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A new procedure for determination of insulators contamination in electrical distribution networks

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ABSTRACT

This paper presents a novel method for determination of insulator contamination (IC) level. ICs caused some problems in electric networks. Some faults occur in electric system due to ICs. These faults sometimes log to a sudden and serious damages to the systems. So ICs reduce power quality and reliability indexes. Usually insulator washing is a solution for this problem and its events. Insulators washing have a heavy cost and if a time table for their washing time can be planned, both time and cost will be saved. In this paper average insulators contamination calculated using line current. Leakage current on insulators surface are coming together with small arcs. These arcs have high frequency component. Proposed method extracts some features from these components using Discrete Wavelet Transform (DWT) and principal component analysis (PCA). Line current data gathered for six month on a 20 kV distribution feeder with 6.4 kHz sampling rate. Results show high accuracy of this method for determining of insulators contamination.

Introduction

Flashover of contaminated insulators in polluted areas has proven to be one of the most important factors influencing the operation of distribution lines and substations [1]. These are power-frequency flashovers on distribution lines without evidence of switching or lightning over voltages and usually take place in wet weather conditions such as dew, fog, drizzle or light rain. Near industrial, agricultural or coastal areas, airborne particles are deposited on insulators and the insulator contamination builds up gradually. When fog or light rain wets the polluted insulator, a conductive layer is formed on the contaminated insulator surface, which initiates leakage current [7,8,15,17]. The prediction of approaching flashover is important for utilities. Contamination-caused insulator flashovers result in expensive power outages. Utilities spend significant amounts of money on preventive maintenance, which includes insulator washing and cleaning [2]. This expensive operation is scheduled by the subjective judgment of line engineers, based on historical experience or total hours of service since last washing. Exact predictions of pollution build-up and identification of the time when the flashover is imminent has significant value to utilities [1].

Obviously, an accurate diagnostic criterion is needed to determine the condition of the insulator surface and to identify the possibility of flashover. So it is necessary to estimate insulator's contamination in order to prediction of approaching flashover [12]. Case studied feeder has approximately 84 poles and passes from desert aria around Yazd-Iran in 20 kV voltage level. Supplied loads by the 20 kV feeder are almost induction motor which are using for utilization in brick furnace. Fig. 1 shows the single line diagram of case studied feeder.

In 1996 Arlando et al. performed a laboratory and field test in order to investigate the pollution level in distribution networks. First they recorded the maximum current that passed from insulator's surface monthly, and then they measured the Equivalent Salt Deposit Density level in the laboratory. Then he correlated the results with the measurement of climatic condition and the amount of pollution on the insulators surface.

In 2005 Song et al. in Korea studied the aging of polymer insulator with using leakage current. This investigation has been executed on a single insulator by high frequency components of insulator leakage current. Song et al. neglect the low frequency components of leakage current and they examined the frequency spectra between 1.25 and 2.5 kHz [6].

In 2005 Zhao et al. in China could determine the insulator's pollution level with using Packet Wavelet Transform and also noise reduction method. They monitor the maximum value of insulator's leakage current passing from insulator's surface and then could predict the flashover by examining the pollution level.

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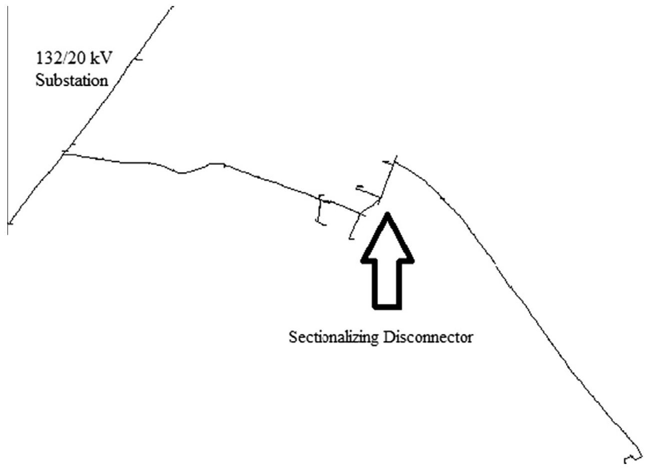

Fig. 1. Case study feeder single line diagram.

In 2006 Memaripour et al. examine the relationship between leakage current and insulator's pollution level in distribution ceramic insulator. They designed a fog chamber and simulated the condition which insulator treated in it. They executed the defined pollution on the insulator's surface and then placed the insulator in the fog chamber. They used the maximum, minimum and average of the leakage current which recorded by the oscilloscope in order to match the defined pollution level with the leakage current [14].

In this paper a different method from the mentioned methods has been proposed. The proposed method can determine feeder insulators contamination level by using the feeder end source current.

In the following and in the second section, basic concepts have been discussed. Data acquisition system identified in part 3 and data processing procedure in part 4 has been discussed. Obtained final curve for insulators contamination are defined in result part.

Basic concepts

Discrete Wavelet Transform (DWT)

Wavelets are classes of functions with properties suitable for the analysis of a wide spectrum of signals for engineering and biomedical applications. The Wavelet transform (WT) was introduced by J. Morlet in 1985 and has attracted much interest in the fields of speech and image processing [3]. Applications of WT in power system are reported for

- Power system transient.
- Power quality assessment.
- Modeling of system components in the wavelet domain.
- Power system protection.

An introduction to Wavelet transform is presented. Wavelet transform is a mathematical tool, much like the Fourier transform in analyzing a stationary signal; this decomposes a signal into different scales with different levels of resolution. For efficient analysis, scales and shifts take discrete values based on powers of two (dyadic decomposition). A dyadic decomposition Wavelet analysis represents a signal as a weighted sum of shifted and scaled versions of the original wavelet, without any loss of information [4,5]. A three-level DWT frequency band is shown in Fig. 2. For implementation of DWT, quadrate mirror filters (QMF) are utilized for hierarchical signal decomposition, and a given signal is decomposed by a series of low- and high-pass filters followed by down-sampling at each stage as shown in Fig. 3.

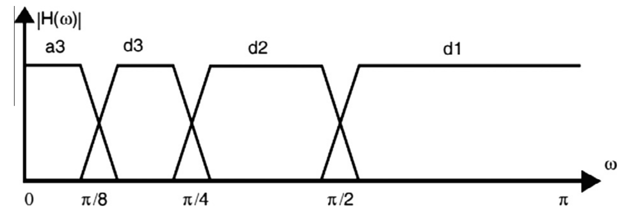

Fig. 2. Three-level DWT frequency band.

The particular structure of the filters is determined by the mother wavelet used for data analysis and by the conditions imposed for a perfect reconstruction of the original signal. The approximation is the output of the low-pass filter, while the detail is the output of the high-pass filter. In a dyadic multi-resolution analysis, the decomposition process is iterated such that the approximations are successively decomposed. The original signal can be reconstructed from its details and approximation at each stage [9–11].

A three-level decomposition signal is illustrated in Fig. 4. Decomposition proceeds until the individual details consist of a single sample. The nature of the process generates a set of vectors a3, d3, d2, and d1, containing the corresponding coefficients. These vectors are of different lengths, based on powers of two. These coefficients are the projection of the signal onto the wavelet at a given scale.

They contain signal information at different frequency bands (a3, d3, d2, and d1) determined by the filter bank frequency response. As expected, these bands are of unequal widths [16]. A variety of different wavelet families have been proposed in the literature. The choice of mother wavelet plays a significant role in time frequency analysis.

The wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. In wavelet analysis, a signal is split into an approximation and a detail. The approximation is then itself split into a second-level

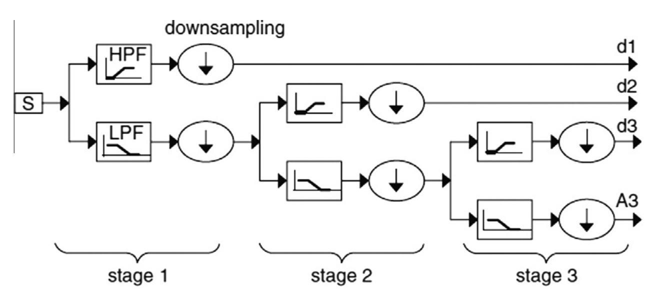

Fig. 3. Three-level DWT.

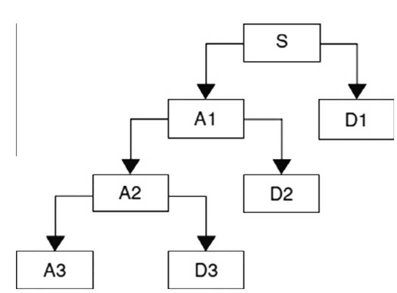

Fig. 4. Three-level decomposition signal in DWT, signal S can be written as S = A3 + D3 + D2 + D1.

approximation and detail, and the process is repeated. For n-level decomposition, there are $n+1$ possible ways to decompose or encode the signal. In wavelet packet analysis, the details as well as the approximations can be split. This yields more than $2^{2^{n-1}}$ different ways to encode the signal. Fig. 5 shows the wavelet packet decomposition tree [2,13].

Principal component analysis (PCA)

The objective of dimension reduction is to reduce the dimension of the pattern recognition problem as much as possible with minimum loss of information. Dimension reduction can be achieved by means of feature extraction or selection. Principal component analysis (PCA, also called K–L transformation) is one of the most widely used dimension-reduction techniques in most practical cases. PCA finds the linear subspace that best represents data without using information of class labels, which is usually called unsupervised dimension reduction method. In PCA a vector is first decomposed into a linear combination of orthogonal basis functions in which the combination coefficients are uncorrelated, and then the dimension of the feature vector is reduced as described below [3,4]. Supposing the distribution of data is Gaussian, the variance–covariance matrix of the feature vectors $\sum$ is

$$\sum = \frac{1}{N}\sum_{j}^{N} X_j X_j^T - \mu\mu^T \tag{1}$$

where N is the number of feature vectors, X is the feature vector and μ is the mean of feature vectors. $\sum$ is symmetrical and positive definite. Thus there exists a matrix similar to $\sum$ which is diagonal, (called $\sum^*$). For this purpose a U matrix is constructed such that

$$\sum^* = U \sum U^T = \mathrm{diag}(\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_N) \tag{2}$$

where λ_i is the λth eigenvalue of $\sum$, and ith row of U is the corresponding normalized eigenvector. U is a transformation matrix that converts the original features into new space with uncorrelated features. If the distribution of data is not Gaussian, the feature in new space will be correlated. It can be shown that the optimum properties of PCA are satisfied if the rows of transformation matrix U are chosen as the m (out of k) normalized eigenvectors corresponding to the largest eigenvalues of diagonal covariance matrix $\sum^*$.

The ratio of eigenvalues to sum of eigenvalues expresses the percentage of MSE (mean square error) introduced by the elimination of the ith eigenvector. So the dimension of feature vectors can be reduced until a desired accuracy is achieved.

$$\mathrm{MSE} = \lambda_i / \sum_{j}^{N} \cdot \lambda_i \tag{3}$$

Data acquisition

A 20 kV feeder in an industrial polluted area was chosen for collection of current data that encompass insulator leakage current (ILC). Feeder length is 5 km and there are 84 insulators on each phase.

Three phases current were recorded at the end source using Hall Effect transducer, QualistarPlus C.A 8335 power analyzer and computer.

CTs were connected on output cables of substation (see Fig. 6).

The data was recorded at a sampling rate 12.8 kHz and due to power analyzer limitation only 1 cycle was recorded on each step. Fig. 7 shows connection of instruments on 132/20 kV substation.

All gathered data can be divided in two sections. At the first section current waveforms were recorded in a six month period, three times a day. So 180 current waveforms have been recorded.

The second section of data gathering has been done in a half an hour period. In this section the feeder middle switch has been opened for five minutes and then closed.

Before, during and after of this process, current waveforms have been recorded thirty times in a minute. Approximately 800 current waveforms have been recorded in this section.

In the second section we can find the effect of insulator numbers. Also we can check that the contamination characteristic features will be constant in recorded data in a few time intervals. Details were explained in next section.

The main factor that influenced by accumulated contamination on insulator's surface is leakage current that is generally measured

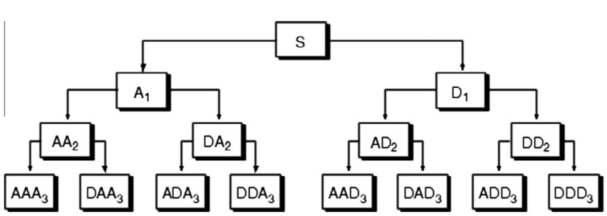

Fig. 5. Three-level decomposition signal in PWT.

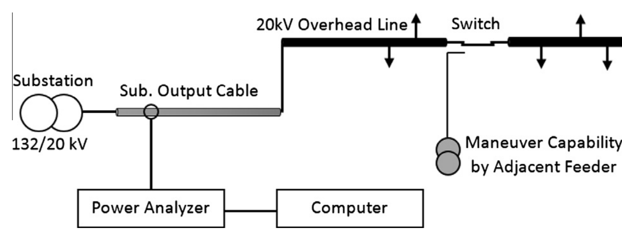

Fig. 6. Schematic diagram of substation, cables, lines, power analyzer, and computer.

Fig. 7. Connection of instruments in 132/20 kV substation.

in mA. This paper proposes a method that is based on analyzing the feeder's current and basically the leakage current effects on it. Since the proposed method is an On-Line method that determines the average pollution level on insulators, so the measured current is total feeder current from the substation to all feeder and is in Amps.

Proposed method

After data recording process, in two sections totally 1000 current waveforms have been recorded. Fig. 8 shows some recorded data.

Since the recorded currents are combination of load current and ILCs, following method has been utilized detection of ILC features from recorded currents. The proposed method can be explained in 5 steps as in the following subsections.

Step 1: Current signals decomposition based on PWT

As mentioned before, 1000 feeder current waveforms are available with time sequence after data recording process.

First of all, each recorded current decomposed unto the third level using all the mother wavelets defined in MATLAB software. For example one of decomposed signal unto third level with using Daubechies family as mother wavelet has been shown in Fig. 9.

Because each recorded current has 256 samples, so the first three levels have 128, 64, and 32 samples respectively. In this step, each current as shown in Fig. 9 was decomposed to 14 sub-signals with specified frequency band according to Table 1.

Step 2: Feature extraction

After executing the first step, totally 53 * 14 * 1000 signals have been received whereas 53 represents the number of mother wavelets which are used, 14 represents total components that decomposed for each signal and finally 1000 represents the number of recorded signals. In this step some features such as mean, maximum, variance, minimum, sum, mean of absolute, max of absolute, momentum, mean of square and sum of absolute have been calculated for each decomposed signal components. Fig. 10 shows an example of these calculations.

Fig. 11 shows values of one feature for all decomposed signals with special mother wavelet.

Part A in the Fig. 11 is corresponding to the six-month data recording (Section 1 in data recording process) and the part B is corresponding to the 30 min of data recording(Section 2 in data recording process) which is corresponding with opening and reclosing the switch in the middle of the feeder.

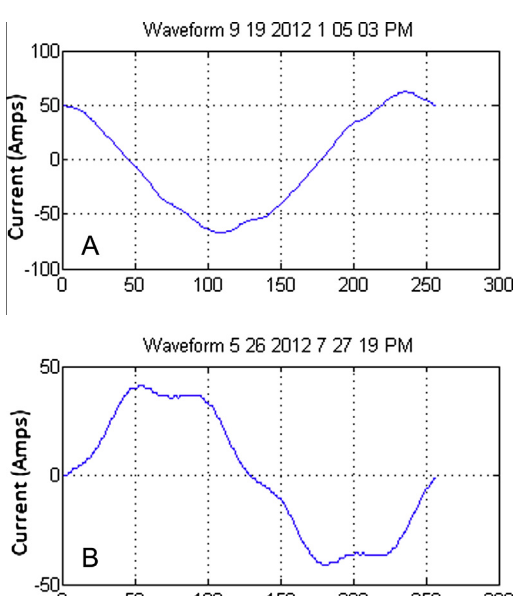

Fig. 8. Recorded current waveforms. A. Waveform 9 19 2012, 1 05 03 PM. B. Waveform 5 26 2012, 7 27 19 PM.

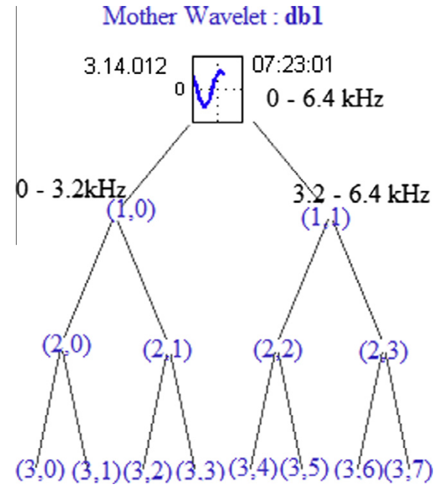

Fig. 9. Current signal decomposition unto third level and some frequency band.

Table 1
Decomposition components and them frequency band.

Level	Component	Frequency band (kHz)
1	(1,0)	0.0–3.2
	(1,1)	3.2–6.4
2	(2,0)	0.0–1.6
	(2,1)	1.6–3.2
	(2,2)	3.2–4.8
	(2,3)	4.8–6.4
3	(3,0)	0.0–0.8
	(3,1)	0.8–1.6
	(3,2)	1.6–2.4
	(3,3)	2.4–3.2
	(3,4)	3.2–4.0
	(3,5)	4.0–4.8
	(3,6)	4.8–5.6
	(3,7)	5.6–6.4

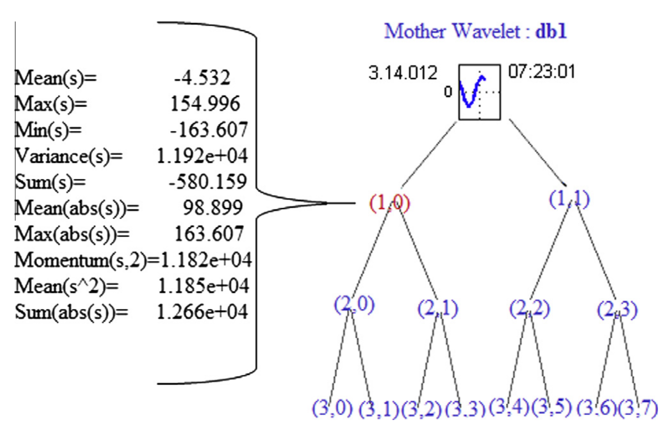

Fig. 10. Calculating 10 features for a sample component.

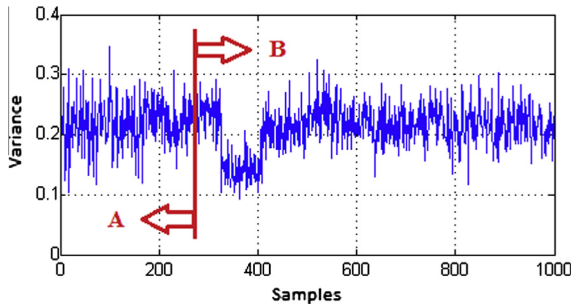

Fig. 11. Values of calculated feature for all decomposed signals, mother wavelet: db3, component: (2,1), feature: variance.

At the end of this step 53 * 14 * 10 curves has been plotted, whereas 10 declares ten mentioned features.

Step 3: Smoothing

Each received curve in previous step has 1000 values that those are corresponding with number of recorded current signals. For increasing the precision of the presented method, limiting the features curve oscillation, being able to extract more information from the data and being able to provide analyses that are both flexible and robust [18], smoothing method was implemented. In this procedure we can use window with variable length such as 10, 20 and so on.

The windows can be overlap with adjacent windows. As example for a window with 20 values length with 10 values overlap, in the first step 1–20 values is used and 11–30 values is used for next window. Finally average of encompassed values by each window is computed and curves with 1000 values converted to new curves with 100 values. Figs. 12 and 13 shows this smoothing with windows length 20 and 50 respectively.

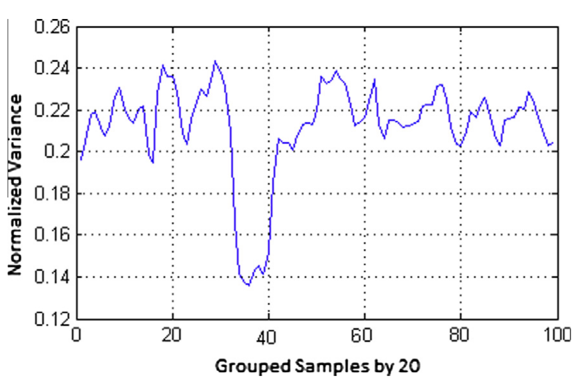

Fig. 12. Smoothed curve by window length 20.

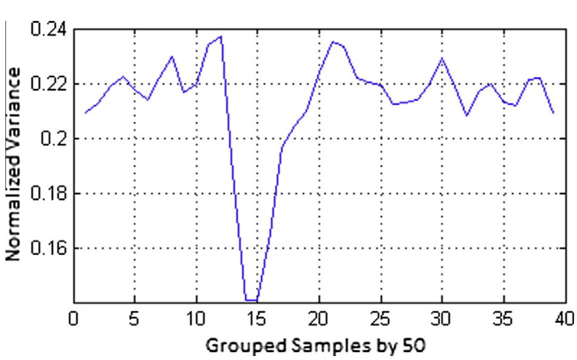

Fig. 13. Smoothed curve by window length 50.

Step 4: Normalization

In order to make the resulted curves in a unit range, normalization method has been intended. For this purpose for each curve the curve value has been divided by its maximum amplitude. So all the curves stand between $[-1,1]$ interval.

Step 5: Features reduction

In the last step, using the principal component analysis has been intended in order to obtain the final curve which is proportional to the total insulators contamination level. All the resulted curves from previous steps have been used as feature vectors in PCA method. Then, as mentioned before, in Basic Concept, mean of feature vectors (μ) and after that covariance matrix for all of them has been calculated. Then the eigenvalues and corresponding eigenvectors calculated. The largest eigenvalue and its corresponding eigenvector have been selected. The PCA process has been continued and signal has been obtained as output.

This output signal that related with contamination is shown in Fig. 14.

Results and discussion

Based on previous explanation, Fig. 14 as output curve is an index that relative to insulators contamination in a feeder. Illustrated curve is extracted from feeder current at source end.

Part A is corresponding to the first section of recorded data for six month. As it shown, this index growth during the spent time, and this is because of increasing pollution on insulators surfaces. The index curve at this part is nonlinear and in a few points may be decreased. This nonlinearity and decreasing in index values are affected from weather conditions.

Part B of index is related to the second section of data gathering for 30 min with disconnecting switch at middle of feeder. As it shown, this part of index has a valley that related to switching time.

During switching time almost half of insulators were out and as it expected, reduction of insulators cause reduction in contamination index.

Before switching time, index has a high and almost constant value. Reconnecting data in a few minutes before switching with stable physical condition caused this feature.

Instantaneously after opening switch, index reduces sharply and this is due to reduction in insulators numbers.

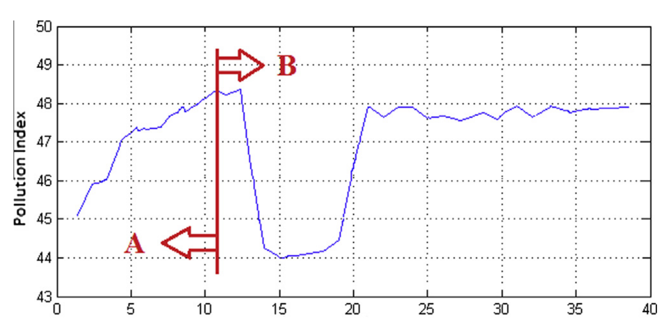

Fig. 14. Insulator's contamination index – part A shows the 6-month period and part B declares the 30 min period. Drop in part B related to disconnection some of the insulators.

Contamination index after reclosing switch growth suddenly and received to an almost constant level.

Although in this part data recording time is short and numbers of insulators are equal, but this level is not equal to contamination value before opening switch. Because when switching off, some insulators condition will be changed since they do not connect to voltage supply, and by reclosing switch it need some times to return to previous condition. Smoothly growth in index after reclosing switch shows this subject.

Notice to corners of valley shows uneven surface. This is due to grouping data as explained in step 3 in previous section.

This paper following a main goal to monitor the accumulated pollution level on insulator's surface in a distribution feeder. The proposed method is based on analyzing the feeder current in order to determine the pollution level. Since the recorded currents are combination of load current and ILCs, the method has been proposed for detecting the ILC features from recorded feeder currents. Hence, the final contamination index that presented in the paper indicating the feeder current relationship with the pollution level during 6 month of data recording.

Also, the main goal that followed by this paper is to propose a new method to monitor the contamination level of total feeder's insulators. The method is based on line current and some introduced signal processing methods. In order to validate the proposed technique for monitoring the pollution in On-Line condition, some chronologically current data was recorded. Afterwards, the proposed method was carried out to analyze the pollution index behavior of the data. It is so useful to determine standard levels based on the recorded data, but it is crucial to access the pollution limits to do that. In other words, determining the standard pollution levels depends on upper and lower limit. Lower limit is corresponding to completely clean insulators data. Upper limit is corresponding to flashover data.

Conclusion

Insulators contamination in polluted area is an important problem. The aperiodic occurrence of widespread contamination related outages cause serious damages to the distribution networks. Thus determination of accumulated pollution level is necessary. This paper is presented a novel index for contamination identification.

Current at the source end of a typical 20 kV feeder in polluted area was used for this procedure. PWT is used for feature extraction and PCA for feature reduction.

Results declare an index that related to average contamination with high accuracy.

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References

[1] Amarh F. Electric transmission line flashover prediction system. PhD thesis and final project report. Arizona State University, May; 2001.
[2] Hanbiao Zhao, Hui Lin, Shenglan Liao, Lili Xie. New method for leakage current detection of insulators based on wavelet transform. High Volt Eng 2005;31(4):34–6.
[3] Sedighi AR. High impedance fault detection in electrical distribution system. PhD thesis and final project report. Tarbiat Modarres University, Winter; 2005.
[4] Haghifam MR, Sedighi AR, Malik OP. Development of a fuzzy inference system based on genetic algorithm for high-impedance fault detection. IEEE Proc Generat, Transmiss Distrib 2006;153(3):359–67. 11 May.
[5] Unser M, Blu T. Wavelet theory demystified. IEEE Trans Signal Process 2003;51(2):470–83.
[6] Song YC, Choi DH. High-frequency components of leakage current as diagnostic tool to study aging of polymer insulators under salt fog. Electron Lett 2005;41(12):684–5. 9 June.
[7] Kumagai S, Yoshimura N. Leakage current characterization for estimating the conditions of ceramic and polymeric insulating surfaces. IEEE Trans Dielectr Electr Insulat 2004;11(4):681–90.
[8] Kanashiro AG, Burani GF. Leakage current monitoring of insulators exposed to marine and industrial pollution. In: IEEE international symposium on 1996 conference record of the electrical insulation; 1996, vol. 1, p. 271–4 [vol.1, 16–19 June 1996].
[9] Driesen J, Belmans R. Wavelet-based power quantification approaches. In: Proceedings of the 19th IEEE instrumentation and measurement technology conference. IMTC/2002; 2002, vol. 1, p. 481–6.
[10] Croes T, Gherasim C, Van den Keybus J, Ghijselen J, Driesen J, Belmans R. In: 11th International conference on power measurement using the wavelet transform of analytic signals. Harmonics and quality of power; 2004. p. 338–42 [12–15 September 2004].
[11] Dehghani MJ. Comparison of S-transform and wavelet transform in power quality analysis. World Acad Sci, Eng Technol 2009;50:395–8.
[12] Richards CN, Renowden JD. Development of a remote insulator contamination monitoring system. IEEE Trans Power Deliv 1997;12(1):389–97.
[13] Barros J, Diego RI. Application of the wavelet-packet transform to the estimation of harmonic groups in current and voltage waveforms. IEEE Trans Power Deliv 2006;21(1):533–5.
[14] Memaripour A, Abrosh H. Study of relationship between leakage current and contamination level in distribution ceramic insulators. In: Power distribution system conference; 2006.
[15] Sato M, Nakajima A, Komukai T, Oyamada T. Spectral analysis of leakage current on contaminated insulators by auto regressive method. In: Annual report conference on electrical insulation and dielectric phenomena; 1998, vol. 1, p. 64–66 [vol. 1, 25–28 October 1998].
[16] Kovacevic J, Goyal VK, Vetterli M. Signal processing Fourier and wavelet representations. Massachusetts Institute of Technology, 22 March; 2012.
[17] Hosseini H, Abrosh H, Yosefi H. Diagnostic criteria for the condition of composite insulators leakage current harmonics in distribution networks. In: Power distribution system conference; 2008.
[18] Simonoff Jeffrey S. Smoothing methods in statistics. 2nd ed. Springer; 1998 [ISBN 978-0387947167].