Neural Networks to Analyze Surface Tracking on Solid Insulators

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ABSTRACT
Surface tracking on solid insulators is one of the most severe breakdown mechanisms associated with polymeric materials under long term service conditions. A wide range of relays can detect failure in a transmission line and prevent a total breakdown in the systems, but due to the non-healing characteristics of solid insulators, in most cases it might be too late to save the insulator after tracking initiation and growth. The method described here is employed mainly in detecting several conditions, such as discharges, leakage current, dry conditions, severe damage and tracking initiation. Initially a BPN (back propagation network) type NN (neural network) is trained with different signal types. Due to the nature of NN, which always require similar values of input nodes, the system uses the FFT (fast Fourier transform) of the input signal, which might have high amplitude frequency components other than the fundamental frequency depending on the condition of the surface. The system works on a real time basis and warns the user with the first indication of severe damage on the surface and can protect the insulator from excessive damage.

1. INTRODUCTION
Previous work [1] has shown that the different forms of electrical activity on the surface of insulating materials, subjected to the IEC587 inclined plane tracking test, are distinguishable by their current waveforms. Leakage current produces a pure sinusoidal waveform, whereas discharges across dry bands cause shoulders on the sine wave near zero current. The intention of the work described here was to enable these different current waveforms to be routinely recognized as an aid to monitoring the surface degradation condition.

2. THE IEC587 INCLINED PLANE TRACKING TEST
Tracking can be expressed as a mixed process of discharge inception, carbon formation and carbon path propagation under the influence of an electrolyte, applied voltage, location of discharge, energy of discharge and molecular composition of the material [2, 3]. In practice, wet tracking occurs due to pollution. During service the surface of insulating is progressively contaminated. When the insulator becomes wetted, a significant leakage current flows through the conducting moist film on the surface, and is therefore mainly resistive. The surface resistance decreases considerably in the presence of pollution and moisture, low resistance leads to higher currents and high power dissipation on the surface. Due to the heat increase, the moisture on the surface evaporates, which in most cases is non-uniform and can lead to dry band formation. Consequently, a small discharge occurs when the voltage across the gap exceeds its breakdown value. If the surface of the insulator is kept moist by continuous precipitation, the discharges will continue; the current is then being limited by the series resistance of the conducting film on the insulator surface. The heat produced by discharging may be sufficient to decompose the underlying insulation and form a short partially conducting carbonaceous track. As time proceeds, these tracks propagate until eventually the full distance between the electrodes is bridged, causing failure of the insulator.

The IEC587 inclined plane tracking test attempts to simulate this tracking behavior in a controlled manner in order that comparisons can be made of the tracking resistance of different insulating materials. In this test a 0.1 ± 0.002% contaminant solution, ammonium chloride (NH₄Cl), flows down the underside of a flat inclined test specimen. The test specimen with the dimensions of 50 × 120 × 6.25 mm³ is mounted at 45° to the horizontal between electrodes designed so that the liquid layer spreads out into a delta shape across the sample width. The electrodes are separated by 50 mm and tests are performed at 23 ± 2°C. The rate of the contaminant release depends on the applied voltage and the resistance in series with the test specimen. For example, at 4 kV and with a series resistance of 33 kΩ, the standard flow rate of the contaminant is 36 ml/h. Within a critical voltage range, the thin film of liquid contaminant boils and the flow is disrupted so that discontinuities occur which produce scintillations primarily just above the ground electrode where the liquid film is thinnest. Ultimately 'rooting' of a single discharge on a 'hot spot' on the surface of the material leads to progressive tracking towards the upper electrode.

3. SETUP OF THE SYSTEM
In this work the IEC587 standard test equipment is operated at 4 kV using unfilled polyester resin specimens. The upper side of the specimen is connected to the HV source, the lower (ground) electrode is connected to ground through a series 100 Ω resistor (Figure 1). The current flow is monitored by measuring the voltage developed across this
resistor. This voltage is delivered to an A/D converter, which processes signals on a real-time basis. The analog input range of the board varies between ±5 V, which corresponds to a current level of ±50 mA peak to peak in the series resistor.

![Figure 1. PC based surface monitoring system.](image)

In the standard test, at 4 kV, with a contaminant flow rate of 36 ml/h, the current level is around 30 mA. The resistance of the specimen varies between 100 and 200 kΩ, depending on the surface condition.

Reproducible signals are required if the various sources of the signals are to be consistently recognized. NN (neural network) can be used effectively in categorizing these signals. However, due to the nature of the back propagation method, variations in the amplitude of the input signals or the point in time at which they initiate may register as different types if presented directly in the time domain. This problem is resolved by transforming the signals into the frequency domain by FFT (fast Fourier transform) calculations.

4. TRAINING THE NN

A computational NN can be described as a connected set of neural nodes. Each neural node takes a number of inputs from other nodes, weights them according to a predetermined strategy and then sums the weighted inputs to produce an output. Nodes are organized in layers. The input layer takes information directly from an outside source; in the case here the sampled data from the FFT of the current measurement. The number of output nodes depends on the number of classifications of signals to be recognized; in this case four. There is also a hidden layer of nodes between the inputs and the outputs which governs the training characteristics of the network.

In this case a BPNN (back propagation network) type NN is used to monitor the surface conditions. Initially the network is trained by applying signals from known sources which are labeled according to their classification. Then the error between the real \((t_e[l])\) and desired output \((t_o[l])\) values is transmitted backwards from the output layer to the intermediate layer [4].

\[
E = \frac{1}{2} \sum_{l=0}^{L} (t_o[l] - t_e[l])^2
\]  

(1)

This process is then repeated until each unit receives a proportion of the error signal. The weighting is adjusted systematically until the total error becomes acceptably small. The network is then considered trained. In this case four different types of signals, leakage current, surface discharge, discharge and dry conditions, are used during the training stage. As illustrated in Table 1, a total number of 76 signals are selected. Leakage current has the highest FFT value (Figure 2) whereas the dry current signal has values near zero, hence for the training stage all signals are assigned to certain output values which represent a specific surface condition. The error limit is selected to be \(< 0.000075\) and the number of iterations is limited to 50000. The trained network is tested by presenting the inputs with signals from known classified sources other than those used in training data. Values within the operation range, which means slightly higher and lower than the real output value, are considered to represent the specific surface condition.

![Figure 2. FFT of various sampled surface signals.](image)

Table 1. Constants assigned to various surface conditions.

<table>
<thead>
<tr>
<th>Surface condition</th>
<th>Output value</th>
<th>Number signals</th>
<th>Operation range</th>
</tr>
</thead>
<tbody>
<tr>
<td>leakage current</td>
<td>0.9</td>
<td>22</td>
<td>0.75 ↔ 1.00</td>
</tr>
<tr>
<td>surface discharge</td>
<td>0.6</td>
<td>14</td>
<td>0.40 ↔ 0.75</td>
</tr>
<tr>
<td>discharge</td>
<td>0.2</td>
<td>38</td>
<td>0.05 ↔ 0.40</td>
</tr>
<tr>
<td>dry condition</td>
<td>0.05</td>
<td>2</td>
<td>0.00 ↔ 0.05</td>
</tr>
</tbody>
</table>

5. SIGNAL PROCESSING

The A/D board has its own software which allows the user to perform several tasks such as filtering, averaging and FFT. During the test period, stable arcing can cause high frequency components. In order to represent accurately the continuous discharge signal with discrete points, the board is programmed to sample the input signal every 25 μs. This process is repeated until the number of samples equals 2048, which is the maximum number of data points that the board can handle for real-time FFT calculations. When the FFT is applied to the real data, half of the output coefficients (\(N/2\)) are redundant due to the symmetry between real and complex conjugates. The A/D board is programmed to calculate the rms value \((32768/\sqrt{2})\) of the binary amplitude of the input data. The FFT represents the sampled signal \(u(t)\) in terms of data values, which are periodic in \(t\) with period \(T = N\tau\), where \(N\) is the total sample number and \(\tau\) is the time between samples. The \(n^{th}\) harmonic has the frequency \(f_n\), where

\[
f_n = nF
\]

(2)

\[
f_n = \frac{n}{N}\frac{1}{\tau}
\]

(3)
Since the input signal is sampled at 40 kHz and a 2048 point FFT is selected, the board returns information about input frequencies to \( f_n = 20 \) kHz. In order to reduce the processing time, only the first 60 frequency components of the FFT are transferred to the PC, which can give information to 1171.8575 Hz. As can be seen in Figure 2, even after the 20\(^{th}\) component (\( \approx 400 \) Hz) the amplitudes of all signals become quite negligible. The fundamental frequency is 50 Hz, hence the third frequency component (\( \approx 58.59 \)), which has the nearest value to 50 Hz, has the highest amplitude.

6. CATEGORIZING THE SIGNALS

During its service life, an insulator has to face various environmental conditions, which vary continuously [5, 6]. Contrary to accelerated tests, an insulator under service experiences almost dry conditions most of the time, where arcing happens rarely. Despite these differences, both mechanisms, inclined plane tracking and outdoor service conditions, cause similar discharge and leakage currents only with different scaled amplitudes. In order to implement a reliable surface monitoring system, initially several tests have been performed to investigate different kinds of surface activity.

![Figure 3. Surface discharge current for polyester resin tested at 4 kV applied voltage and 6 ml/h flow rate.](image)

During the inclined plane tracking test the input signal varies due to the surface conduction of the insulator, which is mainly affected by the contaminant flow rate. However in most cases the magnitude of the current alone is an unreliable indicator of the damage to the specimen [7]. During the test most of the time is occupied by discharges which may be categorized as either surface or ground electrode discharges depending on their location and strength. Surface discharges (Figure 3), which can be described as curtain type scintillations, move rapidly across the specimen following the moving gap between liquid films. These discharges are never steady enough to lead to a progressive track. On the other hand, arcing at the lower ground electrode is much stronger and stable, hence can repeatedly degrade the same spot on the insulating surface adjacent to a particular electrode tooth (Figure 4). Leakage current can occur if the gap between the two electrodes becomes conducting due to the contaminant film (Figure 5). Dry conditions are quite rare and they can be observed only after a very strong discharge which leads to excessive heat dissipation.

![Figure 4. Discharge current for polyester resin tested at 4 kV applied voltage and 36 ml/h flow rate.](image)

![Figure 5. Leakage current for polyester resin tested at 4 kV applied voltage and 6 ml/h flow rate.](image)

7. ESTIMATION OF THE TRACKING INITIATION

Due to the nature of FFT, the accuracy of the algorithm is restricted by the total number of sampled data points. Since a finite number of points are used to calculate the FFT of the signal, some high frequency components have values larger than zero. However due to this small difference, the NN performs well and accurately during the testing stage. The main problem arises when the NN attempts to estimate the tracking signal, because most of the tracking signals already have the same or similar FFT pattern as the ground electrode or surface discharge signal. This problem leads the network to either not converge during the training phase or to make a wrong estimate during the testing period. For this reason NN are not used for estimating the tracking stage. Several tests have been performed to investigate a unique feature of the tracking patterns and it was found that the high frequency components usually are associated with track propagation. Just before track initiation (\( \approx 30\) s) small oscillations are observed at the top of positive and negative half cycles (Figure 6). At each test similar oscillations occurred, regardless of the type of signal. Once arcing becomes stabilized, and hence stronger, the probability of tracking increases and also the signal patterns change considerably. Although the oscillations at the top of positive cycles
Table 2. The number of oscillations observed in various tracking signals.

<table>
<thead>
<tr>
<th>Tracking signal</th>
<th>Count 1st peak</th>
<th>Count 2nd peak</th>
<th>Average count</th>
</tr>
</thead>
<tbody>
<tr>
<td>13JUL1</td>
<td>15</td>
<td>29</td>
<td>22</td>
</tr>
<tr>
<td>13JUL2</td>
<td>61</td>
<td>58</td>
<td>59</td>
</tr>
<tr>
<td>14JUL1</td>
<td>-</td>
<td>9</td>
<td>4</td>
</tr>
<tr>
<td>14JUL2</td>
<td>25</td>
<td>34</td>
<td>29</td>
</tr>
<tr>
<td>14JUL3</td>
<td>34</td>
<td>10</td>
<td>22</td>
</tr>
<tr>
<td>19JUL1</td>
<td>10</td>
<td>8</td>
<td>9</td>
</tr>
<tr>
<td>19JUL2</td>
<td>37</td>
<td>65</td>
<td>51</td>
</tr>
<tr>
<td>20JUL1</td>
<td>9</td>
<td>20</td>
<td>14</td>
</tr>
<tr>
<td>23AUGT1</td>
<td>23</td>
<td>15</td>
<td>19</td>
</tr>
<tr>
<td>24AUGT1</td>
<td>49</td>
<td>10</td>
<td>29</td>
</tr>
<tr>
<td>25AUGT1</td>
<td>62</td>
<td>70</td>
<td>66</td>
</tr>
<tr>
<td>26AUGT1</td>
<td>34</td>
<td>42</td>
<td>38</td>
</tr>
<tr>
<td>30JUN1</td>
<td>24</td>
<td>9</td>
<td>16</td>
</tr>
<tr>
<td>30JUN2</td>
<td>3</td>
<td>12</td>
<td>7</td>
</tr>
<tr>
<td>30JUN3</td>
<td>10</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>30JUN4</td>
<td>11</td>
<td>27</td>
<td>19</td>
</tr>
</tbody>
</table>

The number of oscillations observed in various tracking signals does not increase significantly, only slight variations are observed at negative cycles (Figure 7). In order to detect the tracking phenomenon 16 tracking signals are investigated (Table 2). 50 values before and after the peak value of each signal are considered. Normally in this range the largest difference between adjacent values should be < 100, but due to the noise associated with the test, differences > 200 are found and the number of sign changes in slopes (either from + to – or opposite) is calculated. When the number of changes exceeds 10, which seems to be appropriate by considering the signals in Table 2, this can be considered as excessive local damage. If the same condition is verified in the next signal (after ≈ 2 s), then this phenomenon can be considered as tracking.

![Figure 6. Signal acquired 30 s before tracking initiation.](image)

Counting the change of slopes seems to be quite appropriate in detecting the tracking initiation stage for polyester resin, however oscillations may vary from sample to sample, hence the number of critical count values may need to be changed for each polymeric material. Also, this method cannot be used for polymeric materials which have a tendency to erode rather than track.

![Figure 7. Tracking signal for polyester resin tested at 4 kV applied voltage and 6 ml/h flow rate.](image)

8. CONCLUSIONS

Neural networks can assess the condition of an insulator continuously. However, it is not easy to make an estimate of the remaining lifetime, because even counting and calculating the time spent by discharges cannot give a reliable answer due to the variety of places where discharges occur.

The system works with high accuracy and allows the user to monitor insulator surface activity, to distinguish between harmless and harmful discharges and to signal the onset of potentially damaging tracking. It is believed that by connecting a suitable device across an insulator, it would be possible to monitor a group of insulators simultaneously from a remote center.

REFERENCES


Manuscript was received on 15 July 1997, in revised form 16 November 1997.