CHAPTER 6

CLASSIFICATION OF INSULATION STATUS IN HV ROTATING MACHINERY USING HYBRID INTELLIGENT TECHNIQUES

6.1 EXPERT SYSTEM METHOD - AN OVERVIEW

The insulation condition of HV rotating machinery is really important for ensuring the secured operation of the power system. To be very precise, the life expectancy is predominantly assessed by the condition of the stator insulation system. The insulation failure demands notable repairs, rewinding or replacement of whole apparatus in actual practice. It is a well known fact that the insulation degradation involves number of failure mechanisms. So the condition assessment of the insulation system is an important task due to the variation in insulation materials, design procedures and working locations. In addition, there is no individual diagnostic test which is sensitive to all probable failure mechanisms.

The various diagnostic tests discussed in Chapter 3, together with the predicted results in Chapters 5, yield the real-time data. The measured values themselves speak about the winding insulation condition to onlookers. The trending process in a test result is normally an effective indicator of increasing problem in the HV assets. The data collection process is not so easy to carry out, but it acts as an input information for the expert system based condition assessment. However, when the initial information is
prepared, the data is available permanently and the same will be easily made use of by everybody in the plant. In addition, the performance of new test results is reasonably stress free. If the individual is untrained in interpreting the data, the readings taken are presumed to be worthless. Meanwhile, interpretation proficiency is highly essential for the extensive range of experiments and monitoring techniques, limited persons have the time or grow into experts. An expert system can yield a winding condition of the motors and generators in a plant accurately to the extent possible as like a human expert, so that the expensive task of consulting an expert may be avoided.

Expert system takes efforts to reconstruct the cognitive practices that an expert makes use of for the interpretation of data obtained from the diagnostic tests. On the development of an expert system, it allows the non-experts to convert such data into information with practical exactness as like that of an expert. Another advantage associated with the expert system is gathered data and its information are stored everlastingly which forms a knowledge base to be utilized forever. Recently, utmost attention has been taken on the study about electrical insulation which is highly concerned towards the automation of the diagnostic practice, in an attempt to reduce the want for a human expert for data interpretation. Specifically, for the HV rotating machines, many deterioration mechanisms may happen at the same time, which necessitate the development of appropriate intelligent technique and to perform automatic detection of the stator winding insulation condition. Besides, the expert system method for insulation diagnosis have to be validated effectively.
In general, the existing expert system does not contain off-line test results in it. On the other hand, most of the expert systems consist of a high quantity of information related to the design of the machine and the various failure mechanisms and their warning signs. The initial cost for procuring such existing software is really very expensive due to the high built-in information. This work attempts to eliminate such limitation so that it can act as supporting expert system with the low-cost software tool well suited to help users of motors and generators. This chapter describes the development of an expert system to assist rotating machine maintenance personnel in assessing the insulation condition.

6.2 INSULATION DIAGNOSIS IN HV ROTATING MACHINES

The non-destructive diagnostic measurements like dielectric loss, capacitance test and PD measurements are widely used to identify the condition of the stator winding insulation of large rotating machines. The insulation of HV power apparatus is stressed due to application of high electric field which leads to the occurrence of PD. PD is one of the important sources for degradation of insulation. PD will occur in the voids or cracks present in the insulation system due to various ionization processes in the gas medium. PD is a confined electric failure in the solid dielectric medium that partially bridges between the two conductors due to the application of very high electric stress. Therefore the integrity of the insulation system has to be ascertained through the various non-destructive diagnostic tools. The PD measurement is used to detect the insulation system quality and helpful to govern the remaining life. Similarly, the condition of the insulation system will be determined in the HV stator windings in which the insulation is considered as dielectric medium present between the two conducting plates. The PF test is used to measure the capacitance superiority and loss factor or
dissipation factor of the insulation. Dissipation factor is also called as tan delta which reveals the wellness of the winding consolidation and comment on the presence of air filled void content.

In this context, the power apparatus always requires a suitable maintenance and management procedures. Several techniques are used to assess the equipment condition which in turn gives useful idea on testing methods to be adopted. The insulation condition of the high voltage stator windings must be checked from time to time and commendably to avoid the failure in-service. The testing results are analyzed using statistical techniques using computational intelligent tools. These tools are highly required due to minimum availability of experts to comment on the test results. With the advent of the expert system and its computational algorithms, the diagnosis of the defect in the insulation medium can be easily identified and suitable preventive measures can be programmed. The development and implementation of an expert system guide the personnel involved in maintenance to forecast the presence of fault through the status classification of insulation system.

In the review of literatures, it is evident that soft computing tools are used for diagnosing the reliability of the large motors and generators. It has been reported that the AI plays an important part in the prediction of faults in rotating machinery. The advent of digital systems and signal processing methods helps to automate the data interpretation process. Neural networks are efficient in handling the errors; its learning ability, ease of adaption with the domain and creating own relationship between information.
Feed forward back propagation neural network constitutes multiple layers with several computational units which are interconnected in feed forward fashion.

Back propagation possesses many learning techniques and referred as popular algorithm in neural network. It has several hundreds of spinoff applications and fast resurgence of importance in neural computing. In back propagation, the error values will be calculated in comparing the output values and the target values. The error values will be fed back through various methods to update the connection weights for reducing it. Recently, integrated paradigms are introduced due to the reason that all the available technologies have their own merits and surfeits. Therefore the concept of hybridization exists and plays a vital role in optimization based problems. A hybrid method contains more than one intelligence concept in a synergistic framework. The limitations existing in the ANN adopted for finding the optimal solution will be ruled out when it is merged with GA. Recently, more number of researchers utilized algorithms that are nature inspired for solving complex optimization problems. Hence hybrid ANN with GSA is utilized due to its enhanced features and capability to yield better results.

The experiments are performed on different 11kV and 6.6 kV machines to obtain the various non-destructive quantities which make known their characteristic behavior. The precise estimation of the defect in the high voltage stators is most significant to improve the reliability of the high voltage assets. In this research work, an intelligence system based fault prediction of the stator winding insulation system is proposed. This is an attempt to automate the fault detection process that involves large amount of complex data which in turn provide the comprehensive data interpretation for the power utilities. The diagnosis of insulation status is done using hybrid
technique which is the combination of ANN and GSA. The use of intelligent systems confirms the integrity and ascertains the enduring life of the high voltage rotating machines in service. To validate the proposed hybrid method, the results are compared with ANN and ANN – GA techniques.

6.3 METHODOLOGY

In the past few years, the condition monitoring of rotating machines was done effectively by the diagnostic tests namely, power factor test, Capacitance test and Partial Discharge Test. These non-destructive tests perhaps help to access the gradual degradation of the stator winding insulation. Based upon the obtained characteristic parameters, the state and quality of insulation will be ascertained using hybrid techniques.

6.3.1 Test Data Acquisition

The primary element in high voltage apparatus testing is the test data acquisition process. It requires appropriate measurement setup with experts capable of doing measurements. The quantitative tool should have great power and utility to acquire test data as accurate as possible. The four valuable parameters namely tan delta, leakage current, capacitance and partial discharge magnitude are measured as described in the chapter 3.

6.3.2 Network Model for ANN Aided by GSA

The field of neural network has captured increased attention of researchers working in data-modelling in recent years. Neural networks have achieved greater importance in the analysis of partial discharge that occurs in rotating machinery. The concept of GSA combined with neural network is
used to develop a system for identifying the presence of insulation defects in HV rotating machines.

The combination of ANN and GSA assess the condition of the winding due to the air filled voids in insulation. In this work, a hybrid technique is used to analyze the quality of insulation status in 11kV and 6.6kV machines. The proposed hybrid method uses \( \tan \delta \) and PD test values to access the insulation quality of the stator windings.

![Figure 6.1 Proposed neural architecture for fault prediction](Image)

**Figure 6.1 Proposed neural architecture for fault prediction**

ANN is a computational model that is able to capture and represent the complex input-output relationships. ANN can smoothly approximate and interpolate multivariable data by working in parallel to solve a specific problem. There are three interconnected layers in ANN which have the
capability to learn and acquire information by training process. The training and testing are the two stages in the ANN.

In the training stage, the feature vectors are applied as an input to the neural network. The input layer consists of five neurons, which are based on the parameters that are measured during test data acquisition process. The hidden layer contains fifty neurons which may internally transform the data and the output layer contains a single neuron to classify the machine winding status as healthy or unhealthy. Once trained, the ANN develops a correlation between all inputs and output through its hidden layer. The neural structure used for fault prediction is shown in Figure 6.1. Here, \(X\) represents the input to the neural net and \(w_{ji}\) and \(w_{ij}\) are the connection weights corresponding to hidden layer and output layer of the network respectively. The output node is specified as \(Y_o\). The following steps describe the procedure for training the proposed neural network.

### 6.3.3 Training Algorithm

**Step 1**: The weights of all neurons are allotted randomly for learning the network. The weights are specified in the interval range (0, 1)

**Step 2**: The response of every hidden layer neuron (\(Z_j\)) is calculated using the Equation (6.1) and the signal from all units of hidden layer is directed to output layer.

\[
Z_j = f \left( \sum_{i=1}^{n} w_{ji} X_i - \theta_j \right)
\]

(6.1)

where \(w_{ji}\) is the connection weight between input and hidden layer and \(\theta_j\) is the bias term of the hidden layer.
Step 3: The response of the output layer ($Y_o$) is calculated using the Equation (6.2).

$$Y_o = f\left(\sum_{j=1}^{m} W_{kj}Z_j - \theta_k\right)$$  \hspace{1cm} (6.2)

where $w_{kj}$ is the connection weight between the hidden and output layer and $\theta_k$ is the bias term of the output layer. The sigmoidal activation function given in the equation (6.3) is used to obtain the output response of the network.

$$f(Z_j) = \frac{1}{1+e^{-Z_j}}$$  \hspace{1cm} (6.3)

Step 4: The BP error is evaluated using GSA. In GSA, the optimized parameter of ANN is achieved by minimizing the BP error function.

Step 5: The changes in weights are obtained based on the BP error. The weight updation of each neuron is done using the Equation (6.4) and Equation (6.5),

$$w_{new} = w_{old} + \Delta w$$  \hspace{1cm} (6.4)

$$\theta_{new} = \theta_{old} + \Delta \theta$$  \hspace{1cm} (6.5)

Here, $w_{new}$ denotes the new weight, $w_{old}$ represents the previous weight and $\Delta w$ is the change in weight of each output neuron. $\theta_{new}$ denotes the new bias value, $\theta_{old}$ represents the previous bias value and $\Delta \theta$ is the change in bias value of each output neuron.
Step 6 : Using the following equation, change in weight of the network is evaluated.

\[ \Delta w = \delta Y_o \cdot BP_{error} \] (6.6)

In Equation (6.6), \( \delta \) is the learning rate. Repeat the above steps till the \( BP_{error} \) gets minimized. Once the neural network training process is completed, the network is trained well for predicting the insulation condition of the machine. At this moment the network becomes capable enough to classify the winding status as healthy or unhealthy based on the test data extracted from experimentation. The procedure to determine the \( BP_{error} \) is detailed in the chapter 5.

6.4 RESULTS AND DISCUSSIONS

This section aims at demonstrating the performance of the newly proposed insulation status diagnosis technique for 11kV and 6.6kV rotating machines. The proposed hybrid technique is used to determine the condition of the machine insulation system based on four parameters namely leakage current, capacitance, Tan delta value and partial discharge magnitude measured from the machine. The relationship between the applied voltage and the change in capacitance, tan \( \delta \) and PD magnitude are used to classify the faulty machines from healthy ones. The program for the proposed method is coded in MATLAB working platform. To verify the robustness and effectiveness of the proposed hybrid algorithm, it is compared with the standalone ANN and ANN-GA techniques.

The performance analysis is made on experimental data obtained from 8 machines of 11kV and 6 machines of 6.6kV stator voltage rating as explained in the chapter 5, are utilized. The applied voltage, leakage current,
capacitance, tan δ and PD magnitude of all the 14 machines are fed as input to the neural network for training process. The winding insulation status of the machines are evaluated using ANN, ANN-GA and ANN-GSA techniques.

For experimentation, datasets with varying number of healthy and unhealthy machines data are considered as shown in Table 6.1 and the obtained results are accordingly tabulated in the Table 6.2. The datasets containing 11kV and 6.6kV machine values are analyzed with four characteristic parameters for the proposed method.

Table 6.1 Testing Datasets of 11kV and 6.6kV machines

<table>
<thead>
<tr>
<th>Rated Capacity</th>
<th>Data set size</th>
<th>Number of Healthy Data</th>
<th>Number of Unhealthy Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>11kV</td>
<td>15</td>
<td>10</td>
<td>05</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>6.6kV</td>
<td>15</td>
<td>05</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td>15</td>
<td>15</td>
</tr>
</tbody>
</table>

Table 6.2 Fault prediction results of the proposed method

<table>
<thead>
<tr>
<th>Rated Capacity</th>
<th>Total Number of Test Data</th>
<th>Number of Healthy Data</th>
<th>Number of Unhealthy Data</th>
<th>Correctly Identified</th>
</tr>
</thead>
<tbody>
<tr>
<td>11kV</td>
<td>30</td>
<td>15</td>
<td>15</td>
<td>30</td>
</tr>
<tr>
<td>6.6kV</td>
<td>30</td>
<td>15</td>
<td>15</td>
<td>29</td>
</tr>
</tbody>
</table>

The parameters sensitivity, specificity, accuracy and False Positive Rate (FPR) given in Equation (6.7) to (6.10) are used to validate the proposed
method. Sensitivity and specificity are the most commonly used measures of correctness of the detection. Accuracy is essential for the overall validity of detection process which in turn exhibits strong reliability. The evidence of validity is needed to give confidence that the test will work well.

**Sensitivity** is defined as the ratio of the number of correctly detected true positives to the total number of unhealthy machines among the total machines. Sensitivity is measured in percentage (%) which provides the probability of positive test specified that the machine insulation has an issue. If sensitivity is higher, then the proposed method is said to be efficient.

\[
Sensitivity = \frac{TP}{TP + FN} \times 100
\] (6.7)

**Specificity** is defined as the ratio of the number of correctly detected true negatives to the total number of unhealthy machines among the total machines and calculated in percentage (%). It provides the probability of negative test specified that the machine insulation is in good condition when its ratio yields higher value.

\[
Specificity = \frac{TN}{TN + FP} \times 100
\] (6.8)

**Classification accuracy** of the proposed method is defined as the ratio of the number of correctly classified machines to the total number of machines. The classification accuracy, expressed as a percentage (%) is given by the following mathematical equation stated below

\[
Accuracy = \frac{(TP + TN)}{(TN + FP + FN + FP)} \times 100
\] (6.9)
In a statistical context, in addition to the instances discussed above, the FPR is defined as the percentage of healthy machines which erroneously receive a positive test result.

\[
\text{False positive rate (FPR)} = \frac{F_P}{(T_P + F_P)} \times 100
\]

(6.10)

The description for the input condition of the insulation system and the test results are stated in the Table 6.3.

**Table 6.3 Description of TP, TN, FP and FN**

<table>
<thead>
<tr>
<th>Description</th>
<th>Test Results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Unhealthy</td>
</tr>
<tr>
<td>Input Condition</td>
<td>Unhealthy</td>
</tr>
<tr>
<td></td>
<td>Healthy</td>
</tr>
</tbody>
</table>

The performance measures are calculated for different 11kV machine datasets by the different intelligent techniques for a dataset size of 15 and 30 are carried out. The results obtained from the three methods for a dataset size of 15 are furnished in Table 6.4.

**Table 6.4 Performance measures of 11kV Machine of Data size 15**

<table>
<thead>
<tr>
<th>Methods</th>
<th>T_P</th>
<th>F_P</th>
<th>T_N</th>
<th>F_N</th>
<th>Sensitivity (%)</th>
<th>FPR (%)</th>
<th>Accuracy (%)</th>
<th>Specificity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>4</td>
<td>3</td>
<td>7</td>
<td>1</td>
<td>80.0</td>
<td>30.0</td>
<td>73.3</td>
<td>70.0</td>
</tr>
<tr>
<td>ANN-GA</td>
<td>4</td>
<td>1</td>
<td>9</td>
<td>1</td>
<td>80.0</td>
<td>10.0</td>
<td>86.7</td>
<td>90.0</td>
</tr>
<tr>
<td>ANN-GSA</td>
<td>5</td>
<td>0</td>
<td>10</td>
<td>0</td>
<td>100.0</td>
<td>0.0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
</tbody>
</table>
First, an 11kV Machine dataset of size 15 is considered for analysis. The sensitivity value of 100% is obtained in the proposed method whereas ANN and ANN-GA yields only 80%. From the inspection of the results it is inferred that there is an improvement in the sensitivity value of about 20% in the proposed method. The specificity of 100% is obtained in the proposed method whereas ANN and ANN-GA yields 70% and 90% respectively. On examining the results, there is an increment in approaching the true negative value of about 20% in the proposed method. An accuracy of 73.3%, 86.7% and 100% are achieved during the testing of ANN, ANN-GA and proposed method respectively. Similarly, a higher value of FPR of 30% in ANN and 10% in ANN-GA are attained. The proposed method is capable enough to predict the healthy data of the machine correctly. Secondly, an 11kV Machine dataset of size 30 is considered for analysis and its performance indices are presented in Table 6.5.

Table 6.5 Performance measures of 11kV Machine of Data size 30

<table>
<thead>
<tr>
<th>Methods</th>
<th>T_P</th>
<th>F_P</th>
<th>T_N</th>
<th>F_N</th>
<th>Sensitivity (%)</th>
<th>FPR (%)</th>
<th>Accuracy (%)</th>
<th>Specificity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>13</td>
<td>3</td>
<td>12</td>
<td>2</td>
<td>86.7</td>
<td>20.0</td>
<td>83.3</td>
<td>80.0</td>
</tr>
<tr>
<td>ANN-GA</td>
<td>15</td>
<td>2</td>
<td>13</td>
<td>0</td>
<td>100.0</td>
<td>13.3</td>
<td>93.3</td>
<td>86.7</td>
</tr>
<tr>
<td>ANN-GSA</td>
<td>15</td>
<td>0</td>
<td>15</td>
<td>0</td>
<td>100.0</td>
<td>0.0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
</tbody>
</table>

On increasing dataset size from 15 to 30, an accuracy of 83.3%, sensitivity of 100%, FPR of 20% and specificity of 80% are obtained in the ANN method. Similarly in the testing phase of ANN-GA, an accuracy of 93.3%, sensitivity of 86.7%, FPR of 13.3% and specificity of 86.7% are attained. The proposed method proves its effectiveness by yielding 100% of accuracy, sensitivity and specificity with no False Positives.
The investigation is further continued for a dataset size of 15 and 30 of different 6.6kV machines and its corresponding testing results are furnished in Table 6.6 and Table 6.7.

**Table 6.6 Performance measures of 6.6kV Machine of data size 15**

<table>
<thead>
<tr>
<th>Methods</th>
<th>T_P</th>
<th>F_P</th>
<th>T_N</th>
<th>F_N</th>
<th>Sensitivity (%)</th>
<th>FPR (%)</th>
<th>Accuracy (%)</th>
<th>Specificity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>7</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>70.0</td>
<td>40.0</td>
<td>66.7</td>
<td>60.0</td>
</tr>
<tr>
<td>ANN-GA</td>
<td>8</td>
<td>1</td>
<td>4</td>
<td>2</td>
<td>80.0</td>
<td>20.0</td>
<td>80.0</td>
<td>80.0</td>
</tr>
<tr>
<td>ANN-GSA</td>
<td>10</td>
<td>1</td>
<td>4</td>
<td>0</td>
<td>100.0</td>
<td>20.0</td>
<td>93.3</td>
<td>80.0</td>
</tr>
</tbody>
</table>

**Table 6.7 Performance measures of 6.6kV Machine of data size 30**

<table>
<thead>
<tr>
<th>Methods</th>
<th>T_P</th>
<th>F_P</th>
<th>T_N</th>
<th>F_N</th>
<th>Sensitivity (%)</th>
<th>FPR (%)</th>
<th>Accuracy (%)</th>
<th>Specificity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>13</td>
<td>2</td>
<td>13</td>
<td>2</td>
<td>86.7</td>
<td>13.3</td>
<td>86.7</td>
<td>86.7</td>
</tr>
<tr>
<td>ANN-GA</td>
<td>13</td>
<td>1</td>
<td>14</td>
<td>2</td>
<td>86.7</td>
<td>6.7</td>
<td>90.0</td>
<td>93.3</td>
</tr>
<tr>
<td>ANN-GSA</td>
<td>14</td>
<td>0</td>
<td>15</td>
<td>1</td>
<td>93.3</td>
<td>0.0</td>
<td>96.7</td>
<td>100.0</td>
</tr>
</tbody>
</table>

The analysis for 6.6kV machine is started with a dataset size of 15. The proposed method yields an improvement in sensitivity of 20% compared to ANN-GA and 30% in ANN. The specificity of 80% is obtained for the proposed and ANN-GA techniques which infers an increase of 20% in comparison with ANN. An accuracy of 93.3% is attained for the proposed method whereas ANN-GA and ANN results in 80% and 66.7% respectively.
The simple structure of ANN provides a higher false positive rate of 40%. The gravity search concept incorporated in the proposed method produces only 20% false positives.

On examining the results for dataset size of 30, the sensitivity of 93.3% and specificity of 100% is obtained for the proposed scheme. An accuracy of 96.7% is attained for the proposed method whereas ANN-GA and ANN results in 90% and 86.7% respectively. The false positive rate is low for ANN-GSA when compared to existing methods considered for analysis.

Figure 6.2 and Figure 6.3 illustrate the plot of performance parameters attained for 11kV machines of dataset size 15 and 30 respectively.

Figure 6.2 Statistical measure on 11 kV machines with data size of 15
Figure 6.3 Statistical measure on 11 kV machines with data size of 30

Figure 6.4 and Figure 6.5 illustrate the plot of performance parameters attained for 6.6 kV machines of dataset size 15 and 30 respectively. It is noticeably evident that the proposed method promingly yields better performance parameters and highly proficient in detecting the condition of the insulation system.

Figure 6.4 Statistical measure on 6.6 kV machines with data size of 15
This system serves as a diagnostic tool that helps the power utilities to make an objective and quantitative analysis of condition assessment of machine winding insulation. In general the proposed system based on ANN with the aid of GSA is found to be highly efficient and deserves to be a reliable system for evaluating the condition of insulation of the rotating machines.

6.5 SUMMARY

A proficient ANN aided GSA based hybrid intelligent technique is developed for the prediction and classification of the condition of insulation. This method is justified in terms of classification accuracy, sensitivity and specificity when compared with the other techniques, namely ANN and ANN-GA. The comparison results show that the proposed work is more accurate, sensitive and specific towards the prediction and classification of insulation status in HV rotating machines. The outcome of this research study reveals the suitability of the proposed technique to be adopted for the real time applications and found to be proficient.