Translationally adaptive fuzzy classifier for transformer impulse fault identification

P. Purkait, A. Chatterjee, S. Chakravorti and K. Bhattacharya

Abstract: The determination of transformer fault categories using soft-computing based techniques has been the subject of much research in the recent past. The development of an adaptive fuzzy classifier which can effectively determine various classes or categories of series and shunt impulse faults in a wide range of power transformers is described. The system employs a self-generating module to automatically derive a fuzzy rule base from predefined input and output membership functions (MFs) and a given data set for different fault classes. The accuracy of the system is further improved by translationally adapting output MF(s) either forward or backward, keeping their size and shape invariant. The database for different classes of faults is developed from FFT operation on current and voltage waveforms, obtained for different possible fault conditions simulated for given transformer models (EMTP) using an electromagnetic transients program. This database is used to create training and testing data sets required to design the fuzzy based classifier system. The usefulness of the proposed fuzzy based classifier is demonstrated on the basis of performances shown for four example power transformers of 1 MVA, 3 MVA, 5 MVA and 60 MVA ratings.

1 Introduction

Impulse testing of transformers [1] after assembly is an accepted procedure for the assessment of their winding insulation strength to surge overvoltages. For many years, the applied voltage waveforms and resulting current waveforms were analysed manually by studying oscillographic records [2, 3] for the detection of impulse faults. Such manual interpretation of the waveform patterns was strongly dependent on the knowledge and experience of the experts performing the fault analysis. With the advent of digital recorders and analysers, there has been an increasing trend to use frequency-domain analysis [4–6] for fault diagnosis. The transfer function method [4, 5], which is based on a comparison of frequency domain graphs, eliminates many of the problems of fault diagnosis in the time domain due to deviations in input impulse waveform.

In recent years, soft-computing based techniques such as expert systems [7], neural networks [8] and fuzzy systems [9, 10] have been employed for different types of fault diagnosis in transformers. Adaptive fuzzy based or neuro-fuzzy based alternatives for this problem domain are comparatively new and are increasingly being used at present. Most adaptive and neuro-based fuzzy systems normally improve accuracy at the expense of computational load and simplicity. Various such adaptive fuzzy based function approximators and pattern classifiers are reported in [11–19] and are shown to have their individual advantages and disadvantages. Wang and Mendel developed a simple, early system which could self-construct a fuzzy rule base [11]. Later, researchers developed more accurate systems but with additional computational burden. Simpson’s fuzzy min–max clustering neural network [12] and improvements later proposed in [13, 14] utilised variable fuzzy regions to derive fuzzy rules. Various other types of adaptive fuzzy systems have also been proposed employing either heuristics [15, 16] or fuzzy clustering algorithms [17, 18]. A close inspection of these algorithms reveals that most of these general purpose systems impose too heavy a computational burden to be considered for a large class of problems. Hence the need arose to develop a specific fuzzy classifier for transformer fault classification problems which would not be too complex and at the same time would attain the desired accuracy.

The present paper describes the development of a simple yet robust adaptive fuzzy classifier that can perform impulse fault diagnosis in power transformers based on frequency-domain analysis. The study involves the modelling of faults between any disc and earth and also between any two discs of the transformer windings [6]. The results have been obtained from EMTP models of a wide range of power transformers. The proposed fuzzy classifier implements an algorithm for self-organising a fuzzy rule base from input and output membership functions that was developed by Chatterjee et al. [19]. The present system makes a major extension of the single-pass self-organising algorithm presented in [19] by making it a multi-pass system to further improve system accuracy. This algorithm implements a new adaptive scheme to penalise the relevant output MFs by displacing them translationally in either a forward or backward direction, depending on the nature of the system error. A significant improvement in system error in a very small number of iterations establishes the usefulness of the proposed system. The classification system was implemented separately to classify impulse faults in 1 MVA, 3 MVA, 5 MVA and 60 MVA transformers. An accuracy rate of 100% in the testing phase of the
fuzzy classifier developed for each transformer amply demonstrates the accuracy and robustness of the proposed system.

2 Transformer models

Electromagnetic transient program (EMTP) based high-frequency models [20] of four transformers have been developed for impulse fault analysis in the present study. In all the EMTP models, the delta-connected disc winding of the HV side of the transformers has been represented by a network with lumped parameters. These parameters have been calculated from the practical design data of a number of transformers as summarised in Table 1. To perform EMTP based simulations, the equivalent circuit of one limb of the transformer is employed. The equivalent circuit is as shown in Fig. 1 where \( R \) is the resistance of a coil, \( L \) is the distributed inductance of a coil (i.e., the equivalent value of the self and mutual inductance combined), \( C \) is the series capacitance per disc, \( C_g \) is the ground capacitance per disc and \( R_{sh} \) is the resistance through ground.

2.1 Types of fault

Insulation failures may result in two classes of winding faults in a transformer during impulse tests—namely series and shunt faults. Series faults imply an insulation failure between discs or between turns, while shunt faults represent insulation failure between the winding and earthed components such as the tank, core, etc. In the present study, the entire winding has been divided into three sections—namely the line-end, the mid-winding and the earth-end sections—each involving 33.33% of the total length of the winding. Both classes of faults have been simulated separately at different locations along the length of the three different sections to represent as many fault conditions as possible. Each fault has been made to involve 5–10% of the winding length. The acronyms used for different types of faults considered in this study are given in Table 2.

2.2 Fault detection parameters—the frequency domain approach

For frequency domain analysis, the fast Fourier transform (FFT) of the current and input voltage records was computed. The transfer function was then calculated as:

\[
TF = \frac{FFT(i)}{FFT(v)}
\]  

(1)

Figs 2 and 3 show typical current records of the HV winding of the EMTP model of the 5 MVA transformer for a shunt fault at the mid-winding section and the 3 MVA transformer for a series fault at the earth-end section, respectively, when a 1.2/50 \( \mu s \) lightning impulse of positive polarity was applied. The transfer functions of the windings are shown in Figs 4 and 5 respectively, and were obtained using FFT carried out using the MATLAB toolbox.
Table 2: Types of fault simulated

<table>
<thead>
<tr>
<th>Acronyms</th>
<th>Faults</th>
</tr>
</thead>
<tbody>
<tr>
<td>NF</td>
<td>No fault</td>
</tr>
<tr>
<td>SEL</td>
<td>Series fault at line-end</td>
</tr>
<tr>
<td>SEM</td>
<td>Series fault at mid-winding</td>
</tr>
<tr>
<td>SEE</td>
<td>Series fault at earth-end</td>
</tr>
<tr>
<td>SHL</td>
<td>Shunt fault at line-end</td>
</tr>
<tr>
<td>SHM</td>
<td>Shunt fault at mid-winding</td>
</tr>
<tr>
<td>SHE</td>
<td>Shunt fault at earth-end</td>
</tr>
</tbody>
</table>

Fig. 2 Typical current waveforms for SHM in EMTP model of 5 MVA transformer

Fig. 4 TF for SHM in EMTP model of 5 MVA transformer

Fig. 5 TF for SEE in EMTP model of 3 MVA transformer

Transfer functions (TF) were calculated for both the calibration impulse wave as well as the impulse wave at the basic insulation level (BIL). Detection of the fault type and determination of its location is based upon several parameters derived from the two transfer functions at calibration level and BIL, respectively, for different fault conditions. Several parameters as defined below have been identified from the frequency-domain analyses performed on the four transformers under consideration.

\[
\begin{align*}
ARA &= \text{ratio of areas under the curve for the two TF curves.} \\
ADV &= \text{percentage deviation in the areas under the curve between the two TF curves.}
\end{align*}
\]

\[
\begin{align*}
FF &= \text{ratio of first resonance frequencies of the BIL TF curve and the calibration TF curve.} \\
FM &= \text{ratio of magnitudes of first resonant peak of the two TF curves.} \\
SF &= \text{ratio of second resonance frequencies of the two TF curves.} \\
SM &= \text{ratio of magnitudes of second resonant peak of the two TF curves.} \\
TF &= \text{ratio of third resonance frequencies of the two TF curves.} \\
TM &= \text{ratio of magnitudes of third resonant peak of the two TF curves.}
\end{align*}
\]

The magnitudes of all the above-mentioned variables were calculated considering the waveform at BIL and that at calibration level.

3 Self-organising fuzzy classifier with translationally adaptive output membership functions for impulse fault detection

A self-organising fuzzy based pattern classifier was proposed for automatic detection of fault class in power transformers. The system proposed a parallel bank of such adaptive fuzzy classifiers for a given range of power transformers where each fuzzy classifier system was
dedicated to determine the fault in a specific power transformer. This is necessary because, for the same class of fault in two different power transformers having different ratings, the magnitudes of the variables determined from the transfer functions (obtained from results of the FFT as described in the preceding section) often vary widely. Development of a generalised fuzzy classifier system for the given range of transformers is extremely tedious and almost impossible. Since, within a given range, only a reasonably finite number of transformers are practically available, the proposed development and implementation of a parallel bank of fuzzy classifiers in a PC based system was realistic and a feasible solution.

Let us consider the fault classification system to be a k-input-1-output multi-input, single output (MISO) system where the output variable denotes the class of fault and the k inputs are those variables whose combined effect on the output class needs to be properly classified. Choice of the proper number of inputs to construct the fuzzy based fault classifier and choice of the specific input variables play a crucial role in constructing an optimum system without sacrificing accuracy. Let the training data set of the k-input-1-output MISO system be given by:

\[
\{(x_1^1, x_2^1, \ldots, x_k^1 : y^1), (x_1^2, x_2^2, \ldots, x_k^2 : y^2), \ldots, (x_1^N, x_2^N, \ldots, x_k^N : y^N)\}
\]

which consists of N exemplars. Here the nth exemplar consists of \(x_i^j\) as the nth instance of the ith input attribute \((i = 1, 2, \ldots, k)\) and \(y^j\) as the nth instance of the output attribute. Fig. 6 shows the flow chart for the proposed adaptive fuzzy system for fault classification.

The overall design of the proposed classifier comprises of four stages:

1. Initial construction of input and output membership functions;
2. Initial construction of fuzzy rule base;
3. Choice of defuzzification method;
4. Translational adaptation of output MFs of the fuzzy system to improve accuracy.

**Stage 1: Initial construction of input and output membership functions**

To start with a minimum Mamdani-type fuzzy system, one must define MFs for each input and output variable separately. The proposed algorithm employs unbiased, triangular MFs for each input/output variable where each MF is represented by an isosceles triangle and is constructed having 50% overlap with neighbouring MFs. The universe of discourse of each input variable \(x_i\) is determined as:

\[
x_{\text{low}} \leq x_i \leq x_{\text{high}}
\]

where \(x_{\text{low}} \leq x_{\text{high}} = x_{\text{low}} + \Delta x\). Each MF \(x_i\) can be represented by a triplet \(\{x_{\text{low}}, x_{\text{high}}, \Delta x\}\) where \(x_{\text{low}}\) represents the apex of MF \(x_i\) of variable \(x_i\). The extremities of each MF are so chosen that:

\[
x_{i-1} = x_{i-2} = x_{i-1} = x_{i+1} = x_{i+2} = \cdots = x_{i+\text{constant}}
\]

The number of output MFs is determined by the number of output classes of the system, i.e. the total number of possible classes of fault. The proposed system designates a numerical label to each class of fault and the data set contains the set of possible output values \(y = \{1, 2, \ldots, P\}\) where \(P\) denotes the total number of fault classes. For \(P\) total fault classes there will be \(P\) output classes. Then each MF \(j\) of output \(y\) can be represented by a triplet \(\{y_{(j-1)}, y_{(j)}, y_{(j+1)}\}\).

**Stage 2: Initial construction of fuzzy rule base**

Initial construction of the fuzzy rule base is undertaken once the initial MFs for each input and output attribute are created.
defined. This self-construction of the rule base is adapted from [19] where a specific fuzzy rule base entry is occupied by that rule which has the highest activation strength. The strength of each activated rule, denoted \( A_{\text{rule}} \), can be calculated as
\[
A_{\text{rule}} = \mu_a(x_1^r) \times \mu_b(x_2^r) \times \ldots \times \mu_b(x_n^r) \times \mu_0(y^r)
\]
where \( \mu_a(x_1^r) \) is the membership value of the \( r \)-th exemplar of input \( x_1 \), i.e., \( x_1^r \) in membership function \( A \) and so on. Typically \( 0 < A_{\text{rule}} < 1 \), as each factor contributing to \( A_{\text{rule}} \) is a positive fraction.

**Stage 3: choice of defuzzification method**

Since the proposed fuzzy system implements a Mamdani-type fuzzy reasoning model, the output fuzzy consequence must be defuzzified to derive the analogue output value. The proposed classifier employs the centroid method as its defuzzification strategy, which gives the analogue output value as
\[
y_a = \frac{\int \mu_C(y)y dy}{\int \mu_C(y) dy}
\]
However, for the classifier system each possible output is basically a class, as opposed to any possible analogue output value. Hence the output of the fuzzy classifier system will be given as
\[
y_{\text{class}} = p | p - 0.5 \leq y_a < p + 0.5 \quad p = 1, 2, \ldots, P
\]
where \( P \) is the total number of possible fault types in the power transformers considered.

**Stage 4: translational adaptation of output MFs of fuzzy system to improve accuracy**

In the next step, the initial fuzzy system created is fed with the training data set. In the proposed system, cumulative error for each target class \( p \) (CUME\( p \)) in each epoch is calculated separately, given as
\[
\text{error}^p = |y(\text{target})^p - y(\text{fuzzy})^p|
\]
\[
\text{CUME}^p = \text{CUME}^p + \text{error}^p
\]
where error\( ^p \) is the error for the \( n \)-th exemplar in the \( r \)-th epoch whose target output class is \( p \) (\( y(\text{target})^p \) is the target output class \( p \) for the \( n \)-th exemplar in the \( r \)-th epoch whose target output class is \( p \) and \( y(\text{fuzzy})^p \) is the fuzzy system output for the \( n \)-th exemplar in the \( r \)-th epoch whose target output class is \( p \) and \( \text{CUME}^p \) is the cumulative error for target class \( p \) during the \( r \)-th epoch.

At the end of the \( r \)-th epoch, the average absolute error for misclassification of target class \( p \) (AAE\( p \)) during that iteration is calculated as
\[
\text{AAE}^p = |\text{CUME}^p|/N_p
\]
where \( N_p \) is the total number of exemplars in the training set whose target output class is \( p \). This process of calculating AAE\( p \) for each target output class \( p \) is carried out for each \( p \) \( (p = 1, 2, \ldots, P) \) at the end of each iteration such that
\[
\sum_{p=1}^{P} N_p = N
\]
Now, for each target class \( p \), if this AAE\( p \) is greater than the maximum allowable absolute average error value (AAE\( \text{max} \)) for a class, then the fuzzy system is adapted by modifying its free parameters to improve performance. This adaptation of the fuzzy system architecture is accomplished by modifying an output MF, which gives a fine tuning mechanism for the fuzzy system architecture.

**4 Case studies using adaptive fuzzy classifier**

The proposed fuzzy system architecture has been employed to develop fault classifiers for four power transformers rated at 1 MVA, 3 MVA, 5 MVA and 60 MVA. The training and testing data sets were obtained from the results of FFT operations on current and voltage waveforms, as described in section 2. Experiments have demonstrated that development of two-input-one-output fuzzy systems for each case can give sufficiently accurate results with significantly reduced computational effort. The two input variables are chosen as ARA and ADV, which show significant ordered variation in data for each output fault class for each sample transformer chosen, in comparison to other fault classification parameters mentioned earlier in section 2. Classification is performed for five types of fault, SHM, SHE, SEL, SEM and SEE, as detailed in Table 2. The shunt fault at line-end, i.e. SHL, is excluded from the study since determination of this fault is trivial because the current and voltage waveforms generated for this category of fault are very distinctive and completely different from other types of faults.

**4.1 Case study A: 3 MVA transformer**

Here each input attribute (ARA and ADV) was fuzzified using four MFs and the output fault class using five MFs. Figs. 7a-7c show the MFs chosen. The numerical labels assigned to output fault classes were
\[
\begin{align*}
\text{SHM} & = 1, \quad \text{SHE} = 2, \quad \text{SEL} = 3, \\
\text{SEM} & = 4 \quad \text{and } \text{SEE} = 5
\end{align*}
\]
The fuzzy rule base constructed from initial input-output MFs is shown in Table 3a. On the basis of these initially constructed MFs and rule base, the fuzzy system was implemented using the training data set. The system was implemented with $\lambda = 0.35$. During the first few trial runs in training, the fuzzy system was adapted with an $\alpha$ value of 0.1 and this value of $\alpha$ was gradually increased. The system showed significant improvement by reaching the desired accuracy goal in fewer and fewer iterations. However, with $\alpha$ greater than 0.5, the system became oscillatory and hunting was too pronounced. The optimum value $\alpha = 0.5$ was chosen for this case study. Fig. 7c shows the adapted output MF as dashed lines. The results obtained in the testing phase are demonstrated by the confusion matrix in Table 4. A 100% correct classification ratio with zero misclassification rate for all target classes shows the effectiveness of the proposed algorithm.

4.2 Case study B: 60 MVA transformer

The versatility of the proposed classifier was demonstrated by implementing it for a sample transformer of much higher rating (60 MVA). Figs 8a–8c show the input and output MFs chosen for this case study. Table 3b gives the self-generated fuzzy rule base created. Here we have chosen $\lambda = 0.35$, initial $\alpha = 0.1$ and optimum $\alpha = 0.3$. The performance results obtained again show 100% classification rate for each fault class in the testing phase.

4.3 Case study C and D: 1 MVA and 5 MVA transformers

The classifier was also tested for two other sample transformers of 1 MVA and 5 MVA rating. The universe of discourses for inputs $ARA$ and $ADV$ were chosen as $U_{ARA} = [0.7, 1.0]$ and $U_{ADV} = [0, 30]$ for the 1 MVA transformer and $U_{ARA} = [0.67, 0.97]$ and $U_{ADV} = [1, 31]$ for the 5 MVA transformer. Figs 9a and 9b describe the output MFs and Tables 3c and 3d describe the self-constructed fuzzy rule base for 1 MVA and 5 MVA transformers, respectively. The systems were designed with
Fig. 8 Membership functions constructed for 60 MVA transformer
a input 1 (ARA)  
b input 2 (ADV)  
c output fault class

\[
\text{AAE}_{\text{max}} = 0.35 \quad \text{and} \quad z = 0.5 \quad \text{for the 1 MVA} \\
\text{and} \quad \text{AAE}_{\text{max}} = 0.35 \quad \text{and} \quad z = 0.46 \quad \text{for the 5 MVA} \\
\text{transformer. The excellent performances of the systems are} \\
determined by 100\% \text{ recognition rate for all classes of faults in} \\
each case study, as shown in Table 4.

5 Conclusions

An adaptive fuzzy based pattern classifier was proposed to determine various classes of impulse fault in power transformers by translationally adapting output MFs. The proposed system was developed on the basis of data generated by simulating different possible fault conditions for given transformer models in EMTP. Generation of suitable data sets for each transformer was carried out by performing FFT operations on current and voltage waveforms generated from power transformers under various fault conditions. The effectiveness of the proposed algorithm was checked by implementing it for four example power transformers of 1, 3, 5 and 60 MVA rating. An excellent classification ratio of 100\% with zero misclassification in each case demonstrates the classification accuracy of the proposed system.

6 References


