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A novel algorithm for discerning surface discharge stages of contaminated insulators

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ABSTRACT

A novel algorithm for surface discharge stage recognition of pollution insulators has been proposed in this work based on the detailed analysis of surface discharge characteristics for the purpose of online monitoring and risk prediction of flashover from contaminated insulators. The total recognizing process of the novel algorithm comprises of four steps: first, the discharge stages were recognized based on leakage current (LC) signal through Bayesian-based pattern recognizing algorithm; second, the recognizing result of step 1 was verified immediately through humidity signals; third, if necessary, the stages were re-recognized based on humidity data by applying fuzzy theory and a membership degree was obtained; fourth, the membership degrees of both LC and humidity were input to an arbitration machine and the final recognition decision was made according to the arbitration output. As shown by the results of both intra-group and inter-group verifications, the novel algorithm exhibited good universality, specifically, the algorithm trained using one set of testing data can recognize the discharge stages of other testing data with good accuracy. Moreover, the recognition errors of the novel algorithm were limited and significant errors can be avoided, for incorrectly recognized stages were just adjacent to the correct stages.

1. Introduction

Flashover of HV contaminated insulators has increasingly become one of the most negative factors influencing the reliability of power system as power grid voltage and installed capacity increase. Because the damage and loss from flashover are more serious than that from other factors such as thunder stroke and operating overvoltage [1], it has been predicted that the endangerment of flashover will be much more severe in the future accompanying the rapid development of power system. Therefore, developing an efficient technique to monitor insulator surface discharging and meanwhile predict the occurrence of flashover will be mandatory for preventing flashover as well as improving power network reliability.

Currently, research focus has been mostly on online flashover monitoring, and several monitoring schemes have been reported, among which the schemes based on leakage current signal seem particularly promising due to ease of measuring leakage current (LC) signal. A major difficulty in LC method is short of efficient methods to recognize surface discharge stages therefore predict flashover risk based on comprehensive analyses of the measured LC signals [2]. In this work, we propose an algorithm that can be used to discern surface discharge stages of contaminated insulators on the basis of LC and humidity signals. We hope that the algorithm developed here will be helpful for fulfilling the flashover prediction in the future.

2. Characteristic analysis of surface discharge and corresponding LC

2.1. Experimental setup of artificial pollution test

The artificial pollution flashover test performed in this paper was a constant-voltage and clean-fog test that was conducted by strictly following the corresponding standard [3]. Fig. 1 shows the wiring diagram used in the test in which T is a 50 kVA 220 V/0–110 V powerstat variable transformer, B is a 6.5 kVA 110 V/110 KV potential transformer, and PT is a 150 kV/110 V voltage transformer to measure the output voltage. The power supply had a short current about 10 A. The fog chamber was made of epoxy resin with a size of 1.8 m × 1.8 m × 2.0 m. The XP-70 type suspension cap-and-pin porcelain insulators were selected for the tests. The insulator was artificially contaminated and dried in the shade in advance. After the insulator has been installed in the chamber and the wires have been well connected, the water in tank was heated and the chamber was humidified with fog. Meanwhile, the power supply was turned on and operated at the normal voltage output. The normal voltage in this paper was 63.5 kV. The insulator string was made up of seven single insulators that are equal to the normal configuration in 110 kV

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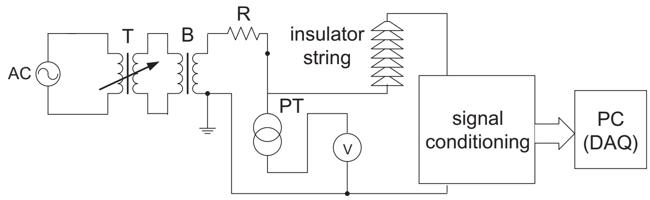

Fig. 1. Wiring diagram of artificial pollution test.

transmitting line. During the test, both the humidity and temperature were controlled.

The leakage current (LC) signals were measured through a DAQ system with a frequency of 5 kHz. For every single measurement, 10 data were obtained, and the mean of data was calculated. Ten mean data were obtained every 20 ms (period of AC supply), and only their maximum was selected by the DAQ and recorded. Therefore, there were 50 data stored per second, providing a sufficient description of LC's envelope. The primary objective of this DAQ scheme was to reduce the amount of data stored. The results showed that the noise can be effectively suppressed via data averaging. Similar to LC signals, the humidity signals were also measured and stored with a frequency of 50 Hz [4].

2.2. LC characteristics

A typical LC variation during the artificial pollution test is shown in Fig. 2. As shown by the LC envelope, the intensity of surface discharge became larger and larger as the humidity increased as well as surface discharge developed. In addition, the entire surface discharge process can be divided into eight stages according to the phenomena and LC impulse [5]. The details are shown in Table 1.

The two major factors that can significantly influence the surface discharge state are environmental humidity and surface contamination accumulation [6], which are usually characterized by relative humidity and equivalent salt deposit density (ESDD), respectively. The more intense the discharge is, the larger the LC value. The heavily contaminated insulators in dry state can still maintain good dielectric strength, and consequently, the LC values are small. On the contrary, slightly contaminated insulators in wet state can lead to large LC pulses [7,8]. Therefore, to be able to distinguish among different discharge stages, LC information alone can not be sufficient. The information of other factors such as humidity will need to be considered.

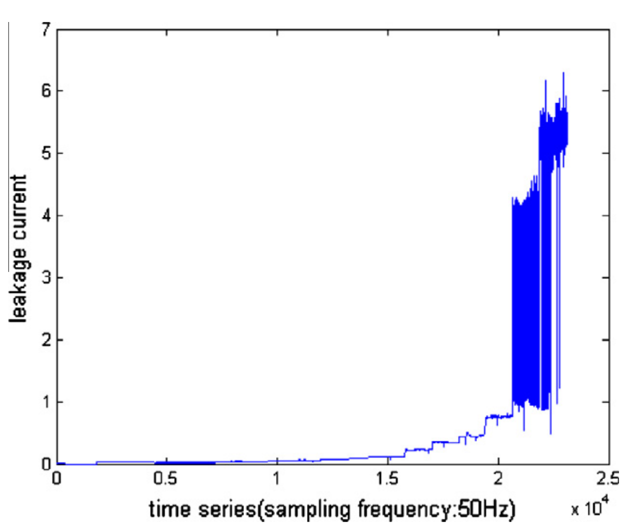

Fig. 2. Experimental leakage current results.

Table 1
Discharge stages in pollution test of XP7 insulators.

Discharge stage	Discharge characteristics
1	No obvious discharge
2	Purple spark, filamentous arc with low voice
3	Yellow or white spark, purple brush arc
4	Orange short arc, continuous discharges with louder voice and frequent impulses
5	1/3 leakage distance arc with lower impulse frequency than stage 4
6	Bright jacinth main arc with longer impulse interval, short arc full of groove
7	Intense discharging with arc up to leakage distance, withstand
8	Intense discharging with red arc, flashover

As shown in Table 1, there were no discharge and impulses in the first stage, which is very likely due to that the surface contamination is dry at the beginning of the test. This stage is pretty similar to the normal state and can be easily recognized. In contrast, very intensive LC impulses as well as high humidity (over 91%) can be observed in the last two stages (stages 7 and 8), i.e., the quasi-critical and critical state of flashover respectively. A careful study of the probability distribution of LC occurrence has been conducted by Dr. Felix Amarh, in which the EVRF (extreme value risk function) was introduced to predict the occurring probability of flashover. This method has been further developed by one of the authors (He Bo) in his doctoral dissertation. His results indicated that EVRF method can provide satisfactory predictions for flashover occurrence in both quasi-critical and critical stages [8]. Therefore, amongst eight stages in Table 1, the stage 1 can be easily recognized, and the stages 7 and 8 (quasi-critical and critical stage) can also be well distinguished from other stages based on LC waveform as well as by applying EVRF method, However, to the best of our knowledge, there are no efficient algorithms available for discerning the stages 2–6. We propose in this study a novel algorithm by which the stages 2–6 (Table 1) can be distinguished based on LC and humidity signals.

3. Introduction to algorithms

The flashover mechanism is complicated. Many factors can influence the flashover process. It is usually very difficult to completely control the occurrence of flashover and the data are necessarily random to some extent. A primary difficulty in online monitoring and predicting of flashover is the universality. Particularly, the algorithm developed based on a specific set of measured data, should be transferable, i.e., should also be efficient when being applied to other data sets [9]. As a result of apparent randomness of pollution test data, the statistics pattern recognizing theory seems particularly promising and will be selected in this paper [10].

3.1. Shortcomings of traditional algorithms

Traditional pattern recognizing algorithms can be divided into two categories [11], that is, the Bayesian-based algorithm and Fisher-based algorithm.

3.2. Characteristics of Bayesian-based pattern recognizing algorithms

Bayesian-based recognizing algorithms are based on Bayes' formula, as shown by Eq. (1).

$$P(\omega_i|X) = \frac{P(X|\omega_i)P(\omega_i)}{\sum_{i=1}^{R} P(X|\omega_i)P(\omega_i)} \tag{1}$$