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A method of real-time fault diagnosis for power transformers based on vibration analysis

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Abstract
In this paper, a novel probability-based classification model is proposed for real-time fault detection of power transformers. First, the transformer vibration principle is introduced, and two effective feature extraction techniques are presented. Next, the details of the classification model based on support vector machine (SVM) are shown. The model also includes a binary decision tree (BDT) which divides transformers into different classes according to health state. The trained model produces posterior probabilities of membership to each predefined class for a tested vibration sample. During the experiments, the vibrations of transformers under different conditions are acquired, and the corresponding feature vectors are used to train the SVM classifiers. The effectiveness of this model is illustrated experimentally on typical in-service transformers. The consistency between the results of the proposed model and the actual condition of the test transformers indicates that the model can be used as a reliable method for transformer fault detection.

Keywords: binary decision tree, fault diagnosis, probability evaluation, power transformer, support vector machine

(Some figures may appear in colour only in the online journal)

1. Introduction

Power transformers are the most important equipment in electric power systems, and the issue of transformer condition assessment has attracted considerable attention. Compared to traditional equipment such as rotating machines, few effective diagnostic methods for power transformers have been proposed. Test methods such as frequency response analysis (FRA) and short-circuit reactance measurement are widely used in transformer diagnosis \cite{1,2}. Compared with them, the vibration method has the advantage that it can be used for online monitoring. Other methods such as dissolved gas analysis (DGA) and partial discharge (PD) detection may lose their effectiveness in detecting structural defects \cite{3,4}. Moreover, as the number of transformers continues to grow, low-cost and non-intrusive methods are urgently needed.

The windings and the core are the two major components inside the transformer tank. A survey performed by a CIGRÉ working group on failures in large transformer samples found that 53 percent were due to mechanical faults \cite{5}. The survey also indicates that the windings are the primary source of transformer failures beside on-load tap changers (OLTCs). As is known, the mechanical structure is connected with the modal parameters which can be identified by vibrations \cite{6}. In this paper, a novel approach with the aim of providing real-time diagnostic information by analyzing the transformer vibration is proposed.

To date, only limited references can be found on transformer diagnosis using vibration method. Bartoletti \textit{et al} proposed several parameters that can roughly distinguish the transformer condition \cite{7}. Ji \textit{et al} found the relation between the fundamental vibration and the excitation source (current...
and voltage) [8]. García et al developed a vibration model that can estimate transformer tank vibrations [9, 10]. Hu et al used a copula-based method to classify the transformer condition [11]. However, few of them provide effective diagnostic techniques, and few practical applications have been demonstrated.

The proposed model consists of two steps: the feature extraction step and the classification step. Although the vibration model that connects the output vibration and the input parameters is regarded as the best way to extract diagnostic information according to our research [12], the model-based method is incapable of dealing with short-time vibrations without additional information. In this paper, we attempt to extract diagnostic information from only the vibration signal. Next, the classifiers should be explored to achieve automated machine fault diagnosis. Recently, some intelligent classification algorithms such as artificial neural networks (ANNs) and support vector machines (SVMs) have been successfully applied to the intelligent fault diagnosis of mechanical equipment [13–15]. The SVM classifier, which is adopted in this research, has superior recognition rates in comparison to other classification methods in most cases. In this paper, the optimized SVM classifiers also provide probability outputs to rank the tested samples from the most probable to the least [16]. As the transformer condition under study can face damages of different severities, a binary decision tree (BDT) is also adopted in the proposed model [17]. During the experiment, vibrations of more than 30 transformers belonging to different classes are acquired. Next, the classifiers are trained using the extracted feature vectors, and the cross-validation method based on grid-search is used to find the optimized parameters.

The rest of this paper is organized as follows. Section 2 gives a brief review of the transformer vibration theory. In section 3, two feature extraction techniques are introduced. The classification model based on SVM and BDT is described in section 4. In section 5, the experimental setup and data sets are introduced. The classification model is trained and real applications are studied in section 6. Section 7 discusses the advantages, limitations and optimizations of the proposed model. The conclusion of this paper is given in section 8.

2. Theory of transformer vibration

The vibration collected from the transformer tank is mainly derived from two components: the windings and the core. The main cause of core vibrations is the magnetostriction phenomenon, which means the ferromagnetic material changes shape and size in a magnetic field [8, 9, 18]. Ideally, the core vibration frequency is twice the power grid frequency (50 Hz in China), and the vibration amplitude shown in (1) is proportional to the voltage (RMS) squared. Because magnetostriction is a nonlinear phenomenon, the induced vibration has components at 100 Hz and its harmonic frequencies

\[ a_{\text{core}} \propto U^2. \]  

(1)

The main cause of winding vibrations is the electromagnetic force [8, 9, 19]. As shown in figure 1, the magnetic leakage field in the tank is generated by the excitation current within the concentric coil. According to the Lorentz law, the interaction of the current and the magnetic leakage flux results in electromagnetic forces acting on the windings. The electromagnetic force frequency is also 100 Hz because the current frequency is 50 Hz. The electromagnetic force on the coil is proportional to the current squared, which is shown in

\[ f(t) \propto i^2(t). \]  

(2)

Large-capacity transformers, which are of the most concerned to maintainers, usually have disk-type windings. The windings can be simplified into a mathematical model, as shown in figure 2. In the model, an insulating block is equivalent to a spring (\( k \)), a single-turn coil of the winding

![Figure 1. Electromagnetic forces acting on concentric transformer windings.](image1)

![Figure 2. Mathematical model of a transformer winding.](image2)
3. Feature extraction

Feature extraction plays an important role in the fault diagnosis and classification procedure. In this study, two diagnostic parameters are proposed through analyzing the transformer vibrations. The first parameter is extracted from the vibration in the frequency domain, which is also known as frequency complexity analysis. The second parameter is obtained by analyzing the vibration stationarity in the time domain.

3.1. Frequency complexity analysis

The Frequency complexity analysis technique is introduced using the information entropy as a measure of the frequency component uncertainty [20, 21]. According to the transformer vibration theory, the fundamental frequency of the winding vibration and the core vibration are both 100 Hz. Although the nonlinear phenomenon will yield high-frequency harmonics, the vibrations should be concentrated in a limited frequency band. As the transformer working condition deteriorates due to mechanical defects, such as winding deformation and clamping force looseness, various anomalous frequency components will increase, resulting in a decrease in its regularity.

Given a discrete vibration signal in the time domain, the vibration in the frequency domain is calculated using the discrete Fourier transform (DFT). Notably, short-time Fourier transform (STFT) analysis may be more suitable for the non-stationary vibrations. Because the transformer generates harmonics at multiples of the fundamental frequency, only the components at \( f = 100, 200, \ldots, 2000 \) Hz are taken into account. The energy proportion of a given frequency is defined as

\[
\alpha_{\text{winding}} \propto I^2. \tag{3}
\]

Although the principle of the transformer vibration is quite easy to understand, the real collected vibrations are much more complicated. First, the produced vibration contains high-frequency harmonics due to the nonlinear characteristic of the magnetostriction phenomenon. Second, the vibrations from the windings and the core are coupled because they are both related to the applied voltage. Last but not least, the vibrations measured from the tank also depend on the complex transmission path.

The parameter frequency complexity defined in (6) represents the degree of the energy concentration, which has a value between 0 and FCA\(_{\text{max}}\). The maximum value is reached when all components have the same energy proportion.

\[
\text{FCA} = - \sum_f p_f \ln(p_f). \tag{6}
\]

The FCA value of a healthy transformer should be close to 0 due to the frequency band being limited, which will be demonstrated in the following experiment.

3.2. Vibration stationarity analysis

Most transformer vibration studies assume that the vibration signals are periodic, and the traditional DFT algorithm is used. It stands to reason that a healthy transformer can be regarded as a deterministic system. In other words, a healthy transformer will always produce the same vibration for the same input and starting condition. According to the principle of transformer vibration, the forces that appear in the core and windings are periodic for healthy transformers, and the resulting vibrations are also periodic. However, when the mechanical structure of the transformer deteriorates, the associated system becomes unpredictable, and the generated vibration exhibits non-stationarity. In this paper, vibration stationarity analysis based on recurrence plots (RPs) is proposed to diagnose transformers.

A recurrence is an instance of the trajectory returning to a location it has visited before. The recurrence plot proposed by Eckmann et al. is a powerful tool to identify spatiotemporal recurrences in multi-dimensional phase spaces [22, 23]. Starting from a discrete time series \( s(t) = \{s_1, s_2, \ldots, s_m\} \), a phase space vector referring to \( x_i \) is reconstructed by applying the time delay method. The trajectory \( X \) in an \( m \)-dimensional space can be expressed in a matrix form where each row is a phase space vector

\[
X = [x_1, x_2, \ldots, x_m]^T, x_i = [s_i, s_i+T, \ldots, s_i+(D_E-1)T]^T. \tag{7}
\]

where \( m = n - (D_E - 1)T \), \( D_E \) is the embedding dimension and \( T \) is the delay time. The recurrence plot converts high-dimensional dynamics into a 2D binary plot. In other words, any recurrence of state \( i \) with state \( j \) is described using a Boolean matrix as expressed in

\[
R_{ij} = \Theta(r - \|x_i - x_j\|), \tag{8}
\]

where \( r \) is a predefined threshold and \( \Theta \) is the Heaviside function. In this paper, the embedding dimension is 3, and the threshold \( r \) is 0.2 of the standard deviation.

Strategies that quantify the small-scale structures in RPs are known as recurrence quantification analysis (RQA). The RQA-based measures appear to be an effective tool for monitoring subtle changes in mechanical structures. Their advantage lies in a high sensitivity and simple computation. Moreover, the probabilistic nature of this method does not require assumptions about the underlying dynamics, like stationarity or linearity [22]. In this study, only one typical approach, which is referred to as determinism, is used to represent the degree of stationarity. The system determinism (or
predictability) is defined as the ratio of recurrence points that form diagonal structures to all recurrence points, which is shown in

$$\text{DET} = \frac{\sum_{l=1}^{m} P(l)}{\sum_{i=1}^{m} \sum_{j=1}^{m} R_{ij}},$$

(9)

where \(P(l)\) represents the number of the diagonal lines with a length of \(l\), and \(l_{\text{min}}\) denotes the minimum value of the diagonal line length. For \(l_{\text{min}} = 1\) the determinism is one. Typically, \(l_{\text{min}} = 2\) is used for a mechanical system, and this is adopted in this study. It is concluded that weak periodic vibration signals or chaotic behaviors cause no or very short diagonals in the recurrence plots. A healthy transformer typically has periodic vibrations, so the corresponding DET value should be close to 1.

4. Classification model

4.1. Brief introduction to SVM

The support vector machine (SVM) first suggested by Vapnik is a powerful classifier based on statistical learning theory [24]. Let us consider a dataset with \(k\) examples \((x_i, y_i)\) \(i = 1, 2, \ldots, k\), where each \(x_i \in \mathbb{R}^d\) is a piece of input data and \(y_i \in \{+1, -1\}\) is the corresponding bipolar label. As illustrated in figure 3, the basic idea of SVMs is to map the training data into a feature space via \(\Phi\) and search for a suitable separating hyperplane.

The maximum margin separating hyperplane in the feature space is defined as

$$w \cdot \Phi(x) + b = 0,$$

(10)

where \(w\) is a weight vector orthogonal to the hyperplane and \(b\) is an offset term. Maximizing the margin is equivalent to solving the following quadratic optimization problem:

$$\min_{w, b} \tau(w) = \frac{1}{2}||w||^2 + C \sum_{i=1}^{k} \xi_i$$

(11)

subject to \(y_i(w \cdot \Phi(x_i) + b) \geq 1 - \xi_i\) and \(\xi_i \geq 0\) for \(i = 1, \ldots, k\),

(12)

where \(C\) is the penalty parameter that imposes a trade-off between the training error and the generalization and \(\xi_i\) is a slack variable. The function \(\tau\) in (11) is called the objective function, while the contents of (12) are called inequality constraints. Together, these equations form a so-called constrained optimization problem, for more details see [25]. One possible solution of this problem is to form an equivalent Lagrangian dual problem, and the final decision function can be given by

$$y(x) = \text{sgn}(f(x)), f(x) = \sum_{i=1}^{k} a_i y_i K(x_i, x) + b,$$

(13)

where \(a_i\) are the Lagrange multipliers determined by solving the dual problem, and the kernel function is defined as

$$K(x_i, x) = \langle \Phi(x_i), \Phi(x) \rangle.$$

(14)

4.2. Probabilistic outputs for SVMs

As stated above, standard SVMs only produce output labels that will be either +1 or −1. Instead of predicting the label, many applications require probabilistic outputs. Compared with other probabilistic models based on SVMs, Platt’s approach which evaluates the posterior probability using a sigmoid function with two parameters has been widely used [16, 26]. The sigmoid model shown in (16) produces probabilistic output using the decision function \(f(x)\) introduced in (13).

$$p(y = 1|f) = \frac{1}{1 + \exp(Af(x) + B)},$$

(16)

where both \(A\) and \(B\) are parameters computed from the minimization of the negative log-likelihood function shown in

$$-\sum_{i} t_i \log p_i + (1 - t_i) \log(1 - p_i),$$

(17)

where \(t_i\) and \(p_i\) are the label and the calculated posterior probability of the training examples, respectively. Note that the original labels are replaced by the new labels: +1 becomes \(t_+\) and −1 becomes \(t_-\). This relabeling procedure is performed to provide soft sigmoid fitting. These new labels are computed using

$$t_+ = \frac{N_+ + 1}{N_+ + 2}, \quad t_- = \frac{1}{N_- + 2},$$

(18)

where \(N_+\) and \(N_-\) are the number of points that belong to the original class +1 and −1, respectively.

4.3. Binary decision tree

The binary decision tree is one efficient approach for solving multi-class problems [17]. In this paper, the proposed model combines a binary decision tree with the probabilistic output
of the SVM classifier. According to practical demands, the transformer condition can be categorized into three groups: class A (health), class B (aging) and class C (anomaly). Because aged transformers can still be used, in some cases, the healthy and aged can be incorporated into one class. In this paper, the binary decision tree shown in figure 4 is proposed, which estimates the probability of membership in each class. In the figure, \( p(h, l) \) represents the probability of the \( l \)th node in the \( h \)th level (\( h = 1 \) corresponds to the root node).

Then, the probability function for each leaf is built as in (19), which means the probability of a test sample belonging to class \( i \) is equal to the product of the probabilities of the nodes visited until reaching the leaf

\[
p(y = i | x) = \prod_{h=1}^{\text{leaf}} p(h, l).
\]  

 Obviously, the probabilities of membership in each class should have a total combined value of 1, which is shown as

\[
\sum_{i=A,B,C} p(y = i | x) = 1.
\]

The adopted measurement system may contain more than one vibration sensor. The diagnostic result of each sensor may be different due to the structure nearby being distinct. Engineers need to take into account the results of all sensors to obtain comprehensive diagnostic information. The suggested diagnosis process for a single vibration instance is as follows. First, the transformer has faults or not is determined by judging whether the anomaly probability is greater than 0.5. If the transformer is diagnosed with no faults, the transformer belongs to class A or class B is determined by which class has a higher probability.

5. Experimental setup

During the experiment, the vibration measuring equipment was placed near the power transformer in the power station. ICP (integrated circuits piezoelectric) accelerometers were used to measure the vibration signals, the sensitivity of which is 50 mV m\(^{-1}\) s\(^{-2}\). In addition, other signals, such as current and voltage, were sampled synchronously. At least six vibration sensors were used to collect vibration signals for one transformer. The sensor positions were selected near the top and bottom relative to the winding structure, which is shown in figure 5. The transformer vibration frequency is mainly concentrated in the range from 0 to 2000 Hz. Therefore, 10000 Hz is an adequate sampling frequency for synchronously collecting all channels. Because the load changes slowly for an in-service power transformer, the measuring equipment collected one-second vibrations every one minute.

The experimental studies were carried out on various in-service power transformers, including healthy, aged and anomalous samples. Based on the input voltage, the tested transformers can be divided into two groups: 110kV and 220kV. All transformer samples are listed in table 1. Most of the transformers are in good condition. The aged transformers are chosen from those that have been running for more than 20 years. However, it is notably difficult to obtain data from anomalous transformers because of safety concerns and of practical constraints. The anomalous transformers mentioned herein were all diagnosed with winding deformations. At least six vibration sensors were used for each transformer, but only the vibrations with distinct characteristics are used to train the classifiers.

6. Results

6.1. Feature analysis of transformer vibrations

Three typical transformers belonging to class A, class B and class C respectively are selected to show further details. First, the vibration from a healthy transformer is analyzed.
The selected transformer (QT\#1), whose model is SSZ10-180000/220, has been running for only two years. Figure 6 shows the time domain and the frequency domain waveforms of the vibration signal. The vibration of the healthy transformer has two distinctive features. First, the vibration is almost periodic. Second, the vibration does not contain any higher frequency components, and the vibration energy is concentrated in a limited frequency band.

Then, the transformer vibration of an aged transformer is analyzed. The selected transformer (JS\#1), whose model is SFSZ7-31500/110, has been running for more than 25 years. The vibration detail of one sensor is shown in figure 7. Although no problems have been reported, the vibration of the aged transformer is quite different from that of the healthy one. The corresponding vibration not only contains higher-frequency components but also has strong vibration intensity.

Lastly, the vibration of an anomalous transformer with deformed windings is analyzed. The transformer (YJB\#2), whose model is SFSZ8-40000/110, has been in use since 1995. The damage to the windings was caused by a lengthy short-circuit current during an accident, and the short-circuit impedance of the phase A winding exceeds 3% of the standard value. The vibration near the phase A winding is shown in figure 8. Compared to the vibrations of the healthy and the aged transformers, a large number of harmonic components are distributed in the high-frequency band between 1000 and 2000 Hz. Besides, the anomalous vibration also contains random noise, which leads to non-stationarity in the time domain.

Next, the feature extraction techniques are applied to all samples listed in table 1. For a multi-sensor measuring system, both methods provide an individual result for each sensor, and the resulting feature vectors of all valid sensors are plotted in figure 9. It is interesting that most healthy transformers are located in the upper-left corner, which means that healthy transformers typically have smaller FCA values and larger DET values.

6.2. Classification using SVM

The next step is to train the SVM classifiers using the obtained feature vectors. In this paper, C-SVM is chosen to complete the classification task. The RBF kernel is selected and only C (the penalty parameter) and γ need to be taken into consideration.
Grid search, GAs (genetic algorithms) and PSO (particle swarm optimization) are commonly used optimized methods for determining the parameters. In this paper, cross-validation with grid search is utilized to perform this parameter selection task. The SVM classifier has been trained using a three-fold cross-validation method, which means the classifier is trained three times, using 2/3 of the data to train the classifier and the remaining 1/3 of the data for testing. Figures 10(a) and (b) show the cross-validation results of SVM1 and SVM2 respectively. The best parameters are selected when the cross-validation accuracy has the highest score, which is also marked in the figures. The accuracy of SVM1 is higher than 90%, which means the proposed classification model can effectively identify the anomalous transformers. Because some aged transformers still work as well as healthy transformers, the accuracy of SVM2 is lower than 90%.

The hyperplanes for SVM classifiers using optimized parameters are shown in figures 11(a) and (b) respectively. Due to the effectiveness of the feature extraction technique, the feature vectors are almost linearly separable in the input space.

The comparison of the classification accuracy between the RBF kernel and other kernels is shown in table 2. Again, three-fold cross-validation is performed to estimate the classification accuracy. Note that the accuracy of the RBF kernel is obtained in the limited interval. However, there are no restrictions for the other kernels. It is proved that the RBF kernel has good performance when appropriate parameters are selected. The polynomial kernel with degree 2 also provides high accuracy in this study due to the well-organized feature vectors.
6.3. Case study

The proposed diagnostic method has already been incorporated into our measurement system. The transformer condition can be evaluated in real time, and three typical cases are illustrated in this section. The first transformer, whose model is ABB SSZ-180000/220, has been in use since 2012. The transformer is also proved to be a healthy sample due to the fact that no exception has occurred during the lifetime. Figure 12 shows the vibrations acquired from this transformer. The feature vectors extracted from the vibrations are shown in table 3. Apparently, each sensor has a low FCA value and a high DET value. Next, the posterior probability of each sensor is calculated, and the health probability of each sensor is approximately equal to one.

The second transformer, whose model is SFSZ10-150000/220, has been put into operation since 2005. The transformer suffered the impact of short-circuit current several months ago, and the operational condition of this transformer is suspicious because the concentrations of certain dissolved gases in the insulating oil exceed the standard level. For details about dissolved gas analysis (DGA), see [3, 5]. The gas concentration of the latest test and the historical data are compared in table 4, and the IEEE-recommended limits are also provided in this table.

The transformer vibrations were also collected during the routine examinations. The time-domain vibrations sampled at 11:00 AM on 2 June 2015 are shown in figure 13. Next, the corresponding feature vector for each sensor is obtained, which is shown in table 5.

Figure 14 shows the posterior probabilities of membership to all classes for all sensors. The surface area of the tank is large enough that the vibration is more susceptible to the mechanical structure nearby, so anomalous vibrations may only appear in a limited area. Sensor 3 is the only one with an anomaly probability greater than 0.5, which means that the location nearby is suspicious and warrants greater attention. Because the aging probabilities of most sensors are large, this transformer is classified as an aged sample, which also indicates that degraded health is detected and routine tests should be performed. During the latest maintenance, the insulating oil was pumped out, and the windings were carefully checked. The results show that slight winding deformations were detected on the windings B and C, which coincides with the conclusion of the proposed method.

At last, the vibrations from an anomalous transformer with severe winding deformations are analyzed. The model of this transformer is OSFPS7-150000/220. The windings were damaged in an accident in which the circuit breaker failed to protect the transformer from overload. Deformations were observed in all windings when the transformer was dismantled in the manufacturer. The vibrations shown in figure 15 were acquired from this transformer immediately after the accident. The corresponding feature vectors are shown in table 6. In contrast to the healthy transformer, the anomaly probabilities of most sensors are close to one.

| Table 3. Feature vector for each sensor of the healthy transformer. |
|-------------------|----------|
| Sensor 1          | 1.24     |
| Sensor 2          | 1.00     |
| Sensor 3          | 0.81     |
| Sensor 4          | 0.58     |
| Sensor 5          | 0.90     |
| Sensor 6          | 0.84     |
The primary goal of this paper is to develop an accurate and efficient diagnostic model including fault detection and quantification for power transformers. The proposed model has many advantages. First, compared with the traditional classification procedure which only provides one or more labels, the proposed model calculates the probability of membership to each class, which is highly attractive because the probabilistic information can be valuable in the decision step. Second, relatively few samples are needed to train the model because it relies on SVM, which is especially useful when the damaged samples are not widely available in practice. Last but not least, the method can provide accurate diagnostic results by analyzing short-time vibrations, which enables us to make decisions efficiently.

It is well known that the key issue when applying pattern recognition approaches to health monitoring is the construction of a database with sufficient samples. In this paper, 110 kV and 220 kV transformers are merged into one database because both have three-phase windings and because their internal structures are similar. According to our research, the
feature extraction methods are also suitable for other types of transformers such as 500 kV and 1000 kV transformers, and the database should be rebuilt. In this paper, all of the anomalous transformers are classified into one class. The information of precise fault types is not provided in this paper due to two reasons. First, this paper aims at providing rapid diagnostic results, which means the vibration data might be insufficient to identify the fault source. Second, because different types of mechanical failure may generate similar vibrations, it is difficult to define classes related to features of different fault types.

In the model, the feature vectors are extracted from short time vibrations. However, one question is the fluctuation of the feature values in one day. Theoretically, the proposed feature vectors are closely related with high-frequency vibrations which are mainly produced by the core. Ideally, the terminal voltage remains constant, and the corresponding feature vector should be kept stable. In practice, the voltage is affected by many factors such as load change and OLTC operation, so the fluctuations of the feature vectors may occur. The feature vector trend of a healthy transformer (QT#1, Sensor 2) is shown in figure 16, and slight fluctuations are observed in the trend. So choosing a suitable measurement time is also very crucial for getting accurate results. According to practical engineering experience, the maximum load usually occurs between 9:00 AM and 11:00 AM. So it is highly recommended to collect the vibrations around 10:00 AM.

Finally, field engineers should render final decisions based on a comprehensive analysis, which means we need to consider other influences besides the model results. For example, we need to make sure that the vibration sensor is working properly and eliminate the interference caused by the environment. Again, the proposed method only provides rough diagnostic results, and the assessment result can be refined through the use of traditional inspection techniques.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>FCA</th>
<th>DET</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor 1</td>
<td>2.24</td>
<td>0.05</td>
</tr>
<tr>
<td>Sensor 2</td>
<td>2.30</td>
<td>0.03</td>
</tr>
<tr>
<td>Sensor 3</td>
<td>2.14</td>
<td>0.09</td>
</tr>
<tr>
<td>Sensor 4</td>
<td>1.79</td>
<td>0.14</td>
</tr>
<tr>
<td>Sensor 5</td>
<td>2.39</td>
<td>0.06</td>
</tr>
<tr>
<td>Sensor 6</td>
<td>2.34</td>
<td>0.21</td>
</tr>
</tbody>
</table>

Table 6. Feature vector for each sensor of the anomalous transformer.
8. Conclusions

In this paper, a probability-based classification model is presented to provide diagnostic information for power transformers. Feature extraction is the first step of the model, and two effective metrics, known as FCA and DET, are extracted from the vibration signal. In this study, the transformer condition is divided into three classes, including health, aging, and anomaly. Next, the SVM classification associated with a sigmoid function is performed to estimate the probability of membership to each class of the binary decision tree.

During the experiments, vibrations of transformers under various conditions are acquired, and the corresponding feature vectors are obtained. The results show that healthy transformers typically have smaller FCA values and larger DET values. Next, the RBF kernel is suggested for practical applications, and the classifiers are trained offline. The cross-validation accuracy of SVM1 is higher than that of SVM2, which means that anomalous transformers may be easier to identify than aged transformers. Lastly, the model is used to assess transformers online by calculating class membership vectors. The results show that healthy transformers offer helpful guidance for inspection tasks.

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References

[18] Li Q, Wang X, Zhang L, Lou J, Zou L 2012 Modelling methodology for transformer core vibrations based on the magnetostrictive properties IET Electric Power Appl. 6 604–10