Chapter 6

Cross-correlation Aided Wavelet Network for Classification of Dynamic Insulation Failures

6.1 Introduction

Cross-correlation features aided Fuzzy c-Means (FCM) method of impulse fault characteristics identification had been discussed in the last chapter. Proposed FCM had localized the impulse insulation faults within 33% of winding length with an acceptable accuracy. However, in the case of insulation failure in real-life transformer, if the fault could be localized closer to the actual location of the fault, it will be helpful to the service personnel to take remedial measures. Moreover, prior to de-tankage of the transformer winding, if they could know the location of failure approximately, it would save the time required for necessary corrective action. Though, several methods have been proposed for identification of insulation failures [16-19][22-23][27][30], owing to the complex nature of the composite insulation of transformer, accurate identification of location of impulse fault is still an open issue. Hence, in the present work, an attempt has been made to identify the actual location of failure accurately by employing wavelet network (WN) classifier as an alternative to FCM classifier.

Zhang et al [81] has introduced WN as a feed-forward neural network supported by wavelet theory, which is emerging as an efficient tool for classification [84-86] and function estimation [82][87]. A stochastic gradient based Multi Dimensional Wavelet Network (MDWN) with $n$
number of input nodes and one output node, has been developed and employed as classifier for identification of fault characteristics of insulation failure. Using typical features extracted from cross-correlation sequence of winding currents of healthy (reference no-fault winding current) and each fault condition of winding, the network identifies the fault characteristics. The required winding currents to extract the cross-correlation features for identification of various fault characteristics are obtained by emulating different dynamic insulation failure in the analog model of 33 kV winding of 3 MVA transformer.

As discussed in Chapter 1, the insulation failures that may arise during impulse testing of transformer due to inadequate / improper insulation are categorized into two types, viz. series (SF) and shunt insulation faults (SH). As stated in Chapter 1 and Chapter 5, based on the condition of involved insulation, the series insulation failures may be categorized into dynamic series insulation failure with different fault establishment times (FET), viz. zero (DSFA), 600ns (DSFB), 900ns (DSFC) and 1200ns (DSFD). Similar to series failure, the shunt insulation failure is also categorized into DSHA (zero FET), DSHB (300ns FET), DSHC (400ns FET) and DSHD (500ns FET). Therefore, the type of insulation failure (SF or SH), the fault establishment time (condition of involved insulation) and location of occurrence of insulation failure are considered as fault characteristics and are to be identified by the proposed WN classifier by analyzing the winding current.

As insulation failure may occur anywhere along the entire length of winding, in the present work, for better localization of actual location of failure, sequentially arranged 88 discs of analog model of 33 kV winding of 3 MVA transformer is divided into twenty two sections, viz. S1, S2, S3,..., S22. Each section consists of consecutive 4 discs and covers approximately 4.6% of the total winding length. WN classifier localizes the insulation failure in any one section among the 22 sections, i.e. the fault is localized within 4.6% of total winding length. Moreover, the classification accuracy of proposed WN for identification of fault
characteristics is also compared with that of Artificial Neural Network (ANN) classification tool. Further, the effect of number of extracted cross-correlation features on identification accuracy of impulse fault characteristics has also been studied. The scheme of impulse fault pattern identification, structure of training and test data, initialization of network parameter and identification accuracy of developed network are discussed in this chapter.

6.2 Scheme of Dynamic Fault Diagnosis during Impulse Test

Owing to complex nature of transformer insulation, accurate identification of insulation failure by manually comparing the winding current waveforms is difficult task even for experienced experts. However, accurate identification of type and location of these failures is necessary for effective remedial measures. Therefore, in the present work, stochastic gradient algorithm based MDWN has been proposed for identification of dynamic insulation failure. Developed MDWN is trained using extracted cross-correlation features. After successful completion of training, the developed MDWN is ready to identify the unknown fault characteristics. For testing (unknown fault characteristics identification), features extracted by correlating the fault currents of healthy and unknown insulation failure are given as input to this trained MDWN. Corresponding to these features, the trained MDWN predicts a target value. Based on the obtained target value the unknown fault characteristics are identified. The schematic representation of fault classification scheme is shown in Fig. 6.1.

6.3 Initialization of Wavelet Network Parameters

Extracted features and assigned target value forms the input-output data pair \{x_p, y_p\} of the wavelet network used for fault identification. As the number of input dimension of WN is more than one, hence the WN employed for fault characteristics identification is referred as Multi Dimensional Wavelet Network (MDWN). The structure of developed MDWN is shown in Chapter 4 in Fig. 4.3. The accuracy of function
Fig. 6.1. Block Diagram representation of fault characteristics identification
estimation or pattern identification is sensitive to number of wavelets used to develop the MDWN. However, the identification accuracy may vary from case to case depending upon the type of mother wavelet and nature of input-output data used. In the present approach, fault characteristics identification accuracy is tested with four different MDWN developed using four mother wavelets, viz. Gaussian, Morlet, Mexican Hat and Shannon, respectively.

The convergence of gradient based algorithms is sensitive to the initial values of the wavelet network parameters, viz. \( g \) (output mean), weights \( (W_i) \), translation vectors \( (t_{ji}) \), dilation vectors \( (D_{ji}) \) and rotation matrix \( (R_i) \). Hence, for better convergence of training error the MDWN parameters are initialized properly following the guidelines stated in Section 4.4.3. The rotation matrix is initialized as identity matrix by assigning proper values to the rotation angles. The \( g \) is initialized by the mean of the assigned target values corresponding to each fault characteristics. Weights \( (W_i) \) are set to zero initially. To initialize the translation \( (t_{ji}) \) and dilation \( (D_{ji}) \), different input dimensions are handled separately following the procedure stated in Section 4.4.3 of Chapter 4 [81]. It has been found that the error convergence of developed MDWN with proper initialization of network parameters is better compared to that of randomly initialized MDWN. In addition to proper initialization, the input-output data pair is also normalized suitably for better convergence in error, which improves the fault characteristics identification accuracy further.

### 6.4 Structure of Training and Test Data of WN

The dynamic series and shunt insulation failures are emulated by short circuiting the respective discs or disc to earthed components with appropriate fault emulator, respectively. Thus temporal variations of winding currents due to different insulation failures are acquired by placing the respective fault emulator at 87 different positions along the discs of analog model of transformer. The fault emulator is connected in the analog model of transformer appropriately before the application of impulse sequences for emulation of faults. Therefore, all together 696 (2x4x87) temporal variation of winding current due to series and shunt insulation failure with four different FETs each, at 87 different locations of the winding are acquired. Moreover, the reference impulse no-fault winding current is also acquired to extract the features using cross-
correlation technique. Nine typical features, $F_1$ through $F_9$, are extracted from cross-correlation sequence of each fault pattern for identification of fault characteristics of dynamic insulation failure. The detailed procedure of cross-correlation based feature extraction is explained in detail in Chapter 5. In addition to the above mentioned nine features, in the present work, some additional features, viz., index of maximum value ($F_{10}$), Kurtosis ($F_{11}$) and Skewness ($F_{12}$) of faulted winding current, i.e. altogether, 12 features are extracted. Developed WN is trained with these 12 extracted features and fault characteristics have been identified using the trained network.

Sensitivity analysis has been performed on number of input nodes (number of features to be used for fault characteristics identification) of developed WN. The influence of 6 to 12 numbers of extracted features on the fault characteristics identification accuracy of Gaussian MDWN, i.e. the network developed with Gaussian mother wavelet is presented in Table 6.1.

<table>
<thead>
<tr>
<th>Number of features</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault characteristics identification accuracy (%)</td>
<td>79.07</td>
<td>85.47</td>
<td>87.27</td>
<td>88.08</td>
<td>88.08</td>
<td>86.08</td>
<td>87.27</td>
</tr>
</tbody>
</table>

It may be observed from Table 6.1, that the reduction in the number of features has considerable impact on the prediction accuracy of unknown dynamic series insulation failures, e.g. reduction in number of features from 12 to 6 has reduced the prediction accuracy to 79.07% from 87.27%. On the contrary, addition of more than eight features does not show any significant improvement in fault pattern identification accuracy. This may be due to the fact that the extracted features $F_{10}$ through $F_{12}$ has not shown any distinct variation for different fault characteristics and hence addition of these features has not shown any significant improvement identification accuracy. Therefore, for present impulse fault pattern identification, nine ($F_1$ through $F_9$) extracted features are considered to be the best (optimum) number of features. Moreover, selected nine features, $F_1$ through $F_9$, had identified the fault type, condition and
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location of the insulation failure with acceptable accuracy, compared to that of other feature combinations. However, one may choose more or other features for further study depending upon the nature of the pattern identification problem.

Corresponding to each fault characteristics at 87 different location of the winding, a random target value within specified limit is assigned. The specified ranges to assign target value for each fault characteristics has been properly chosen based on the linear function given in Eqn. 6.1

\[ A1 = -10t_1 + 1760 + \text{randbetween}(0,10) \] (6.1)

where, \( A1 \) is the target value and \( t_1 \) is the sequence number corresponding to that fault. The feature sequence number \( (t_1) \), abbreviation assigned to each insulation failure and number of discs involved in each section are shown in Tables 6.2 to 6.5. The 696 x 9 extracted features and 696x1 assigned target values form the input and output data for developed MDWN, respectively. Each section consists of 4 discs, out of which the extracted features of insulation failure at arbitrary selected 2 disc locations are used to train the developed MDWN network. Thus the training data consist of 352 x 9 (≈ 50%) numbers of feature vector and their corresponding assigned target values, 352 x 1. After completion of the training, the performance (test) of the developed network is assessed with the remaining feature vectors. Thus, the test data consists of 344 x 9 (≈ 50%) numbers of feature vectors, i.e. two sets of features from each of sections S1 to S22, with their corresponding assigned target values, 344 x 1.

In addition to sensitivity analysis of number of features, the effect of specified span of target values for a particular fault characteristic (like 1-50, 1-100 and 1-1000) on the performance of developed WN for identification of fault characteristics has also been studied. It has been found that for target values chosen in the span of 1-10 to 1-1000, there is no significant change in the fault characteristics prediction accuracy. Hence, the target values are assigned within the specified spans of 10 corresponding to each fault characteristics.
<table>
<thead>
<tr>
<th>Section No.</th>
<th>Discs involved</th>
<th>Dynamic SF with Zero(Static) FET (DSFA)</th>
<th>Dynamic SF with 600 ns FET (DSFB)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Abbrev. used</td>
<td>Feature seq. No. (t&lt;sub&gt;1&lt;/sub&gt;)</td>
<td>Specified range for target value</td>
</tr>
<tr>
<td>S1</td>
<td>1-4 DSFA1</td>
<td>1 1751-1760 DSFB1</td>
<td>23 1531-1540</td>
</tr>
<tr>
<td>S2</td>
<td>5-8 DSFA2</td>
<td>2 1741-1750 DSFB2</td>
<td>24 1521-1530</td>
</tr>
<tr>
<td>S3</td>
<td>9-12 DSFA3</td>
<td>3 1731-1740 DSFB3</td>
<td>25 1511-1520</td>
</tr>
<tr>
<td>S21</td>
<td>81-84 DSFA21</td>
<td>21 1551-1560 DSFB21</td>
<td>43 1331-1340</td>
</tr>
<tr>
<td>S22</td>
<td>85-88 DSFA22</td>
<td>22 1541-1550 DSFB22</td>
<td>44 1321-1330</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Section No.</th>
<th>Discs involved</th>
<th>Dynamic SF with 900 ns FET (DSFC)</th>
<th>Dynamic SF with 1200 ns FET (DSFD)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Abbrev. used</td>
<td>Feature seq. No. (t&lt;sub&gt;1&lt;/sub&gt;)</td>
<td>Specified range for target value</td>
</tr>
<tr>
<td>S1</td>
<td>1-4 DSFC1</td>
<td>45 1311-1320 DSFD1</td>
<td>67 1091-1100</td>
</tr>
<tr>
<td>S2</td>
<td>5-8 DSFC2</td>
<td>46 1301-1310 DSFD2</td>
<td>68 1081-1090</td>
</tr>
<tr>
<td>S3</td>
<td>9-12 DSFC3</td>
<td>47 1291-1300 DSFD3</td>
<td>69 1071-1080</td>
</tr>
<tr>
<td>S21</td>
<td>81-84 DSFC21</td>
<td>65 1111-1120 DSFD21</td>
<td>87 891-900</td>
</tr>
<tr>
<td>S22</td>
<td>85-88 DSFC22</td>
<td>66 1101-1110 DSFD22</td>
<td>88 881-890</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Section No.</th>
<th>Discs involved</th>
<th>Dynamic SH with zero (Static) FET (DSHA)</th>
<th>Dynamic SH with 300 ns FET (DSHB)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Abbrev. used</td>
<td>Feature seq. No. (t&lt;sub&gt;1&lt;/sub&gt;)</td>
<td>Specified range for target value</td>
</tr>
<tr>
<td>S1</td>
<td>1-4 DSHA1</td>
<td>176 01-10 DSHB1</td>
<td>154 221-230</td>
</tr>
<tr>
<td>S2</td>
<td>5-8 DSHA2</td>
<td>175 11-20 DSHB2</td>
<td>156 231-240</td>
</tr>
<tr>
<td>S3</td>
<td>9-12 DSHA3</td>
<td>174 21-30 DSHB3</td>
<td>152 241-250</td>
</tr>
<tr>
<td>S21</td>
<td>81-84 DSHA21</td>
<td>156 201-210 DSHB21</td>
<td>134 421-430</td>
</tr>
<tr>
<td>S22</td>
<td>85-88 DSHA22</td>
<td>155 211-220 DSHB22</td>
<td>133 431-440</td>
</tr>
</tbody>
</table>
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### Table 6.5. Winding sections, discs involved, abbreviation used for DSHC and DSHD

<table>
<thead>
<tr>
<th>Section No.</th>
<th>Discs involved</th>
<th>Abbrev. used</th>
<th>Feature seq. No. (t)</th>
<th>Specified range for target value</th>
<th>Abbrev. used</th>
<th>Feature seq. No. (t)</th>
<th>Specified range for target value</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>1-4</td>
<td>DSHC1</td>
<td>132</td>
<td>441-450</td>
<td>DSHD1</td>
<td>110</td>
<td>661-670</td>
</tr>
<tr>
<td>S2</td>
<td>5-8</td>
<td>DSHC2</td>
<td>131</td>
<td>451-460</td>
<td>DSHD2</td>
<td>109</td>
<td>671-680</td>
</tr>
<tr>
<td>S3</td>
<td>9-12</td>
<td>DSHC3</td>
<td>130</td>
<td>461-470</td>
<td>DSHD3</td>
<td>108</td>
<td>681-690</td>
</tr>
<tr>
<td>S21</td>
<td>81-84</td>
<td>DSHC21</td>
<td>112</td>
<td>641-650</td>
<td>DSHD21</td>
<td>90</td>
<td>861-870</td>
</tr>
<tr>
<td>S22</td>
<td>85-88</td>
<td>DSHC22</td>
<td>111</td>
<td>651-660</td>
<td>DSHD22</td>
<td>89</td>
<td>871-880</td>
</tr>
</tbody>
</table>

### 6.5 Training and Test Methodology of WN

The MDWN training is based on the samples of input-output pairs \( \{x_p, y_p\} \), where, \( x_p \) is the features corresponding to particular dynamic insulation failure and \( y_p \) is the assigned target value corresponding to that failure. As stated earlier, stochastic gradient algorithm has been used to estimate the target value \( y_p \). In stochastic gradient algorithm all the wavelet network parameters of MDWN, viz. \( W, L, D, R \), are accumulated in a vector \( \theta \) and the output of particular input \( p \), \( g(x_p) \), is calculated using Eqn.4.6, shown in Chapter 4. By optimizing these wavelet network parameters the gradient based algorithm minimizes the objective function during training. For fault characteristics identification of dynamic insulation failure, the square of the difference between the obtained and actual target values, as given in Eqn.6.2 [81], is used as the objective function

\[
c(\theta, x_p, y_p) = \frac{1}{2} [g(x_p) - y_p]^2
\]  

(6.2)

After each observation of training set \( \{x_p, y_p\} \), to minimize the error, the wavelet network parameters are modified in the backward direction using derivatives of objective function. The modified value of the network
parameters after every observation is obtained by Eqn.6.3 (similar to Eqn. 4.9 of Chapter 4)

$$\theta_{new} = \theta - \gamma \times \text{grad}c(\theta, x_p, y_p)$$ (6.3)

where, $\gamma$ is the learning factor, $1<j<k$, and $1<p<N$, where, $j$ is the number of input dimensions (number of features $F1$ to $F9$) and $N$ is the total number of training data. For dynamic fault characteristics identification, the optimized values of the network parameters are obtained at the cost of slower learning rate. The fault characteristics prediction accuracy during training is assessed by Root Mean Square Error (RMSE) as given in Eqn.6.4 [81]

$$RMSE = \sqrt{\frac{1}{N} \sum_{p=1}^{N} (g(x_p) - y_p)^2}$$ (6.4)

where, $N$ is the number of feature vectors to train the developed MDWN.

After completion of training, the obtained best (optimized) values of network parameter are used to develop the MDWN for estimation of target value of unknown impulse fault characteristics and is referred as testing. The performance of fault characteristics identification of the developed network used for testing is assessed by Figure of Merit (FM), $\delta(g_a)$, as given in Eqn.6.5 [81]. Lower is the value of FM, higher will be the unknown fault characteristics identification accuracy.

$$\delta(g_a) = \sqrt{\frac{\sum_{a=1}^{M} (g_a(x_a) - y_a)^2}{\sum_{a=1}^{M} (y_a - \bar{y})^2}} \quad \bar{y} = \frac{1}{M} \sum_{a=1}^{M} y_a$$ (6.5)

where, $g_a(x_a)$ is predicted output from MDWN for test input-output pair $(x_a, y_a)$, $\bar{y}$ is the mean value of the expected outputs and $1<a<M$, $M$ - number of test cases.

### 6.6 Results and Discussions

To obtain the MDWN with minimum training (RMSE) and test (FM) error, sensitivity analysis has been carried out in details separately on four
different MDWN developed with four mother wavelets. During the sensitivity analysis the values of training parameters, viz. learning factor ($\gamma$) and number of wavelons (WL) have been adjusted and the corresponding training (RMSE) and test (FM) errors are noted. The training parameters which give the minimum RMSE and FM have been considered as the best value of training parameters. Consequently, the network developed with these best values of obtained parameters, i.e. with the best number of wavelons and best leaning factor, is referred as the best network. However, one may arrive at some other network structure as the best one if the limit of acceptable error is varied. This best network has been used for the prediction of unknown dynamic insulation fault characteristics. The fault characteristics identification accuracy of four MDWN developed with four different mother wavelets is given in Table 6.6. It is evident from Table 6.6 that the network developed with Gaussian mother wavelet is more suitable for identification of fault characteristics compared to the other networks developed with Mexican, Hat, Morlet and Shamnan mother wavelets, respectively. Hence, in the present study, the network developed with Gaussian mother wavelet has been used for identification of fault characteristics. The best values of training parameters are obtained by trial and error method. During the trial and error process, the network is developed with a particular number of wavelons (WL), and the RMSE and FM are noted for wide range of learning factor ($\gamma$). The variations in the errors for Gaussian MDWN obtained using 352x9 training and 344x9 test data for different values of learning factor ($\gamma$) are given in Table 6.7. These results were obtained with 7 wavelons after 1000 iterations. It may be observed from Table 6.7, that the learning factor ($\gamma$) of 0.03 has given minimum values of training and test errors. Hence, 0.03 has been considered as the best value of learning factor. Then, using this obtained best value of learning factor ($\gamma$), the RMSE and FM values are noted with different number of wavelons after 1000 iterations. Table 6.8 shows the impact of number of wavelons (WL) on RMSE and FM of MDWN developed with Gaussian mother wavelet using the same training and test data. From the comparative results of Table 6.8, the 17 number of wavelons has been found to give
minimum values of errors and hence it has been considered as the best number of wavelons.

Table 6.6: Fault identification accuracy of MDWN developed with different mother wavelets

<table>
<thead>
<tr>
<th>S. No</th>
<th>Name of the mother wavelet</th>
<th>Overall fault identification accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Gaussian</td>
<td>90.70</td>
</tr>
<tr>
<td>2</td>
<td>Mexican Hat</td>
<td>87.21</td>
</tr>
<tr>
<td>3</td>
<td>Morlet</td>
<td>84.88</td>
</tr>
<tr>
<td>4</td>
<td>Shannon</td>
<td>81.10</td>
</tr>
</tbody>
</table>

Table 6.7: Effect of $\gamma$ on RMSE and FM

<table>
<thead>
<tr>
<th>$\gamma$</th>
<th>0.01</th>
<th>0.02</th>
<th>0.03</th>
<th>0.04</th>
<th>0.05</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>0.00053</td>
<td>0.00117</td>
<td><strong>0.00028</strong></td>
<td>0.00131</td>
<td>0.00154</td>
</tr>
<tr>
<td>FM</td>
<td>0.02502</td>
<td>0.03255</td>
<td><strong>0.02406</strong></td>
<td>0.03592</td>
<td>0.04281</td>
</tr>
</tbody>
</table>

Table 6.8: Effect of number of wavelons on RMSE and FM

<table>
<thead>
<tr>
<th>WL</th>
<th>13</th>
<th>15</th>
<th>17</th>
<th>19</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>0.001732</td>
<td>0.001186</td>
<td><strong>0.000549</strong></td>
<td>0.000792</td>
</tr>
<tr>
<td>FM</td>
<td>0.012209</td>
<td>0.010621</td>
<td><strong>0.007975</strong></td>
<td>0.008936</td>
</tr>
</tbody>
</table>

Thus the network developed with 17 number wavelons and learning rate ($\gamma$) as 0.03 gives the best results, and the developed network with these parameters is referred as best network. These values are obtained with 1000 iteration. However, this developed best network is permitted to execute as many numbers of iterations as required till it reaches the assigned training accuracy (error goal). It is evident from Table 6.9, that the MDWN has required 9370 iterations to reach the required accuracy level of $1e-06$. The value of test error is $5.41e-04$, which is acceptable for all practical purposes. The typical RMSE curve during training phase for 1000 iterations is given in Fig.6.2.

Table 6.9: Performance of best values of network parameters for impulse fault identification

<table>
<thead>
<tr>
<th>$\gamma$</th>
<th>No. of WL</th>
<th>No. of iterations</th>
<th>RMSE</th>
<th>FM</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.03</td>
<td>17</td>
<td>9370</td>
<td><strong>0.000001</strong></td>
<td>0.000541</td>
</tr>
</tbody>
</table>
The number of successful predictions of unknown dynamic insulation failure at line end (S3), middle (S12) and earth end (S20) sections of the winding using the network with best value of parameters is shown in Table 6.10. Among four discs in each section the features of insulation failure of arbitrarily selected particular location of disc used for training are shown as $T$ and the features used for testing are referred as $P$ in Table 6.10. It may be observed from Table 6.10 that the Gaussian MDWN with best values of network parameter has successfully identified the fault characteristics. In the present study, the location of insulation failure along the length of 33 kV winding has been identified accurately within 4.5% ($4/88 \approx 4.54\%$) of winding length, i.e. the algorithm located the section of winding where the dynamic insulation failure has occurred. The network has successfully identified 313 test cases out of 344 and the overall classification accuracy of MDWN approach for dynamic insulation failure characteristics identification is approximately 91%.
Table 6.10. Detailed number of successful predictions in three sections among 22 different section of the analog model 33 kV winding of 3 MVA transformer

<table>
<thead>
<tr>
<th>Section No</th>
<th>Fault type</th>
<th>Fault location within the section</th>
<th>Number of successful prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>S3</td>
<td>DSFA3</td>
<td>T T P P</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>DSFB3</td>
<td>T P T P</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSFC3</td>
<td>T P P T</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSFD3</td>
<td>T T P P</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSHA3</td>
<td>P T T P</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSHB3</td>
<td>P T P T</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSHC3</td>
<td>T P T P</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSHD3</td>
<td>P T T P</td>
<td>2</td>
</tr>
<tr>
<td>S12</td>
<td>DSFA12</td>
<td>P P T T</td>
<td>2</td>
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<tr>
<td></td>
<td>DSFB12</td>
<td>T P T P</td>
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<tr>
<td></td>
<td>DSFC12</td>
<td>P T P T</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSFD12</td>
<td>P P T T</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSHA12</td>
<td>T T P P</td>
<td>2</td>
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<tr>
<td></td>
<td>DSHB12</td>
<td>T P T P</td>
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<td></td>
<td>DSHC12</td>
<td>T P T T</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSHD12</td>
<td>T T P P</td>
<td>2</td>
</tr>
<tr>
<td>S20</td>
<td>DSFA20</td>
<td>P T T P</td>
<td>2</td>
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<tr>
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</tr>
<tr>
<td></td>
<td>DSFC20</td>
<td>T P T P</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSFD20</td>
<td>P T T P</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSHA20</td>
<td>P P T T</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>DSHB20</td>
<td>T P T P</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSHC20</td>
<td>P T P T</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSHD20</td>
<td>P P T T</td>
<td>2</td>
</tr>
</tbody>
</table>

Overall identification accuracy from S1 to S22: 90.98%

Faults occurred in a real life power transformer under impulse test have also been identified using the proposed approach. A real life 50 MVA, 132/33 kV, 3 phase, 50 Hz, YNd1, OFAF transformer was tested in the high voltage laboratory of Jadavpur University as a part of the acceptance test carried out by the manufacturer in this laboratory. Impulse test results indicated a fault which was discernible from oscilloscopic traces. But it was difficult to identify the exact location of fault from manual
observation of oscilloscopic traces. As a part of this research work the manufacturer was requested to provide the relevant design parameters of the transformer so that an EMTP model could be created and different types of faults could be simulated in that digital model. Features were extracted from the current waveforms obtained from the EMTP model and added to the training data set of the WN. The WN was subsequently trained with the extended data set. The number of successful prediction of each fault classes of three different sections at line ($S_2$), middle ($S_9$) and earth end ($S_{14}$) of 50 MVA transformer is given in Table 6.11. The winding of the 50 MVA transformer has been divided into 17 sections, each comprising 4 discs. 544 fault current waveforms are obtained, out of which 272 are used for training and the other 272 are used for testing. The trained MDWN has successfully identified 249 test cases out of 272 giving an overall identification accuracy of 91.54% for the 50 MVA transformer. It may be noted here that the training is to be carried out using all the training data obtained from various transformers so that the trained MDWN can perform fault classification in the case of transformers of different ratings. Then recorded winding current of the actual transformer which indicated the fault was fed to the feature extractor and extracted features were then given to the trained network as input. The network identified a location for this fault, which was within 5.5% of the exact location as noted by the manufacturer upon inspection of the winding subsequent to the test. It may be added here that the accuracy is slightly less in this case. This is because of the fact that the network has been trained using digital model data and the fault location has been done using real life data.

The efficiency of MDWN and extracted features for identification of dynamic insulation failure is compared with ANN based classifier [83]. The extracted features $F_1$ through $F_9$ form the input of ANN classifier and the assigned target values corresponding to fault type, condition and locations along the winding form the output of the ANN network.
Table 6.11. Detailed number of successful predictions in three different sections of the 50 MVA transformer winding

<table>
<thead>
<tr>
<th>Section No</th>
<th>Fault type</th>
<th>Fault location within the section</th>
<th>Number of successful prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>S2</td>
<td>DSFA2</td>
<td>P P T T</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSFB2</td>
<td>T P P T</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSFC2</td>
<td>P T T P</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSFD2</td>
<td>P T P T</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSHA2</td>
<td>T P T P</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSHB2</td>
<td>T P P P</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSHC2</td>
<td>P T P P</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>DSHD2</td>
<td>P P P P</td>
<td>2</td>
</tr>
</tbody>
</table>

| S9         | DSFA9      | P T T P                            | 2                               |
|            | DSFB9      | T P T P                            | 2                               |
|            | DSFC9      | P T P T                            | 2                               |
|            | DSFD9      | T T T T                            | 2                               |
|            | DSHA9      | T T P P                            | 2                               |
|            | DSHB9      | T P T P                            | 2                               |
|            | DSHC9      | T P P P                            | 2                               |
|            | DSHD9      | T T P P                            | 2                               |

| S14        | DSFA14     | P P T T                            | 1                               |
|            | DSFB14     | P T T T                            | 2                               |
|            | DSFC14     | T P T T                            | 2                               |
|            | DSFD14     | P P T T                            | 1                               |
|            | DSHA14     | P T T P                            | 2                               |
|            | DSHB14     | T P T P                            | 2                               |
|            | DSHC14     | T P T P                            | 2                               |
|            | DSHD14     | P T T P                            | 2                               |

Overall identification accuracy from S1 to S17: 91.54%

The same number of training and test cases, which were used for MDWN, has been employed to compare the accuracy of fault characteristics identification. Sensitivity analysis has been performed with different values of learning rate ($\eta$) and momentum constant ($\alpha$). The effect of number of neurons in the hidden layer for fault identification has also been studied by varying the hidden layer neurons from 16 to 56, and the results are presented in Table 6.12, which shows that 37 neurons in the
hidden layer gives best training and test RMSE. The results shown in Table 6.12 are obtained using best values of learning rate and momentum constant after 1000 number of iterations. Hence the feed-forward network based ANN classifier with sigmoidal activation function using error back propagation algorithm is developed with 9 input node, 37 hidden neurons and 1 output node. Table 6.13 shows the obtained classification accuracy of ANN. The ANN has successfully identified 262 fault patterns out of 344 test cases and thus the overall identification accuracy is 76.16%. It is evident that the MDWN has identified the type, condition and location of dynamic insulation failure more accurately compared to ANN classifier.

<table>
<thead>
<tr>
<th>Number of hidden layer neurons</th>
<th>Number of iterations</th>
<th>Training RMSE</th>
<th>Test RMSE</th>
</tr>
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<tbody>
<tr>
<td>16</td>
<td>1000</td>
<td>0.091860</td>
<td>0.44790</td>
</tr>
<tr>
<td>32</td>
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<td>0.004884</td>
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<td>36</td>
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<td>0.29915</td>
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<td>37</td>
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<td>48</td>
<td></td>
<td>0.027310</td>
<td>0.53360</td>
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</table>

<table>
<thead>
<tr>
<th>Architecture of ANN</th>
<th>Number of training sets</th>
<th>Number of test sets</th>
<th>Number of successful predictions</th>
<th>Accuracy of prediction for test cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>8:37:1</td>
<td>352</td>
<td>344</td>
<td>262</td>
<td>76.16%</td>
</tr>
</tbody>
</table>

**6.7 Conclusions**

A method for identification of fault characteristics of dynamic insulation failure during impulse testing of transformers using correlation features aided MDWN is discussed. Classification results show that the proposed cross-correlation features aided wavelet network has successfully
identified not only the fault type and fault establishment time but also the location of the fault within 4.6% of winding length with good accuracy. It may be observed from the study that the extracted cross-correlation features played a major role in fault pattern identification. As the acquired winding current contain the signatures of the impulse fault characteristics, a good feature extractor may improve the fault characteristics identification accuracy of any classifier. Though, cross-correlation technique is a good feature extractor, due to necessity of accurate identification of unknown fault characteristics, an attempt has been made to use another feature extractor. Recently, cross-wavelet transform based feature extraction has become popular in the field of signal processing, as it gives feature in both time and frequency domain. Therefore, an attempt has been made to identify fault characteristics using cross wavelet transform features, which may give better results than that of MDWN based classifier. The cross-wavelet transform feature extraction and fault classification characteristics of Bacterial Forging Optimization algorithm is presented in the next chapter.