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Condition Monitoring of Stator Winding Insulation in High Voltage Rotating Machines Using BPN Algorithm

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Abstract: The condition of the insulation of an machine can be assessed by measuring the various parameters of the insulation like capacitance, leakage current, dissipation factor, polarization index, surge voltage with standing strength etc. To assess these parameters of the insulations used in high voltage rotating machines a number of measurements have been conducted on actual stator coils of machines manufactured using resin rich technology for various test voltages, the capacitance and dissipation factors were measured and correlated as a function of test voltages. Attempts were made using Neural Network tool to predict the possibilities of establishing a correlation between the applied test voltage and the maximum variation of capacitance and dissipation factor in relation to the volume of the air filled voids in the insulation.

Key words: Rotating machine insulation, diagnostic ageing, dissipation factor, capacitance, partial discharge magnitude and neural network

INTRODUCTION

High-Voltage (HV) generator failures due to insulation breakdown may cause catastrophic damages to the equipment and expensive losses. Stator winding insulation of generators is prone to Partial Discharge (PD) activity as a result of voids within insulation and air gaps adjacent to insulation under high voltage stress. Partial discharges are "sparks" involving the flow of electrons and ions when a small volume of gas breaks down. The term partial is used since there is a solid insulation, such as epoxy-mica, in series with the void, which prevent a complete breakdown. Depending on the size of the void, the dielectric constant and the temperature, the stress on the gas within the void may become high enough for breakdown to occur. In most cases, the electric filed will not be uniform and this will tend to lower the breakdown voltage. Partial discharges are often the result of damages caused by other thermal, mechanical, electromagnetic and chemical stresses acting on the stator winding. These discharges also contribute to the ageing of the machine's dielectric system by eroding away or deteriorating the insulation system. Therefore, partial discharge activity is good indication of insulation deterioration. Partial discharge testing can assess the condition of stator winding insulation and thereafter help to establish a condition based maintenance program. Condition monitoring and predictive maintenance of stator insulation brings users benefits of reliable operation, optimal number of maintenance outages and maximal lifetime of their generators (Anonymous, 1998).

DISSIPATION FACTOR

The tan δ is a valuable quantity that gives integral information about the condition of the insulation. The tan δ is considered proportional to the total volume of discharging voids, which increases with the degree of aging. In electrical machines, as in other electrical equipment, the tan δ measurement is used as a traditional diagnostic method. The dielectric losses in insulation can be divided into three components, whose sum results in the tan δ of the insulation:

$$\text{Tan}\,\delta = \tan\delta_c + \tan\delta_p + \tan\delta_{PD} \qquad (1)$$

where:

- $\tan\delta_c$ = The conducting loss factor caused by free-charge carries, the ions and electrons (conducting losses).
- $\tan\delta_p$ = The polarization loss factor caused by the polarization processes (polarization losses).
- $\tan\delta_{PD}$ = The partial discharge loss caused by PD in the insulation (ionization losses).

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In practice, in high voltage rotating machines, it is very significant that, in addition to the absolute value of tan δ at a certain test voltage, the tan δ as a function of the applied test voltage, e.g., from 0.2-1.2 U_N is measured at 2 designated voltages is named del tan delta (Δtan δ) or tip-up.

In good insulating systems of high voltage rotating machines, the change in tan δ is very small with increasing applied test voltage. But, an increase in the number and size of the voids or the information of delimitations in the insulating system during its service life caused by different stresses can lead to a large increase in the value of tan δ with applied voltage (Sathiyasekar *et al*., 2007).

CAPACITANCE

In absence of cavities or voids within a solid insulation the change of the capacitance with test voltage is inconsiderable. In presence of voids within the insulation the occurrence of a partial discharge within these voids can ionize the gas for several milliseconds. The ionized gas has sufficiently high conductivity that the void is shorted out. This means that the effective thickness of insulation is reduced which leads to an increase of the capacitance. However, one void shorted out by PD will have no measurable effect on the capacitance of the test object, but if there are many voids, all undergoing PD, then there will be a noticeable increase in the capacitance. In this case, as long as an increasing number of voids begin to undergo to discharge with rising voltage the value of capacitance will increase continuously. The z (C_0), which is measured at low voltage, is the capacitance at high voltage is the capacitance of the solid insulation alone, because the voids have been shorted out by the PD. By taking the different the capacitance of the voids can be estimated. Therefore, it should be possible to estimate the void content within insulation by the capacitance tip-up measurement.

The electrical stress control coating can also have an influence on the capacitance measuring results of complete machines. The moisture content and winding contamination can also increase the initial value of Capacitance (C_0). If the end-winding of a stator is polluted with a partly conductive contamination, then the ground potential of the stator core partly extents over the end-winding and this increases the surface area of the capacitor plate (Sathiyasekar *et al*., 2007).

PARTIAL DISCHARGE MEASUREMENTS

Partial discharges (ionization processes) occur in micro voids and other inhomogeneties present in the body of the insulation. Partial Discharges also occur in gas gaps between stator bar surface and core and in the end winding area. The occurrence of insulation deterioration mechanisms can be determined by measuring partial discharge activity in the winding. These discharges cause thermal ageing, mechanical erosion and chemical deterioration at localized defect sites leading to failure. In this test, partial discharge magnitudes of the highest partial discharge pulses at various voltages are measured.

EXPERIMENT ON STATOR COILS

The measurement of dissipation factor and capacitance tip-up was done by using schering bridge at different test voltage from 1-11 kV at a frequency of 50 Hz. The stator coils used for this investigation being to an insulating system with a rated voltage of 11 kV. The insulation is based on the resin rich technology (Warren *et al*., 1998). The coils are finished with semi-conducting anti corona varnish and stress grading tape to prevent partial discharges. In practice the electrical stress plays the main role in the development of insulation deterioration and the final breakdown, while other stresses such as thermal, mechanical, thermo-mechanical and environmental stresses are mostly the inception factor for creation of defects in insulating systems. The electrical stress can cause partial discharges in voids and cavities, which erode insulating materials and may lead to electrical treeing, which is often referred to as the most important degradation mechanism in solid insulation. Therefore, the ability of detection of such deterioration processes is very important and it is necessary to investigate the characteristic parameters, which are able to describe the condition of the insulation (Fig. 1).

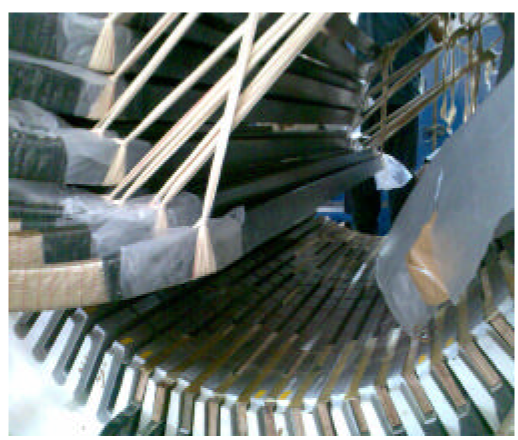

Fig. 1: Experiment on 11 kV stator coils

The experimental results on the simple epoxy resin specimens confirm that the relative volume of the air-filled voids within insulation can be estimated from the changes of capacitance as a function of the applied voltage (Binder *et al*., 2000).

BACK PROPAGATION NETWORK

Architecture: Figure 2 shows a 3 layer neural network suitable for training with BPN algorithm. The input (first) layer serves only as distribution points; they perform no input summation. The input signal is simply passed to the weights on their outputs. Each neuron in the subsequent layers produces output signals according to the activation function used. A neuron is associated with the set of weights that connects to its input. This network is considered to consist of three layers. The input or distribution layer is designated as layer 0, the second layer called hidden layer is denoted as layer 1 and the output layer as layer 2. The activation function used in the BPN is the sigmoidal function. Training is generally commenced with randomly chosen weight values. Typically, the weights chosen are small (between-1 and +1 or-0.5 and +0.5), since larger weight magnitudes may drive the output of layer 1 neurons to saturation, requiring large amounts of training time to emerge from the saturated state. The learning begins with the feed forward recall phase. After a single pattern vector x is submitted at the input, the layers responses z and y are computed in this phase. Then, the error signal computation phase follows. The error signal vector must be determined in the output layer first and then it is propagated toward the network input nodes. Negative gradient descent technique is used for calculation of the error factor and for the calculation of the weight matrix adjustment. First, the weight matrix connects the hidden layer and the output layer is adjusted and then the weight matrix connects the input layer and the hidden layer is adjusted. The training is stopped if the cumulative error is with in the limit or the number of training epoch reaches a maximum set value. The raining algorithm for the BPN network is given later in this chapter (Freeman *et al*., 2005).

Sigmoidal activation function: The sigmoidal function relates the output of a neuron to the weighted input or net input (y) as follows:

$$f(y) = \frac{1}{1+e^{(-y)}} \tag{2}$$

for binary sigmoidal function.

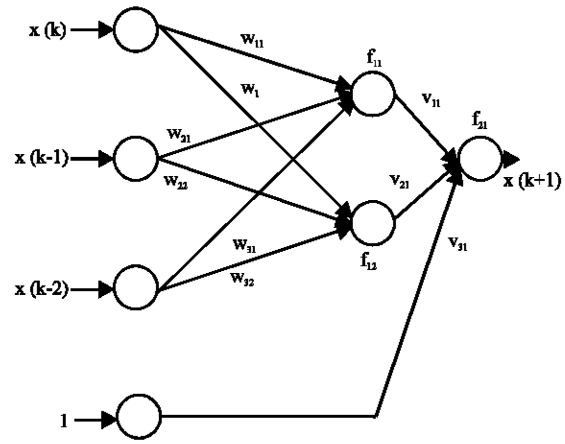

Fig. 2: A three layer neural network

$$f(y) = \frac{2}{1+e^{(-y)}} - 1 \tag{3}$$

for bipolar sigmoidal function (Lee and Yang, ????).

An overview of training: The objective of training the network is to adjust the weights so that application of a set of inputs produces the desired set of outputs.

For reasons of brevity, these input-output sets can be referred to as vectors. Training assumes that each input vector is paired with a target vector representing the desired output; together these are called a training pair. Usually, a network is trained over a number of training pairs. The activation function used for the analysis is bipolar sigmoidal function.

Choice of learning rate and momentum factor: Weight changes in BPN networks are proportional to the negative gradient of the error; this guideline determines the relative changes that must occur in different weights when a training sample (or a set of samples) is presented, but does not fix the exact magnitudes of the desired weight changes. The magnitude change depends on the appropriate choice of the learning rate η. A large value of η will lead to rapid learning but the weight may then oscillate, while low values imply slow learning. This is typical of all gradient descent methods. The right value of η will depend on the applications. Values between 0.001 and 0.9 have been used in many applications (Sathiyasekar *et al*., 2008).

Back propagation leads the weights in a neural network to a local minimum of the mean squared error. Possibly substantially different from the global minimum that corresponds to the best choice of weights. This problem can be particularly bothersome if the "error surface" is highly uneven or jagged, with a large number of local minima. To avoid this, Rumelhart, Hinton and Williams suggested that the weight changes in the i^{th} iteration of the BPN algorithm depend on immediately preceding weight changes, made in the $(i-1)^{th}$ iteration. The implementation of this method is straight forward and is accomplished by adding a momentum term to the weight update rule,

$$\Delta w_{jk} = \alpha d_k z_j(s) + \eta \Delta w_{jk}(old) \qquad (2.3)$$

Use of momentum term in the weight update equation introduces yet another parameter α, whose optimal value depends on the application and is not easy to determine a prior. A well-chosen α can significantly reduce the number of epochs for convergence. A value close to 0 implies that the past history does not have much effect on the weight change, while a value closer to 1 suggests that the current error has little effect on the weight change.

RESULTS AND DISCUSSION

This study illustrates the performance of the proposed procedure for the classification of PD measurements. For all the experiments, with the chosen learning rate and momentum factor, the bias for both hidden and output layers are set to 1. The initial weights are randomized between -0.5 and + 0.5 (Sathiyasekar *et al.*, 2008).

PD measurements from seven machines are used for training the network. Three machines are of 11 kV rating and the rest are of 6.6 kV rating. Finally the network is tested with the eighth machine of 11 kV rating (Table 1).

This problem is tested with conventional BPN algorithm. Three trial sets are used. Each trial weight consists of 10 sets of randomized weight samples. The performance results are shown in Table 2. Epoch Vs Error characteristics for one set of randomized weight samples is shown in Fig. 3.

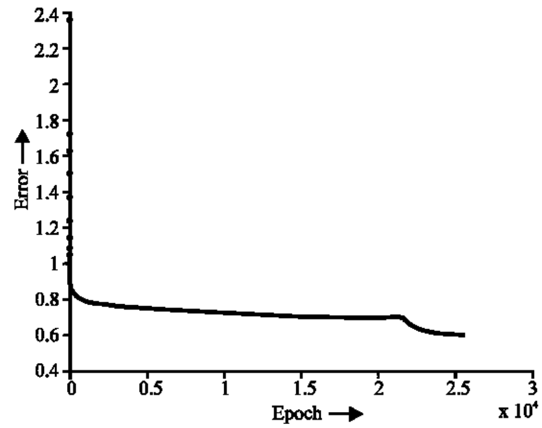

Fig. 3: Cumulative error Vs epoch

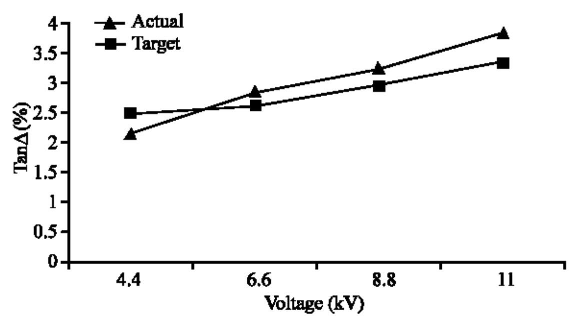

Fig. 4: Actual output Vs target output-R phase

Table 1: PD Measurement of 11 kV machine (Used to test the trained network)

Phase	Ground terminals	Applied voltage in (kV)	Leakage current in (mA)	Capacitance in (nF)	Tan value in (%)	PD magnitude (pC)
R	Y and B	4.40	135.7	99.73	2.458	1500
		6.60	202.9	99.85	2.586	2200
		8.80	269.5	99.49	2.923	4800
		11.00	339.5	100.30	3.315	6000
Y	B and R	4.40	137.8	101.00	2.421	1200
		6.60	205.8	100.90	2.549	2000
		8.80	275.5	101.30	2.856	4700
		11.00	341.1	100.50	3.372	6500
B	R and Y	4.40	136.1	99.97	2.462	1600
		6.60	203.6	100.10	2.592	2200
		8.80	272.1	100.20	2.898	4800
		11.00	340.7	100.40	3.343	6200

Table 2: Classification of PD Measurements using BPN

Trial No.	Failures	Minimum epoch	Maximum epoch	Mean epoch	Standard deviation	Minimum time (sec)	Maximum time (sec)	Mean time (sec)	Mean misclassifications (%)
1	3	25763	29075	27468	1036.90	296.51	334.63	316.13	0.00
2	6	16943	30056	24694	4945.20	193.65	343.52	282.24	0.00
3	5	24343	30294	26925	1957.50	272.01	338.51	300.86	0.00

Classification of PD Measurements BPN, Input neurons:3 Functional Inputs:3, Hidden neurons:3, Output neurons:1 Bias:1, Learning Parameters: Learning, Rate = 0.1 Momentum Factor = 0.85, Activation Function: Bipolar Sigmoid, Max.Failures:10 Training Tolerance = 0.59 Test Tolerance = 0.04

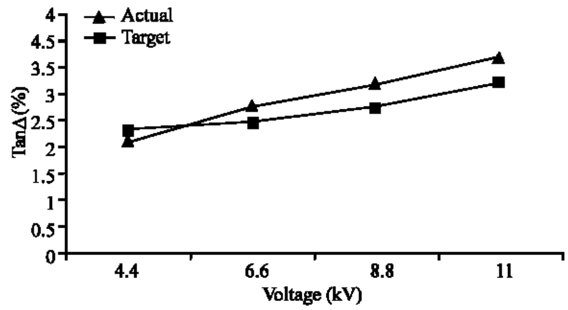

Fig. 5: Actual output Vs target output-Y phase

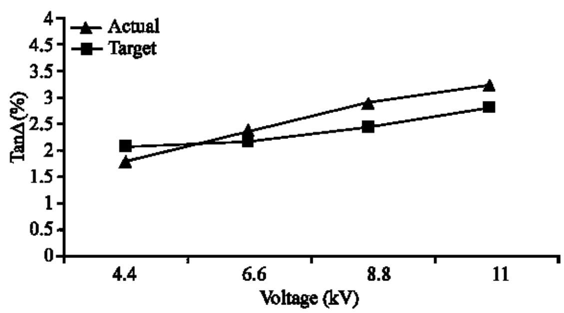

Fig. 6: Actual output Vs target output-B phase

Figure 4-6 shows that target output and actual output comparison for the test machine of R, Y and B phases respectively.

CONCLUSION

The condition of insulation of stator winding of the rotating machine is determined by the measurement of leakage current, capacitance and dissipation factor. We analyzed the above said parameter for seven machines by neural network particularly using BPN algorithm and to train the network. Now the above data of the machine undertest are fed to the network from this the dissipation factor of the insulation of the 11 kV machine under test can be predicted. This network is found to be suitable for predicting the results close to the actually measured values.

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