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Artificial neural network approach in transmission line with prpd statistical analysis

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Abstract- The reliable operation of power system is likely to be threatening mostly by the flashover of power transmission line insulators. This paper is concerns with the prediction of flashover occurs in the polymeric insulators that are used in power transmission line applications with the help of condition monitoring technique developed by PRPD signal pattern using Neural Network technique. The experiments were carried out in laboratory with the polymeric insulators as per the IEC 60507 under AC voltage. Prominent features from the time frequency map and PRPD pattern at various states of pollution were extracted. The use of Artificial Neural Network (ANN) with back propagation algorithm (BPA), the prediction of flashover of polymeric insulators was automated. From the results, it can be summarized that with the extraction of PRPD signal feature beside with back propagation classification is a well matched technique to predict the flashover of polymeric insulators.

Keywords- PRPD signal, insulator, flashover, S-Transform, BPA.

1. Introduction:

In power transmission and distribution systems the use of Ceramic and polymeric insulators are widely distributed. In recent times, because of the superior insulation and surface hydrophobicity characteristics compared with other insulators [1, 2] the silicone rubber polymeric insulators are mostly preferred. This is because hydrophobicity of silicone rubber material offers high electrical surface resistance. Due to the chemical stability and diffusion of low molecular weight contents from bulk volume to the surface of the material [3], the maintenance of the hydrophobicity of silicone rubber insulator is in long term. However, pollution starts builds up gradually on the surface of the insulator, when these insulators are installed near industrial, agricultural or coastal areas, which results in the flow of leakage current (LC) under wet conditions and finally leads to arcing and flashover. Power outages, waste of time and money and sometimes equipment damage are the problem caused by the formation of pollution due to flashover of outdoor insulators. In addition to this, insulation strength is decreased due to the presence of continuous arcing on the surface of the insulator results in material degradation and reduction in hydrophobicity. Therefore electrical utilities are in need of eager in the development of better diagnostic tool for predicting the exact surface condition of polymeric insulators during severe pollution conditions.

The analysis of the surface deterioration of the polymer insulators is a very complex process due to the formation of surface discharges. To predict the flashover and surface degradation of outdoor insulators different approaches were used [4-14]. R.S.Gorur et al., [7] to identify the surface condition of non-ceramic insulators the surface resistance are measured. Many research papers deal with the measurement and analysis of LC, because it is directly related to arcing phenomena occurring on insulator [8-11]. S.Kumagai et al., [13] the LC characteristics and aging of porcelain and polymeric insulator have compared in both field and salt fog tests. They have come to the conclusion that for estimating the conditions of ceramic and polymeric insulating surfaces, the time variations of cumulative charges and their component ratios were used.

It is clear that LC follows different pattern during the development of flashover, from lightly polluted conditions to heavily polluted conditions, according to the earlier reported investigations. L.H.Meyer et al., [14] there was a good correlation exists between the harmonic power components of dry band arcing and the surface temperature of silicone rubber samples.. Proper understanding of different LC pattern and its time-frequency characteristics is very important for evaluating the surface condition of polymeric insulators.

However, wavelet analysis is suffered from the difficulty in selection of suitable mother wavelet in identifying the best one for a better classification. In addition to this, the information provided is sparse and also the spectral regions are not unique and different dilations have overlapping spectral responses, irrespective of good time-frequency resolution provision.

For exact prediction of the point of transition to severe arcing of outdoor insulators, a diagnostic tool is given more importance in the development of consideration.It offers good localization in both time and frequency domain, which allows it applicable for time-frequency analysis. .

To monitor the surface condition of the polymeric insulating material, S-transform is proposed as a methodology, in the present work. For various pollution levels the LC measurements are carried out in the laboratory on silicone rubber insulator. S-Transform is used for evaluating the Time-frequency and Energy content outline characteristics and also point of transition to severe arcing is identified.

2. PRPD Pattern

Initially, without applying any pollution, silicone rubber insulator specimen was tested with an application of

11kVrms voltage under dry surface conditions (i.e. at relative humidity level of 30-40 %). Then following this a test was conducted by placing the silicone rubber insulator inside the fog chamber without applying any pollution at a relative humidity level inside the fog chamber which maintained above 98 %. The Figure 1 and 2 shows the typical PD pattern obtained at this condition. Phase reference signal needed for this system is used from the sine waveform used in the PD pattern and its amplitude is not given in vertical scale.

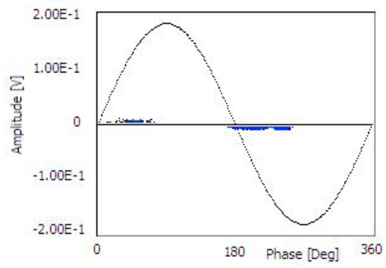


Fig.1. PD Pattern viewed at Clean Dry

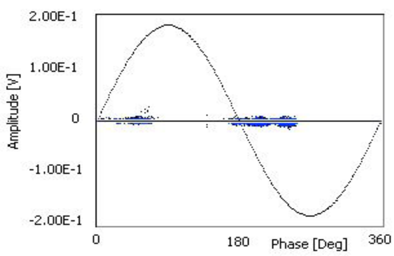


Fig.2.PD Pattern viewed at Clean Wet Surface

It is observed from the results, that noise signals are only present during this measurement and PD signal is completely not present. The Silicone Rubber insulator was also tested similarly with polluted (0.12ESDD). The PD pattern obtained with polluted dry surface is shown in Figure 3. The result obtained has a similar test results to those obtained with clean surface. It is clear that the surface wetness plays an important role in the formation of partial discharge irrespective of whether the surface is clean or polluted.

Typical PRPD pattern of thermal aged polymeric insulator obtained at 100% RH under clean wet surface is shown in Figure 4. It can be noted that there are only a moderate discharges which are not continuous and there is no significant variations in the amplitude.

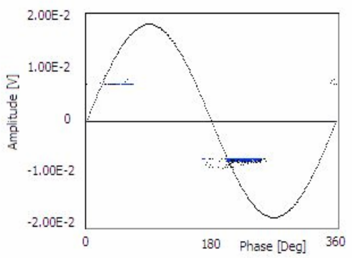


Fig. 3. PD Pattern viewed at Polluted (0.12 ESDD) Dry Surface

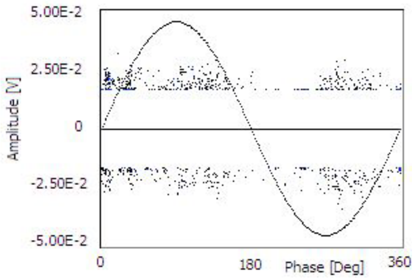


Fig.4. Thermal Aged Clean Wet Surface

3. Statistical Features From PRPD Pattern

For the on-line outdoor PD measurements on transmission tower insulators, various PD sources produce a significant noise and/or pulses which are active and also will make pollution severity diagnosis of insulators more difficult even for skilled operators. Therefore effective noise/disturbance rejection plays an important role in the successful and accurate diagnosis based on PD analysis and for the purpose of identification the collection of a large amount of statistical information on the PD signals is needed.

Hence, with reference to both positive and negative polarity an analysis of the stochastic features of PD-pulse sequences is carried out in the following. Skewness is the commonly used parameter in statistical analysis to check the distribution of data in a given range. In addition to that a special attention was given to the mean value of the shape parameter of the Weibull function of the PD amplitude distribution. PD inception phase angle and the mean phase angle are other parameters derived from the distribution and are also assessed. Among these parameters, each one is relevant to a particular PD characteristic, only those having a range of variation in distinct and well-defined intervals.

The mean values of shape parameter, along with 95% confidence intervals, at various surface pollution levels are shown in Figure 5 a. It can be noticed that β value decreases, with increase in both. Heavily polluted surface condition is reached, when the β value falls below

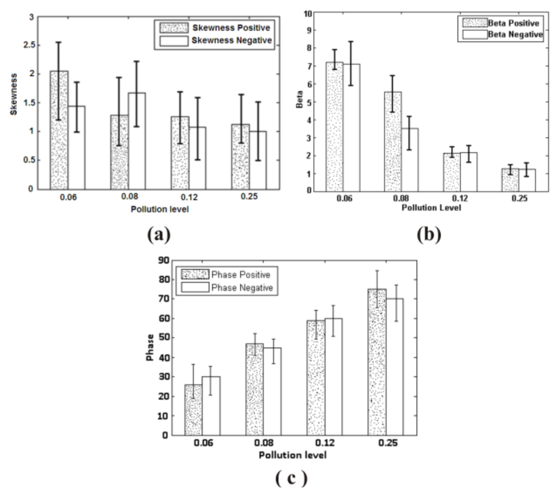
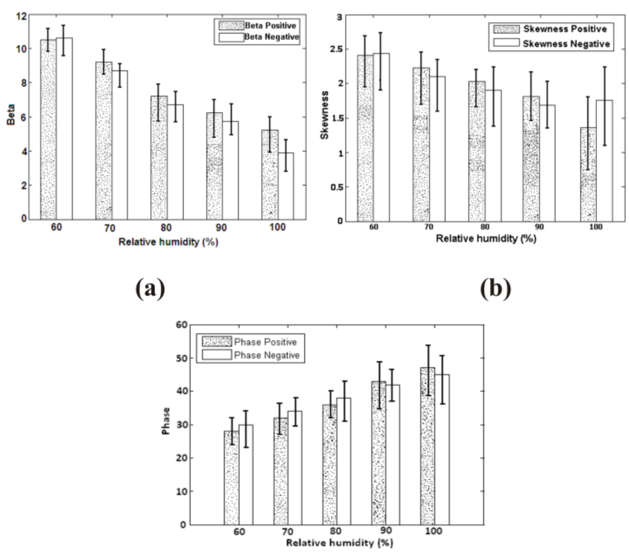


Fig.5. Variation of (a) Shape Parameter (b) Skewness and (c) Average Phase of PD Pattern with Respect to Different Pollution Levels Represented in ESDD at a Constant 100 %

Relative Humidity Level. The 95% Confidence Intervals are Also Reported

Report on mean values of PD amplitude skewness, along with 95% confidence intervals, at various surface pollution levels is shown in Figure 5.b. It is noted that the value of skewness considerably reduced as the pollution level starts growing, which point out the data symmetry at high pollution level is increases. However, variation range of skewness is restricted to quite low value, and therefore identification of severity of surface pollution is very difficult by just using only this parameter. Similarly, the Figure 5.c shows variation of mean phase value with respect to pollution level. It is observed that there is considerable increase with the pollution level. It is also speculated that highly polluted surface condition indicated when it goes beyond 45 degrees.

The figure 6 shows changes in shape parameter skewness of amplitude distribution and mean phase of PD patterns obtained at constant pollution level of 0.08 ESDD with various relative humidity levels. It is observed that when the mean phase increases with relative humidity, shape parameter value become small as relative humidity increases. The limit values of shape parameter and mean phase value corresponding to highly polluted surface are generally extended above 90% relative humidity condition. Hence, it can be argued that at relative humidity conditions more than 90%, the probability of formation of severe partial discharges on the surface of the tested insulator is high.

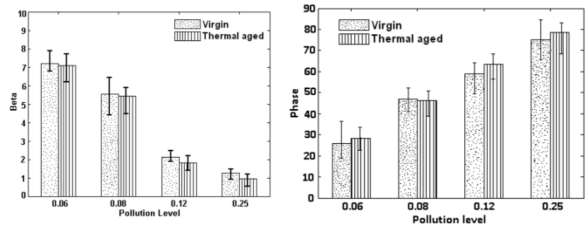


(a) (b)

(c)

Fig.6 Variation of (a) Shape Parameter (b) Skewness and (c) Average Phase of PD Pattern with Respect to Different Relative Humidity Levels at a Constant Pollution Level of 0.08 ESDD. The 95% Confidence Intervals are Also Reported

Based on the above, it can be speculated that there is a close relationship between the surface pollution conditions as the shape parameter and mean phase value changes and therefore, become adequate diagnostic markers. On the contrary, it appears that the extraction of pollution severity information from the PD amplitude skewness is quite difficult. In addition, for identifying the surface pollution severity the extracted information such as time length of pulse, rise time of pulse and frequency domain characteristics of PD pulse from the time domain analysis of PD pulse are very useful. In order to rule out the influence of sensor frequency response, the trending of these parameters is needed.



(a) (b)

Fig.7 Variations in the (a) β and (b) Mean Phase of Virgin and Thermal Aged Silicone Rubber Insulators at Different Pollution Levels

It is observed from the PRPD pattern analysis that amplitude of PD pulse increases with increase in pollution level. Hence, for the prediction of flashover of polymeric insulators stochastic features such as PD amplitude and phase variations and its dispersion can be used as an important identification marker. In the present work, shape parameter (β) of Weibull PD amplitude distribution is calculated as a measure of PD amplitude dispersion. Also, for each measured PRPD pattern , the Mean value of PD amplitude and PD phase is calculated.

The variations in the β and mean phase of polymeric insulator at different pollution levels are shown in Figure 7. a and 7.b respectively. It is noted that value of β reduces as the pollution level increases, which is a clear indication of increase in data dispersion with increase in pollution level. The flashover occurs possibly as the value of β reaches below 3 which is an indication if heavily polluted surface condition. With increase in pollution level there is a considerable increase in the mean phase value of PRPD pattern. When it goes beyond 45 degrees then it is a clear indication of highly polluted surface condition and is also an indication of possible flashover.

4. Prediction of surface pollution severity using artificial neural network

Artificial Neural Network (ANN) was used in order to automate the prediction of flashover of polymeric insulator. ANN learns a task by generalization of case studies of the tasks since, it is a highly parallel, adaptive learning system. The Multilayer Feed Forward network with back propagation learning algorithm has been used in this present work, because it has a good generalization capability. The Table 1 shows the details of the neural network parameters.

Table 1 Neural Network Specifications

No. of Inputs	6
No. of Neurons in Hidden Layer	12
No. of Neurons in Output Layer	6
Learning Rate (η)	0.02
No. of Iterations	4500
No. of Training Sets	230
No. of Test Input Sets	120
Convergence Criteria	0.01

Multilayer feed forward neural network with an input layer, one hidden layer and an output layer is used in this present work. The inputs given to the neural network are Shape parameter (β) of PD amplitude distribution, mean PD amplitude, mean PD phase, mean equivalent time length, PD repetition rate and mean equivalent bandwidth. No discharge, short duration discharge, long duration discharge and flashover were used for classifying the four output neurons. The training phase has iterative presentation of the six inputs with the estimated output, depending on the resultant error the weights and biases are adjusted. The convergence takes place only when the error between the measured and the desired output is less than convergence criteria. The error is back propagated in this network and in order to minimize the Mean Square Error (MSE) the weights and biases are readjusted conveniently, MSE is the average of sum of the errors for all set of inputs and corresponding outputs, which is evaluated as follows,

$$MSE = \frac{1}{m}\sum_{k}^{m}\left(S_k - Y_k\right)^2$$

Where S_k and Y_k are respectively the desired and measured output for the k^{th} input set and m is the total number of input sets.

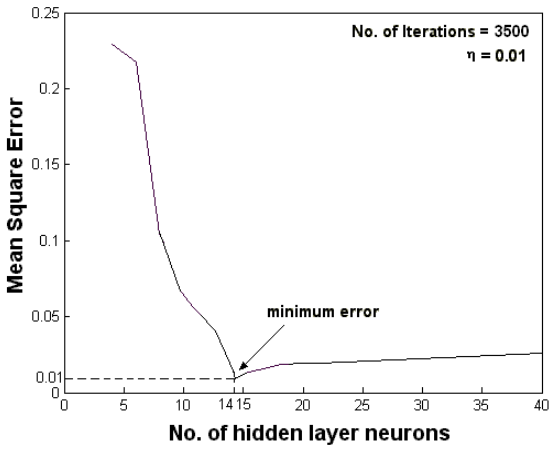


Fig.8.Evaluation of the Mean Square Error of the Neural Network at Different no. of Hidden Layer Neurons

The performance of the neural network influenced by several factors and therefore for the implementing the efficient diagnostic system optimization of neural network parameters is important.

Initially, for different number of hidden layer neurons the MSE was calculated as shown in Figure 8 It is observed that evaluated MSE value is minimum with 14 hidden layer neurons. The neural network takes longer time to learn as the number of hidden layer neurons increases.

The performance of the network during training with 14 hidden layer neurons at different iteration numbers are shown in Figure 10 It clearly points out that the present network take nearly 3500 iterations for convergence. The identification rate of the network for different no. of iterations at optimized value of hidden layer neurons and learning rate are shown in the Figure 9

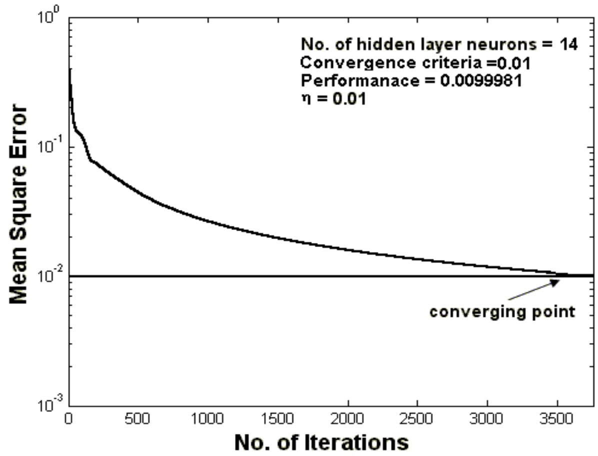


Fig.9. Evaluation of Mean Square Error of the Neural Network at Different no. of Iterations

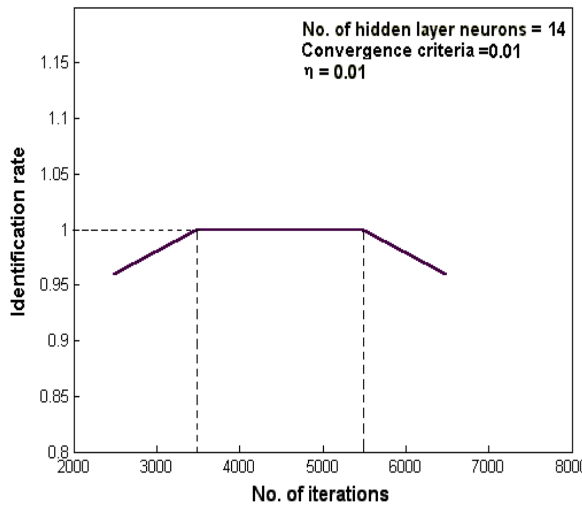


Fig.10.Evaluation of Identification Rate at Different no. of Iterations with Optimized Value Neural Network Parameters

It clearly points out that for achieving 100% of success rate it takes 3500 to 5000 no. of iterations and therefore for the successful training of the optimized neural network 3500 iterations is sufficient. In the back propagation network, the speed and accuracy of the learning process i.e. the learning rate η plays an important role in the updating the weights. The Table 2 shows the Identification rates of back-propagation network with different learning rates. In the neural networks, with higher learning rate fast convergence takes place but it leads to reduction in accuracy and the identification rate. The optimum value of learning rate is found to be 0.01.

Identification results of the output of the neuron in the output layer of the optimized neural network (no. of hidden layer neurons = 14, η = 0.01, convergence criteria=0.01, no. of iterations=3500) is shown in Figure. For example, the output layer of four neurons are trained for a pattern (1 0 0 0), if the input pattern corresponds to 'no discharge' case. Hence, when not trained 'no discharge' case in NN is given as an input, the expected output pattern will be closer to (1 0 0 0).

Table 2 Identification Rates of ANN at Different η

Learning Rate η	0.01	0.1	0.2	0.3
Identification Rate	100	100	97	95

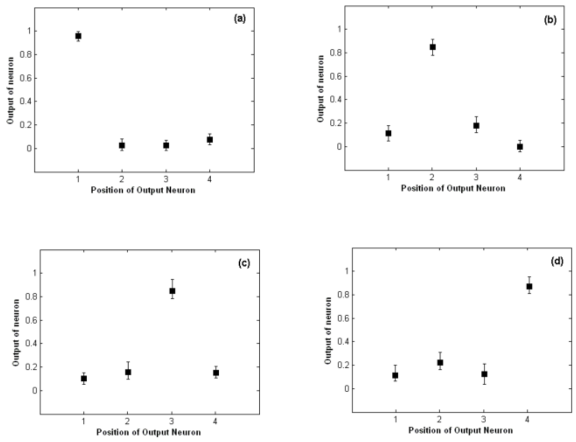


Fig.11.Output of Neurons in the Output Layer of the Neural Network (a) No Discharge (b) Short Duration Discharge (c) Long Duration Discharge (d) Flashover

From the equivalent time length-equivalent bandwidth analysis and the reported partial discharge characteristics such as PRPD pattern, PD pulse-frequency spectrum, repetition rate the estimation of flashover of polymeric insulators are carried out by looking at the evolution of PD- related quantities in the course of time. On comparing with PD test results of virgin insulators under similar experimental conditions, it is observed that surface erosion and degradation occurs due to the increased PD activity of thermal aged silicone rubber insulator. The flashover and pollution severity of polymeric insulators are effectively predicted by artificial neural network approach with back propagation training algorithm.

5. Conclusion

The analysis of partial discharge pattern and Laboratory measurement and PD pulses of silicone rubber insulators has been presented in this paper. As per IEC 60507 test procedure, at different relative humidity and pollution levels laboratory tests are performed Laboratory tests are performed. It is shown that the surface PD test results of virgin insulators are closely related to the close relationship between time and frequency domain characteristics of PD pulses, it is also noticed that thermal aged silicone rubber insulator shows increased PD activity, which will certainly lead to surface erosion and degradation. The increase in pollution level on the surface of insulator is shown in the equivalent time length-equivalent bandwidth plane and for the predicting the flashover of insulator this can be used as a diagnostic tool. In polymeric insulators, the extracted features from PRPD pattern and time-frequency map are used as an identification marker for flashover. The flashover of polymeric insulators is effectively predicted by using artificial neural network approach with back propagation training algorithm. The lab results on the thermal aged polymeric insulator points out that, these are exposed to large thermal and ambient stress variations for the entire life span when they are applied in tropical regions which will increase the surface degradation of the material under severe pollution conditions, which might reduces the insulation strength and possible occurrence of flashover.

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