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Prediction of Flashover and Pollution Severity of High Voltage Transmission Line Insulators Using Wavelet Transform and Fuzzy C-Means Approach

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Abstract – Major problem in the high voltage power transmission line is the flashover due to polluted ceramic insulators which leads to failure of equipments, catastrophic fires and power outages. This paper deals with the development of a better diagnostic tool to predict the flashover and pollution severity of power transmission line insulators based on the wavelet transform and fuzzy c-means clustering approach. In this work, laboratory experiments were carried out on power transmission line porcelain insulators under AC voltages at different pollution conditions and corresponding leakage current patterns were measured. Discrete wavelet transform technique is employed to extract important features of leakage current signals. Variation of leakage current magnitude and distortion ratio at different pollution levels were analyzed. Fuzzy c-means algorithm is used to cluster the extracted features of the leakage current data. Test results clearly show that the flashover and pollution severity of power transmission line insulators can be effectively realized through fuzzy clustering technique and it will be useful to carry out preventive maintenance work.

Keywords: Insulator, Flashover, Power transmission line, Wavelet transform, Fuzzy c-means, Distortion ratio

1. Introduction

Major problem faced by electrical utilities in the high voltage power transmission line is the flashover due to polluted insulators, which results in power outages, waste of time and money, cause frustration to customers, equipment damage and potentially, catastrophic fires. Therefore, electrical utilities spend significant amount of money on preventive maintenance, which includes washing and cleaning of insulator at regular intervals, but it is an expensive operation and difficult to automate [1, 2]. Many approaches are used to quantify the flashover and pollution severity of power transmission line systems in order to carry out preventive maintenance work [3-5]. Measurement and analysis of leakage current (LC) pattern in the polluted insulator will provide useful information for the development of efficient diagnostic system for power transmission line [6-8].

Nowadays, development of condition monitoring systems using the data acquisition systems and control is a basic tendency in automation of power system equipments and control [9, 10]. Intensive growth of the information systems which are based on the internet and web-technologies creates the possibility to access to these condition monitoring systems from anywhere in the world. Development of the web-based diagnostic system using the data acquisition systems for several practical applications is a vital and hot research issue.

Therefore concept of remote management of high voltage power transmission line insulators over the internet from anywhere in the world can be a reality with existing technologies. In addition, the use of the internet technology reduces exploitation costs of existing communication channels. However, collection of LC signal using data acquisition systems over a period of time results in a huge amount of data, which makes it difficult to implement the web based technologies for the pollution severity monitoring system [11]. In order to avoid huge amount of data transmission in the development of web based monitoring systems, it is necessary to extract important features from the LC data and to use effective data mining techniques to predict pollution severity of power transmission lines.

Gorur et al., [12] identified that the frequency contents of the leakage current signal obtained with insulators varies during surface discharge and flashover conditions. Similarly Sesha H. Jeyaram et al., [13] have shown that the variation in third harmonic components of leakage current waveform and the formation of arcing path of polymeric insulators have a good correlation. Therefore time-frequency information of LC signal is an important feature to be considered for the development of condition monitoring system. Multi resolution signal decomposition method of discrete wavelet transform is very useful to

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extract time-frequency information from the LC data [14]. Data mining using fuzzy clustering is useful for exploration and analysis of large quantities of data in order to extract meaningful patterns and useful information [15].

Considering the above facts, the aim of the present work is to develop a structured method of analyzing the LC data using discrete wavelet transform technique and fuzzy data mining approach for the development of efficient pollution severity diagnostic system for power transmission lines.

2. Experimental Setup

Fig. 1 shows the overall structure of the proposed web based diagnostic system for power transmission lines. Leakage current is the important parameter measured from the high voltage transmission line tower insulator. It is then processed in the data acquisition system and stored in the server for further processing. The client will have the access to the data in the server through TCP/IP connection.

Fig. 2 shows the schematic diagram of the laboratory experimental setup used for implementing the web based diagnostic system. Tests were conducted as per IEC 60507 clean fog test procedure [16]. The single disc porcelain insulator was suspended vertically inside the fog chamber. A 100 kV, 10 kVA high voltage test transformer with control panel was used to supply the required test voltage. The test voltage was maintained at 11 kV rms, 50 Hz. To reproduce saline pollution typical of coastal areas, a contamination layer consisting of NaCl and 40g of kaolin mixed with 1 litre of deionized water was applied to the surface of insulator. Four ultrasonic nebulizers were used to maintain the required relative humidity level inside the fog chamber. Relative humidity was measured using a hygrometer instrument and its value was maintained closer to 95%. The leakage current was measured using a Pearson High Frequency Current Transformer (HFCT) Q-1903 in the ground lead. It has a sensitivity of 1 V/A, lower cut off frequency of 15 Hz and higher cut off frequency of 500 kHz. A high sampling rate data acquisition system (National Instruments, USB 6251, 1.25 MSa/sec) was used in the present study to access analog and digital signal. This system is capable of measuring 16 analog input signals, 12 or 16 bits. All the signals were captured at a sampling rate of 5 kHz. A LabVIEW software system developed in the server provides the user with the complete LC waveforms, which are therefore available for further signal processing.

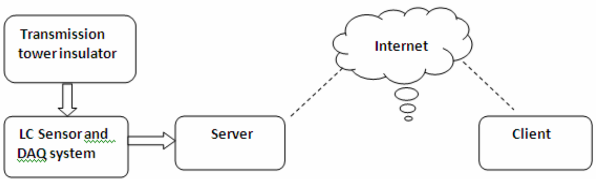

Fig. 1. Overall structure of the system

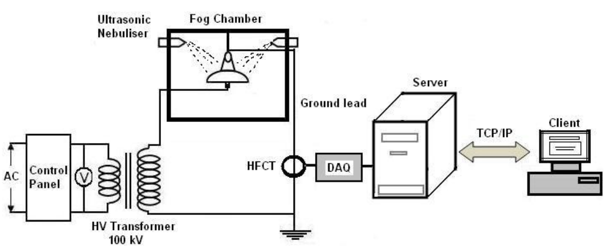

Fig. 2. Schematic diagram of experimental setup

3. Discrete Wavelet Transform

Extraction of salient features of the LC data, which in turn actively drives diagnostic knowledge out of the raw data, plays a major role in the novel condition monitoring technologies. In order to develop an efficient diagnostic system, it is necessary to perform both time and frequency domain analysis of LC signals. Discrete wavelet transform technique has been found to be efficient to extract features from the leakage current data. Multi resolution signal decomposition analysis of the Discrete Wavelet Transform aims at ultimately producing a time-scale representation of the given discretized signal x(n) at various decomposition levels [14]. Let $c_0[n]$ be the original signal sequence. After convolution with h and g quadrature mirror filters, it is decomposed into an approximation component $c_1[n]$ and a detail component $d_1[n]$ at scale 1. Then approximation component $c_1[n]$ is further decomposed into $c_2[n]$ and $d_2[n]$ at the next scale and so on. This type of hierarchical decomposition can be mathematically represented as,

$$c_m[n] = \sum_k h[k-2n]c_{m-1}[k] \tag{1}$$

$$d_m[n] = \sum_k g[k-2n]c_{m-1}[k] \tag{2}$$

where m represents the scale of decomposition, n represents the sampling points and k represents translation coefficient. It is well known that Daubechies 4 wavelet is very much useful in identifying any transition in the signal due to high frequencies and it is successfully applied as a mother wavelet in earlier papers [14, 17]. Therefore in the present work, Daubechies 4 wavelet has been chosen for the analysis. The LC signals were decomposed up to 7 levels and the corresponding frequency band of detailed components is shown in Table 1. The standard deviation can be considered as a measure of the energy present in the signal with zero mean. Therefore, the standard deviation values (STD_MRA) are calculated for detailed components to identify the transient energy present in the signal at different level of decomposition (D1 to D7). Standard deviation of the n^{th} level of detailed signal is calculated using the formula,

Table 1. Frequency band of detailed components of DWT

Detailed components of DWT	Frequency band (Hz)
D1	1250-2500
D2	625-1250
D3	312.5-625
D4	156.25-312.5
D5	78.125-156.25
D6	39.0625-78.125
D7	19.53125-39.0625

$$std = \sqrt{\frac{1}{N_n - 1}\sum_{j=1}^{N_n}[d_n(j) - \mu_n]^2} \quad (3)$$

where μ_n is the mean of the vector d_n and N_n is the length of the vector d_n. In order to understand the high frequency distortions of the leakage current signal, distortion ratio (DR) has been calculated as the ratio of STD-MRA values of (D3+D4+D5) to fundamental component D6 [14]. In the present work, leakage current magnitude and distortion ratio are considered as important features for the diagnosis of pollution severity of power transmission system.

4. Data Mining using Fuzzy C-Means Clustering

Data mining is the process of exploration and analysis of large quantities of data in order to extract meaningful patterns and useful information. Clustering is the method of grouping objects into meaningful subclasses so that the members from the same cluster are quite similar [18]. In recent times, for accurate analysis and classification of signals with complex characteristics, fuzzy c-means clustering technique has been proposed as an effective tool [19, 20]. Fuzzy c-means approach minimizes intra-cluster variance when compared with conventionally used k-means algorithm. When compared with neural network and simple fuzzy logic techniques, it is the best suited method for overlapped data set with increase in outliers [21, 22]. Fuzzy c-means is a method of clustering which allows one elements of the data set to belong to two or more clusters. In this method, each point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely to just one cluster. Thus, points on the edge of a cluster may be in the cluster to a lesser degree than points in the center of cluster. In real time leakage current data measurements on insulators, probability for the occurrence of overlapped data is very high and therefore, in the present work, Fuzzy c-means clustering technique has been adopted for diagnosing the surface pollution condition of the insulators.

Fuzzy c-means algorithm is based on the concept of fuzzy C partition. Let $X_i \in \mathbf{R}^p$, i=1, …, N, denote the data elements represented as n real-valued columns vectors of dimension p. Let $C_j \in \mathbf{R}^p$, j=1, .., C, represent the center of cluster, with $2 \leq C < N$. Let $\mathbf{U} \in \mathbf{R}^{C\times N}$ denote the partition matrix comprised of fuzzy memberships. The elements of **U** satisfy the following constraints,

$$\begin{cases} 0 \le u_{ij} \le 1 \\ \sum_{j=1}^{c} u_{ij} = 1 \end{cases} \quad (4)$$

The fuzzy c-means clustering is based on the following optimization function, under the constraints in (4),

$$\min_{u,c} \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| X_i - C_j \right\|^2, 1 \le m \le \infty \quad (5)$$

where m is any real number greater than 1, it controls the amount of “fuzziness”, u_{ij} is the degree of membership of X_i in the cluster j, and $\|.\|$ is any norm expressing the similarity between any measured data and the center. The cluster centers C can be measured by,

$$C_j = \frac{\sum_{i=1}^{N} u_{ij}^m . X_i}{\sum_{i=1}^{N} u_{ij}^m} \quad (6)$$

Fuzzy partitioning is carried out through an iterative optimization of the objective function, with the update of membership u_{ij} and the cluster centers C_j by,

$$u_{ij} = \left[\sum_{k=1}^{c} \left(\frac{\left\| X_i - C_j \right\|}{\left\| X_i - C_k \right\|} \right)^{2/(m-1)} \right]^{-1} \quad (7)$$

The following algorithm finds a solution that converges to a local minimum of (5) for the Fuzzy C-Means method,

Step 1: Initialize **U** = {u_{ij}} matrix, $\mathbf{U}^{(0)}$
Step 2: At k-th iteration: calculate the center vectors $\mathbf{C}^{(k)}$ = [c_j] with $\mathbf{U}^{(k)}$, using (6).
Step 3: Update $\mathbf{U}^{(k)}$ to be $\mathbf{U}^{(k+1)}$ using (7).
Step 4: Stop rule: If $\max_{ij}\left\{\left|u_{ij}^{(k+1)} - u_{ij}^{(k)}\right|\right\} < \varepsilon$ where ε is a small number between 0 and 1, then stop. Otherwise, $k = k$+1, and return to Step 2.

5. Results and Discussion

Fig. 3 shows the schematic diagram of the diagnostic system developed for the pollution severity monitoring of the transmission line insulators. Extracted features such as LC_{peak} and DR are given as an input to the fuzzy c-means clustering algorithm and then output of this module is given to the pollution severity meter, which indicates the

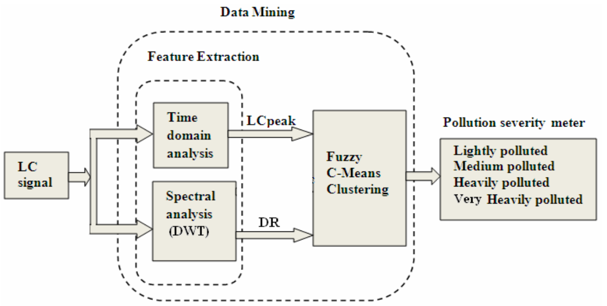

Fig. 3. Schematic diagram of diagnostic system

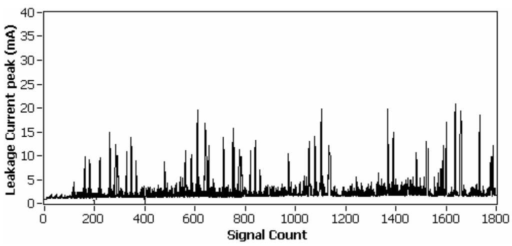

Fig. 4. Trend followed by LC_{peak} at medium pollution

level of pollution of the insulator and hence the flashover possibility to the substation operator.

5.1 Analysis of LC_{peak}

Initially, variations in the peak value of the LC are monitored over a period of time. In this case, test voltage is applied continuously to the insulator specimen at a constant pollution level in the fog chamber and LC_{peak} is captured. Fig. 4 shows the trend followed by the LC_{peak} at medium pollution condition of porcelain insulator. It is observed that peak value of LC is highly intermittent in nature and also it is not steadily increasing over a period of time. It is highly fluctuating and varies randomly from 2 mA to 30 mA. It is very difficult to arrive at any decision on the pollution level of the insulator, just only from the analysis of peak value of LC at any time. Therefore, in the present work, LC signal is processed in both time and frequency domain and the important features such as LC_{peak} and Distortion Ratio (DR) are extracted from the LC data.

5.2 Analysis of wavelet transform distortion ratio

Figs. 5 (a, b, c, d) shows the typical LC waveform patterns obtained during experimental studies at different pollution conditions and corresponding Discrete Wavelet Transform STD-MRA plot with distortion ratio. For a given insulator, LC waveform evolution depends essentially on the changes occurring at the surface pollution layer and surface wetness of the insulator. From the results, it is clear that there is a significant increase in the magnitude of the leakage current with increase in pollution level.

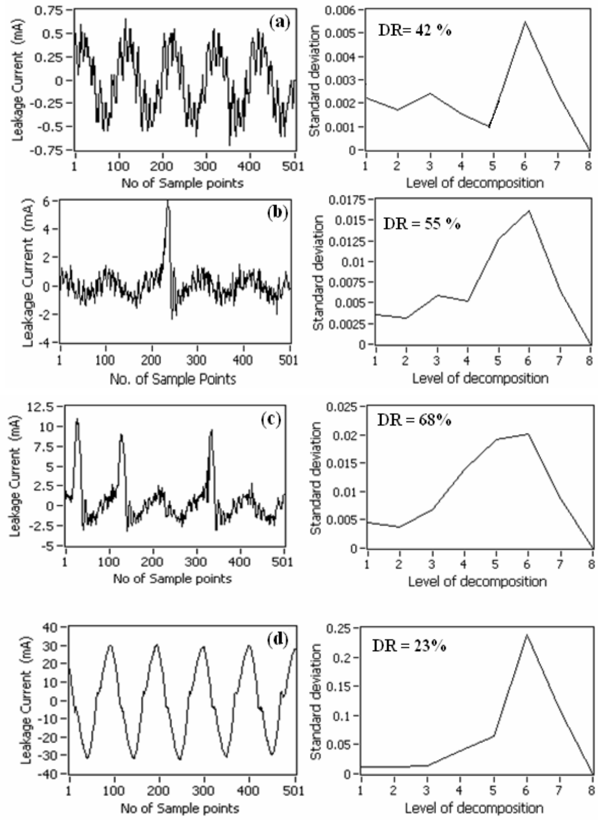

Fig. 5. Typical leakage current signals obtained during experimental study: (a) lightly polluted; (b) medium polluted; (c) heavily polluted; (d) very heavily polluted and corresponding DWT STD-MRA plot with DR value

In this work, DWT based spectral analysis of LC is developed in the LabVIEW software to understand the distortion ratio of signal at various pollution levels. Under lightly polluted conditions (Fig. 5(a)), the magnitude of LC is small without any visible surface discharges and the DR lies in the range of 25-45%. Under medium polluted conditions, presence of short duration discharges (which lasts for half or one cycle) as shown in Fig. 5(b) were noticed and the DR value lies in the range of 40-60%. These short duration discharges are the precursors for the development of long arcs which will lead to flashover. It is observed in the corresponding STD-MRA plot that the magnitude of D5 component (Table 1) is increased when compared with other high frequency components. This indicates that when the frequency of occurrence of short duration discharges raises, the magnitude of third harmonic component increases in the LC signal.

Under heavy pollution, the frequency of occurrence of short duration discharges increased considerably (as shown in Fig. 5(c)) and the DR value also reached above 55% with a considerable increase in third harmonic content. Under very heavy pollution, discharges were observed for duration of 5-25 continuous cycles (Fig. 5(d)) and the discharge pattern almost looks like a sinusoidal waveform, with DR value lying in the range of 10-30%. Significant increase in magnitude of the fundamental component of LC and reduction in high frequency components is noticed in the corresponding STD-MRA plot. From the above experimental results, it is clearly noticed that distortion ratio (DR), estimated from the DWT, increases considerably during the formation of short duration discharges (Figs. 5-(b, c)), while a significant reduction occurs during the formation of long arcs (Fig. 5(d)).

5.3 Fuzzy c-means clustering

Since the LC data is captured continuously and it is also highly intermittent in nature, it is necessary to cluster the captured data over a period of time by using recent data mining techniques. As a data mining function, cluster analysis can be used as a stand-alone tool to gain insight into the distribution of data, to observe the characteristics of each cluster, and to focus on a particular set of clusters for further analysis. It may also serve as a pre-processing step for characterization and classification of events.

In order to identify the groups of similar objects and to discover distribution of leakage current patterns, fuzzy c-means clustering models were built by MATLAB. Extracted features from the leakage current data such as LC_{peak} and DR values were given as an input to the Fuzzy c-means clustering algorithm. Fuzzy clustering process stops when the objective function improvement between two consecutive iterations is less than ε (set ε=1e-5), or when the maximum number of iterations (set as 100) is reached. The LC data were captured over a period of time, at a set pollution level of insulator, during the experimental studies and they were used for the fuzzy clustering process. Four clusters (pollution conditions) are considered in this study, namely, 'lightly polluted', 'medium polluted', 'heavily polluted' and 'very heavily polluted'.

Fig. 6 (a) shows the LC_{peak}-DR relationships captured at lightly polluted conditions before fuzzy clustering. In Fig. 6(b), LC_{peak}-DR relationships after fuzzy clustering are shown, where the markers '*', 'x', '+' and 'o' denote four

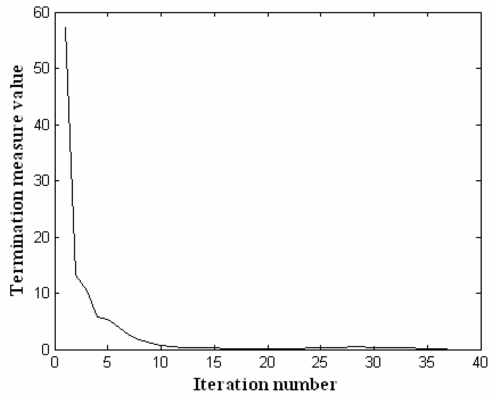

Fig. 7. Typical plot of fuzzy clustering process convergence criterion with respect to number of iterations under lightly polluted conditions

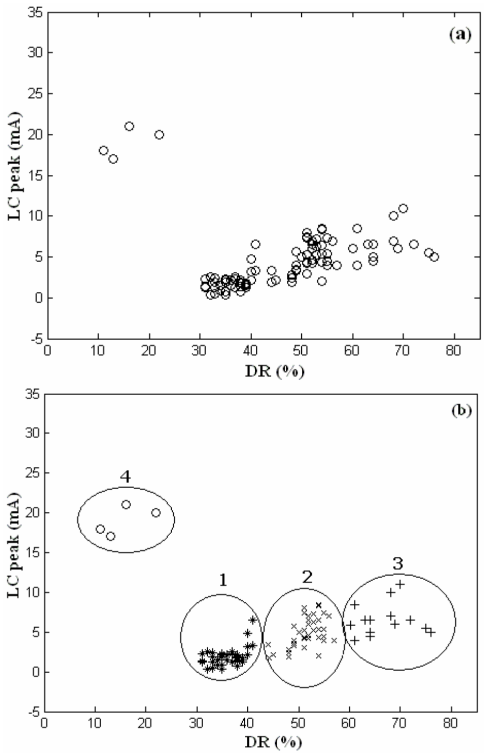

Fig. 6. Typical LC_{peak}-DR data of LC signals under light pollution: (a) before clustering; (b) after clustering

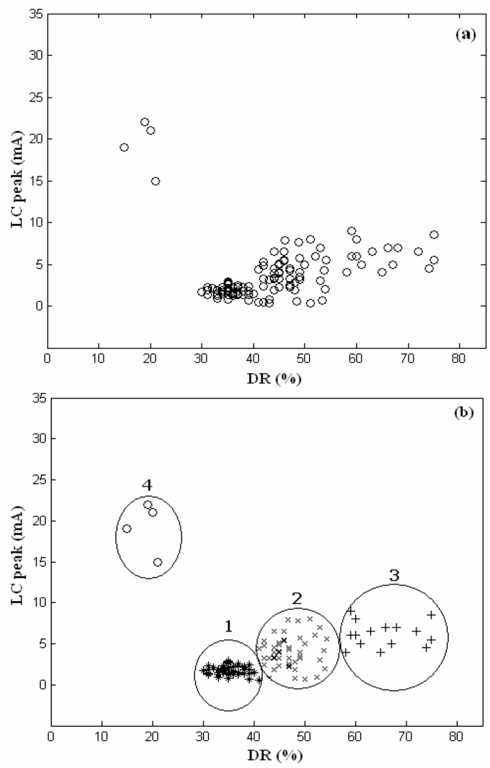

Fig. 8. Typical LC_{peak}-DR data of LC signals under medium pollution: (a) before clustering; (b) after clustering

cluster of data corresponding to 'lightly polluted', 'medium polluted', 'heavily polluted' and 'very heavily polluted' respectively and these clusters are also marked as '1', '2', '3', '4' respectively. During lightly polluted conditions, since the LC_{peak} is small, it is observed that cluster 1 which corresponds to lightly polluted conditions is having large number of data points when compared with other clusters 2, 3 and 4. Cluster 1 data corresponds to low magnitude leakage current signals. Fig. 7 shows the typical plot of fuzzy clustering process convergence criterion with respect to number of iterations under lightly polluted conditions. It is clear that termination measure value is reached within 15 iteration numbers and it is clearly observed that the computation time is very less and fuzzy clustering process is fast.

Fig. 8 shows the LC_{peak}-DR relationships captured at medium polluted conditions. When compared with lightly polluted conditions, the number of data points in the cluster 2 is slightly increased. However, there is no significant increase in data points corresponding to cluster 3 and 4. Cluster 2 corresponds to short duration discharges with low magnitude of leakage current.

Similar plots of LC_{peak}-DR relationships captured at heavily polluted and very heavily polluted conditions are shown in Figs. 9 and 10 respectively. From these figures, it is clear that number of data points in cluster 3 and cluster 4 increases considerably with respect to increase in pollution. Cluster 3 corresponds to repetitive short duration discharges with high magnitude of LC and Cluster 4 corresponds to severe arcing or flashover with increase in arc length and magnitude of leakage current. This fuzzy clustered LC plots clearly indicates the pollution condition and flashover of the insulators. It can be speculated that cluster density above certain threshold value could warrant corrective actions and which will be useful for substation operator to start preventive maintenance work.

The correctness of fuzzy c-means clustering algorithm results should be verified by using appropriate criteria and techniques. There are several methods proposed in the literatures to validate the accuracy of the clusters [23]. Measuring the distance between the clusters is a common approach, which is done by measuring the distance between the closest members or the distant members of the clusters. However, measuring the distance between the centers of the clusters (or) centroids aims at finding the best clustering scheme. In this paper, measuring the distance between the centroids method is used to measure the cluster accuracy.

Fig. 11 shows the centroids of the clusters obtained at four different polluted conditions as discussed earlier.

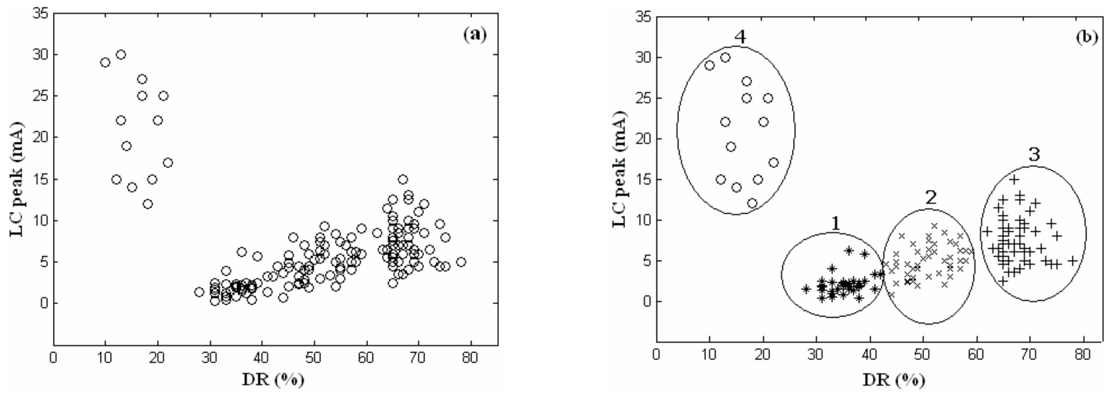

Fig. 9. Typical LC_{peak}-DR data of LC signals under heavy pollution: (a) before clustering; (b) after clustering

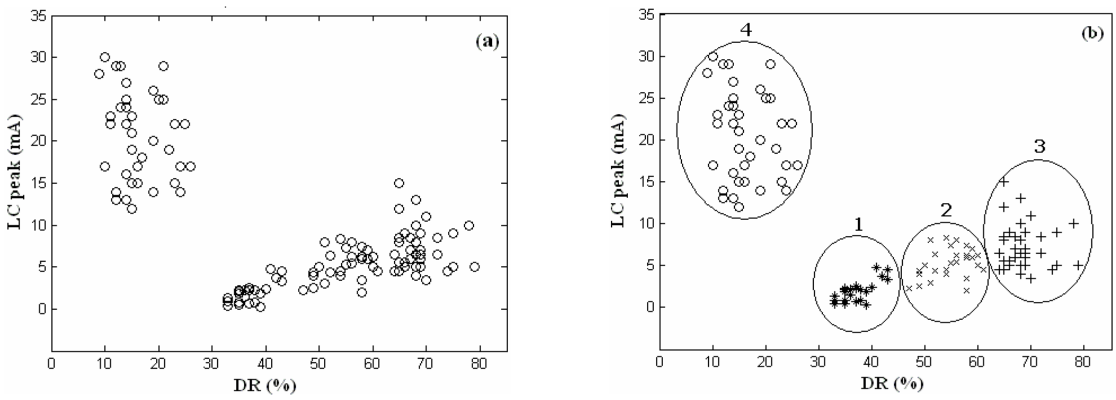

Fig. 10. Typical LC_{peak}-DR data of LC signals under very heavy pollution: (a) before clustering; (b) after clustering

Distance between the centroids of the clusters is denoted as D12, D13, D14, etc. as shown in Fig. 11. At each pollution condition, the distance between the centroids of the clusters *i* and *j* were calculated using the equation,

$$D_{ij} = \sqrt{\left(x_2 - x_1\right)^2 - \left(y_2 - y_1\right)^2} \tag{8}$$

where *x* and *y* are the *(x,y)* coordinates of the respective centroid point. Fig. 12 shows the bar chart of the distance between the centroids calculated at four different pollution conditions. It is observed that the distance between the centroids of the clusters are closely located at each pollution condition.

In order to understand the deviation in the distance between the cluster centroids, standard deviation is calculated. The standard deviation values obtained for each distance between the centroids are also shown above corresponding bar chart in Fig. 12. It is observed that standard deviation value varies from 0.4 to 1.7, which is very less and within acceptable limit. It clearly indicates that the fuzzy c-means technique is more reliable for clustering the leakage current data of the power transmission line insulators.

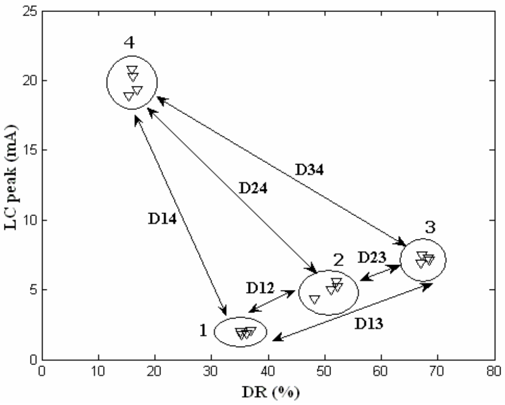

Fig. 11. Centroids of the clusters at different pollutions

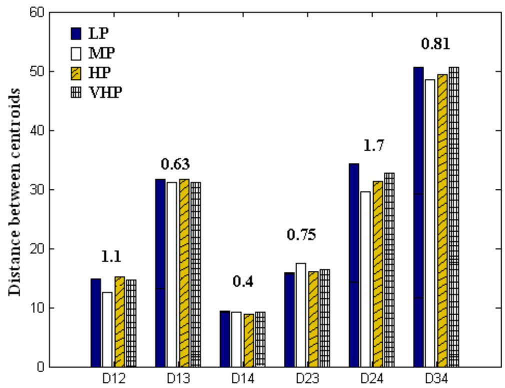

Fig. 12. Distance between centroids and its standard deviation at different polluted conditions, LP- Lightly polluted, MP- Medium polluted, HP- Heavily polluted, VHP- Very heavily polluted

From the above reported results, it is noticed that the fuzzy c-means clustering technique is very much useful for easy prediction of flashover and surface pollution severity of insulators used for high voltage applications. It is also observed that the leakage current magnitude and DR relationships are directly related with surface pollution severity. This can be easily understood from the cluster plot of insulator obtained at different pollution conditions. The proposed diagnostic system results show that it can effectively realize the flashover and pollution severity of outdoor transmission line insulators and this system is easily applicable for real time web based measurements.

6. Conclusion

In this paper, a diagnostic system for the flashover and pollution severity analysis of power transmission line insulators using wavelet transform and fuzzy data mining technique was proposed. It was developed in such a way to take into account the important features of leakage current of insulator such as LC_{peak} and DR. Test results in this work clearly indicate that it is simple to implement web based technologies for the development of condition monitoring system of power transmission lines using the DWT feature extraction and fuzzy c-means clustering technique. Based on the fuzzy cluster results, it is easier for the substation operator to take decisions or initiatives for preventive maintenance work.

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