study the effect of DSV and SC, all of the conditions employed with group 1 are not tested and the effect of DSV is examined only in one location (between discs 6 and 7), whereas the effect of SC is examined in two locations (between discs 1, 2 and 2, 3). Similar to group 1, the measured results in this group show that the winding faults (AD, RD, DSV and SC) affect the TFs and modify them. For example, the measured $TF_{SC}$ is shown in Fig. 4.

### 5 Fault identification

In this work, the SVM is used to classify the winding faults. Fault identification using SVM is formed from three steps: in the first step measurements should be carried out to acquire TFs needed. The second step is related to feature extraction, in which the most proper features are found for classification. In the third step, using features found in the prior step, the classification will be done. Extracted features in previous items are used for training SVM. Then, using trained SVM decision will be made on new data.

#### 5.1 Feature extraction

One of the important stages in any pattern recognition process is the feature extraction. If proper features are selected for a problem, pattern recognition will be done more successfully.

In detection of transformer winding fault, features extraction is based on using the information of TFs. At the intact conditions, the measured TFs are considered as a reference TF and the other TFs (in faulted conditions) are compared against the reference one.

One of the methods for comparison of TFs against the reference TF is developed by application of the mathematical indices such as IFR and IAR. Therefore the defined indices in (3) and (4) can be applied as an input to SVM.

Realising that the coefficients of numerator and denominator of rational functions of TFs (1) change when faults occur in the winding [25], indirectly TFs are compared through examination of these coefficients that can be detected by VF method [30]. Absolute ratio of these coefficients in numerator and denominator of faulted transformer TF with respect to those parameters related to the transformer in intact conditions are used as an efficient index for fault detection. The following relations show how these indices are evaluated

$$Ra_i = \frac{a_{ji}}{a_{mi}}$$

$$Rb_i = \frac{b_{ji}}{b_{mi}}$$

where $a_{ji}$ and $b_{ji}$ are the values of $ith$ coefficient for the faulted conditions, whereas $a_{mi}$ and $b_{mi}$ are the values of $ith$ coefficient for the normal conditions.

### 5.2 Training procedure

To train SVM, first of all, its structure (input/output data) should be determined. In order to improve the classification performance, two different sets of indices are employed for SVM training.

The first set of indices is those of (3) and (4) that are used for training of SVM. Its input matrix which is related to feature 1 can be defined as follows

$$input_{feature\ 1} = \begin{bmatrix}
IFR_{1,AD} & IFR_{1,RD} & IFR_{1,DSV,w} & IFR_{1,SC} \\
IFR_{2,AD} & IFR_{2,RD} & IFR_{2,DSV,w} & IFR_{2,SC} \\
\vdots & \vdots & \vdots & \vdots \\
IFR_{k,AD} & IFR_{k,RD} & IFR_{k,DSV,w} & IFR_{k,SC}
\end{bmatrix}$$

Expression (8) shows the input data format for training of SVM. Equation (9) shows the input matrix which is related to feature 2

$$input_{feature\ 2} = \begin{bmatrix}
Ra_{1,AD} & Ra_{1,RD} & Ra_{1,DSV,w} & Ra_{1,SC} \\
Ra_{2,AD} & Ra_{2,RD} & Ra_{2,DSV,w} & Ra_{2,SC} \\
\vdots & \vdots & \vdots & \vdots \\
Ra_{m,AD} & Ra_{m,RD} & Ra_{m,DSV,w} & Ra_{m,SC}
\end{bmatrix}$$

$$input_{feature\ 2} = \begin{bmatrix}
Rb_{1,AD} & Rb_{1,RD} & Rb_{1,DSV,w} & Rb_{1,SC} \\
Rb_{2,AD} & Rb_{2,RD} & Rb_{2,DSV,w} & Rb_{2,SC} \\
\vdots & \vdots & \vdots & \vdots \\
Rb_{n,AD} & Rb_{n,RD} & Rb_{n,DSV,w} & Rb_{n,SC}
\end{bmatrix}$$

where $k, i$ represent the number of trough and peak points in TFs, respectively; $j, s$ show the level of AD and RD, respectively; $w$ illustrates the location (state) of DSV; $z$ shows level of DSV and $l$ demonstrates the location of SC.

The second set of indices is those of (6) and (7) which are used for training of SVM. The following relations show how the input matrix which is related to feature 2
where $m$, $n$ represent the number of numerator and denominator coefficients in estimated TFs, respectively.

Output of SVM in each of two states can have four different classes (according to four faults) which are

Class number 1: AD;
Class number 2: RD;
Class number 3: DSV;
Class number 4: SC.

As a result, the output of SVM is single dimension vector that shows type of fault.

After finding features 1 and 2 from the first group of transformers, the results of these calculations are applied to SVM as an input. The input matrix sizes for features 1 and 2 are $20 \times 96$ and $80 \times 96$, respectively.

It should be noted that in order to obtain a suitable measure for comparison, the extracted features (8) and (9) should be normalised using the following equation

$$X = \frac{x - \mu}{sd}$$

where $x$ represents each row of the matrix [in (8) and (9)], $\mu$ and $sd$ denote the mean value and standard deviation of $x$ and $X$ is the normalised vector of $x$.

### 5.3 Classification results and discussion

After training, the obtained data from group 2 transformers are applied to the SVM as a testing input for prediction of fault classes. In this case, the sizes of the input matrices are $20 \times 19$ and $80 \times 19$ for features 1 and 2, respectively. SVM parameters were chosen in a trial and error process.

The obtained results show that choosing a value between 4.5 and 5.5 for $\sigma$ and a value between 100 and 120 for $C$ could provide a good performance for our tests.

The best results obtained have been shown in Tables 3 and 4. A close examination of these tables shows that in most cases the SVM has identified the fault type correctly.

To prove the capabilities of the proposed method, the SVM is compared against past methods [16, 24, 25]. Meanwhile, the results of fault detection using ANN are given in Tables 3 and 4. In which, a three-layer perception structure having input, hidden and output layers based on back-propagation learning algorithm is employed as another classifier. The elements of (8) and (9) are used as input and the outputs of the ANN are the fault classes. Choice of the ANN parameters was based on trial and error. The best obtained results through ANN are presented in Tables 3 and 4.

As displayed in Table 4, the accuracy of SVM in the detection of fault type is better than other methods. In SVM

### Table 3 Results of fault type detection using different methods (wrong detection is italicised)

<table>
<thead>
<tr>
<th>Fault type</th>
<th>Method</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Feature 1</td>
<td>Feature 2</td>
<td>Feature 1</td>
</tr>
<tr>
<td>AD1</td>
<td>AD</td>
<td>AD</td>
<td>AD</td>
</tr>
<tr>
<td>AD2</td>
<td>AD</td>
<td>AD</td>
<td>AD</td>
</tr>
<tr>
<td>AD3</td>
<td>AD</td>
<td>AD</td>
<td>AD</td>
</tr>
<tr>
<td>AD4</td>
<td>AD</td>
<td>AD</td>
<td>AD</td>
</tr>
<tr>
<td>AD5</td>
<td>AD</td>
<td>AD</td>
<td>RD</td>
</tr>
<tr>
<td>AD6</td>
<td>AD</td>
<td>RD</td>
<td>RD</td>
</tr>
<tr>
<td>RD1</td>
<td>AD</td>
<td>RD</td>
<td>RD</td>
</tr>
<tr>
<td>RD2</td>
<td>AD</td>
<td>RD</td>
<td>RD</td>
</tr>
<tr>
<td>RD3</td>
<td>AD</td>
<td>RD</td>
<td>RD</td>
</tr>
<tr>
<td>RD4</td>
<td>AD</td>
<td>RD</td>
<td>RD</td>
</tr>
<tr>
<td>DSV1</td>
<td>DSV</td>
<td>AD</td>
<td>DSV</td>
</tr>
<tr>
<td>DSV2</td>
<td>DSV</td>
<td>AD</td>
<td>DSV</td>
</tr>
<tr>
<td>DSV3</td>
<td>DSV</td>
<td>DSV</td>
<td>DSV</td>
</tr>
<tr>
<td>DSV4</td>
<td>DSV</td>
<td>DSV</td>
<td>AD</td>
</tr>
<tr>
<td>DSV5</td>
<td>DSV</td>
<td>DSV</td>
<td>AD</td>
</tr>
<tr>
<td>SC1</td>
<td>DSV</td>
<td>SC</td>
<td>RD</td>
</tr>
<tr>
<td>SC2</td>
<td>DSV</td>
<td>SC</td>
<td>SC</td>
</tr>
</tbody>
</table>

### Table 4 Accuracy (in per cent) of different methods in detection of fault type

<table>
<thead>
<tr>
<th>Fault class</th>
<th>Method</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Feature 1</td>
<td>Feature 2</td>
<td>Feature 1</td>
</tr>
<tr>
<td>class 1 (AD)</td>
<td>87.5</td>
<td>62.5</td>
<td>50</td>
</tr>
<tr>
<td>class 2 (RD)</td>
<td>75</td>
<td>75</td>
<td>75</td>
</tr>
<tr>
<td>class 3 (DSV)</td>
<td>100</td>
<td>60</td>
<td>60</td>
</tr>
<tr>
<td>class 4 (SC)</td>
<td>0</td>
<td>100</td>
<td>50</td>
</tr>
</tbody>
</table>
Table 5 Some of the selected results from feature 2 (normalised)

<table>
<thead>
<tr>
<th>Index</th>
<th>Fault</th>
</tr>
</thead>
<tbody>
<tr>
<td>AD_1</td>
<td>AD_2</td>
</tr>
<tr>
<td>RI_2</td>
<td>-0.028 1.015 1.086 -1.226 -1.165 -0.145 -1.165 1.215</td>
</tr>
<tr>
<td>RI_12</td>
<td>1.231 0.596 0.373 -1.278 -1.178 0.245 -0.065 1.624</td>
</tr>
<tr>
<td>RI_29</td>
<td>-0.007 0.825 1.011 -1.271 -1.202 -0.210 -1.271 2.723</td>
</tr>
<tr>
<td>RI_8</td>
<td>1.286 0.439 0.337 -1.281 -1.128 1.001 1.065 2.191</td>
</tr>
<tr>
<td>RI_121</td>
<td>1.387 0.930 1.018 -1.279 -1.032 0.288 0.925 1.162</td>
</tr>
</tbody>
</table>

Table 6 Some of the selected results from feature 1 (normalised)

<table>
<thead>
<tr>
<th>Index</th>
<th>Fault</th>
</tr>
</thead>
<tbody>
<tr>
<td>AD_1</td>
<td>AD_2</td>
</tr>
<tr>
<td>IFR_1</td>
<td>-0.457 -0.779 -1.128 0.485 0.449 -0.401 -0.343 1.412</td>
</tr>
<tr>
<td>IFR_2</td>
<td>-0.492 -0.667 -0.752 0.310 1.226 -0.356 -0.322 0.757</td>
</tr>
<tr>
<td>IFR_12</td>
<td>-0.272 -1.049 -1.460 0.013 0.052 0.071 0.092 0.525</td>
</tr>
<tr>
<td>IAR_29</td>
<td>-0.285 -0.683 -1.179 -0.193 -0.364 -0.248 -0.014 0.291</td>
</tr>
<tr>
<td>IAR_12</td>
<td>0.058 -1.021 -1.577 -0.035 -0.158 0.083 0.316 1.405</td>
</tr>
</tbody>
</table>

both features (1, 2) have come up with appropriate results, although the accuracy of feature 1 is higher than feature 2. It can be explained that the number of training samples in SVM method is not of a great significance and the number of input data that are located in boundary regions (these data generate support vectors) are the most important factor on its accuracy. With the identification of support vectors, the border line between data is determined and SVM utilises these vectors for pattern recognition. It is obvious that the number of training samples in feature 2 is more than in feature 1. However, some of the data in feature 2 do not vary in different states of faults and are similar to each other. For example, as it is shown in Table 5, the amount of RI_3 in DSV_2 is equal to RD_4 (similarly RI_29 in DSV_2 is equal to RD_3). Therefore it is difficult for SVM to determine support vectors in these cases and it may lead to wrong detection of SVM.

However, the number of data in feature 1 are counted by the number of peak and trough points which are clearly observable in measured TFs. The major variations appeared in measured TFs are related to those in peak and trough points and the trend of these changes for various degrees of a fault is nearly identical and differs from other faults (see Table 6). Consequently, it is possible for SVM, in feature 1, to easily determine support vectors and border line between various faults.

It can be summarised that an SVM classifier with feature 1 produces the best results in comparison with the other classifiers. Thus, it can be used as a reliable method for detection of transformer winding fault type. Nonetheless, it will be very beneficial if a combination of some of the classifiers studied in this work be employed for fault detection. This can cover weakness of one method with strength of the other one. For example, if SVM classifier with feature 1 is employed (that failed only in identification of AD_1) in combination with FI or α indices that were successful in identification of AD_2 there would be no failure. Therefore it seems proper to develop a classifier with conjunction of these indices and SVM method for precise detection of fault types.

6 Conclusion

Determination of transformer winding fault type is an important subject for transformer manufacturers as well as the transformer owners. However, a reliable method cannot be found for this purpose, in the literature. A new method for winding fault type determination is proposed by application of SVM technique, in this paper. The proposed method is able to accurately distinguish different fault types of AD, RD, DSV and SC. For training and testing purposes of the SVM algorithm, the measured data related to two groups of transformers is employed. After extracting the features of the measured TFs by mathematical indices (feature 1) and VF method (feature 2), they are applied to SVM algorithm, for its training. Similar measured parameters from group 2 transformers are used for testing of the method. The verification process reveals that the proposed method, based on SVM using feature 1, has a high accuracy. Comparing with the available methods in the literature and ANN, this can be recognised as a reliable method for detection of transformers winding fault type.

7 Acknowledgment

Authors would like to thank Dr. Amiri, faculty member of Zanjan University, for his ideas and suggestions which helped the authors to present the paper in a better form.

8 References

15. Karmirfard, P., Gharahpetian, G.B., Tenbohlen, S.: ‘Localization of winding radial deformation and determination of deformation extent...


