A Neuro-Fuzzy Approach for the Detection of Partial Discharge

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Abstract—Dielectric surfaces exposed to partial discharges (PD) undergo aging, which is reflected by changes in the discharge pulse form. An approach is described in which fuzzy logic and neural networks are used in conjunction with the wavelet transform to identify the parameters in the PD pulse form for the purpose of classifying the aging phenomena due to partial discharge degradation.

Index Terms—Instrumentation, measurements, neuro-fuzzy, partial discharge.

I. INTRODUCTION

The aging of a dielectric may be caused by electrical and thermal stresses and by the occurrence of partial discharges (PD), which is due to electrical stress [1], [2]. Partial discharge activity at a dielectric surface is influenced by chemical degradation products, which are formed due to the presence of the partial discharges themselves as bombardment of the dielectric surface by charge particles causes chain scission and the polymer radicals react with the oxygen of the air.

During the aging process of the dielectric, the PD behavior exhibits considerable changes: it begins mainly with spark or rapid rise time pulses (Fig. 1), which are characterized by a short duration (some tens of nanoseconds) and a short rise time (a few nanoseconds); in the second phase, low magnitude partial discharge pulses with slower rise time appear. These small discharge pulses are frequently referred to as pseudoglow discharges. Further degradation of the dielectric surface may lead to the appearance of a pulseless or glow discharge. In many cases, all three types of partial discharge (rapid rise time pulse with high magnitude, slow rise time pulses with low magnitude, and pulseless glow discharges) may occur simultaneously.

The two principal PD pulse-type development stages, which arise from surface degradation effects, may be easily distinguished by means of their pulse shapes.

The pulse form parameters or attributes, which may be taken into account for pulse type identification purposes, have been enumerated in [3], [4]: 1) rise time of the PD pulse; 2) pulse amplitude; 3) pulse width; 4) pulse decay time; 5) apparent charge connected with the discharge pulse, which is proportional to the PD pulse area.

The goal of the present paper is the identification of partial discharge pulse form, using a neuro-fuzzy technique in conjunc-

Fig. 1. Rapid rise pulse or spark discharge.

tion with wavelet transformation. The use of soft computing to solve this problem has already been proposed in [4], where a neural approach has been introduced, while here the work focuses on fuzzy logic. Fuzzy logic may be employed to classify systems [5], [6] due to the fact that fuzzy sets permit clustering on an array of input data. A critical point in this approach is the tuning of the characteristic parameters of the membership functions and inference rule set. In order to accomplish this task, an interesting approach involves the application of the neural technique to the fuzzy function identification [7].

II. USING WAVELET TRANSFORMS FOR PARTIAL DISCHARGE ANALYSIS

Wavelet transforms are an interesting evolution of the more traditional transforms employed in signal theory. The use of wavelets allows the extraction of more information in comparison with frequency spectrum analysis [7]. Wavelet transformation is accomplished by passing from a one-variable approach (frequency) to a two-variable approach (time–frequency or space–frequency), using a smaller number of parameters. This feature can be usefully employed for impulsive phenomena of which partial discharges are a classic example. The PD pulse form is a function of aging, so that a quantitative analysis of the pulse shape allows the determination of the degree of aging in the insulating material and thereby perhaps the estimation of the time to breakdown. For an insulating surface that is not aged, the PD pulse has a wide frequency component and may be considered “time concentrated,” while with an aged insulation surface, the PD
wavelet spectrum is less defined in time. The analyzed aged specimen’s signal shows a rise time and a duration greater than in the previous state of not aged. Sometimes constant current landings have been found instead of exponential decay. Moreover, with an aged insulation surface, the PD pulses lose their periodic characteristic (synchronization with the main frequency) and the characteristic of temporal localization.

Starting from the foregoing considerations, it is possible, by means of a discrete wavelet transformation of the sampled signal, to extract information related to the aging characteristics. In the literature, different bases have been proposed for wavelet transformation. The optimum base has to be chosen according to the phenomena model. For example, the Gabor transformation can be successfully applied to partial discharges as shown in [8]. However, Malvar wavelets have been selected for their closer relation with sinusoidal signals [9]. This makes the analysis more intuitive, providing the definition of the rule base for the fuzzy system.

III. PD MECHANISM ANALYSIS BY MEANS OF MALVAR TRANSFORMATION

The purpose of this section is the analysis of the PD pulse shapes and of their corresponding Malvar transformation. In the application of the Malvar transformation, the frequency components whose amplitude is less then 10% of the normalized signal peak value will be considered noise. First, the rapid rise-time large-magnitude pulses, characteristic of insulation surfaces that are not aged, will be considered. The application of the Malvar transformation to a rapid rise time PD pulse allows the extraction of a level diagram such as the one depicted in Fig. 2. In this diagram, the abscissa is the time-axis, while the ordinate is the frequency-axis. It is possible to observe that rapid rise time PD pulses of spark type discharges are characterized by a wide frequency spectrum only in a narrow time window. With aging of the dielectric surface, the PD pulse magnitude diminishes and the rise time decreases; the related level diagram for this aging stage is illustrated in Fig. 3, which indicates a time window wider than that of the rapid time pulse. The level lines for the aged insulation surface PD pulse are very different from those observed in the previous case. It can be perceived that the pattern is orthogonal with respect to the previous one. Here, the lines are concentrated in a row pattern, while in the rapid rise time pulse case, the lines were concentrated in a column pattern. The ultimate aged stage—i.e., just prior to voltage breakdown of the specimen—exhibits a level diagram of the type given in Fig. 4, where it is possible to define neither frequency nor time concentration.

IV. CLUSTERING OF PD MECHANISM BY FUZZY LOGIC

The previous analysis allows the definition of a set of classification rules for the numeric algorithm. A second step is required to define the clustering structure. The previous analysis permits the formulation of “common sense” criteria and subsequently the fuzzy rules. For this purpose, the following variables have been selected: i) number of time samples with zero-value components (a large value of this parameter allows the identification of a rapid rise time pulse or spark type mechanism)—Fig. 2; ii) number of low frequency order components (a large value of this parameter infers aging of the insulating material)—Fig. 3; iii)
number of nonzero-value components (the value of this parameter increases as the insulation approaches breakdown)—Fig. 4. These parameters allow the definition of a fuzzy system capable of automatically indicating the stage of aging.

V. FUZZY SYSTEM CHARACTERISTICS: SIMULATION RESULTS AND EXPERIMENTAL ANALYSIS

The fuzzy system approach is easily realized by employing commercial software tools. The adaptive fuzzy modeller (AFM) by SGS-Thomson has been selected here. This package is able to automatically define the fuzzy system parameters by applying neural algorithms. It is then possible to estimate the target function just by providing an input set of sampled data. Local rules can then be introduced for a local adjustment in the input–output function. Here, a three-input-one-output function was utilized, where i) $N_0$ (input value): nonzero number of components of the wavelet transformation; ii) $N_1$ (input value): nonzero number of components of the wavelet transformation on the first row; iii) $N_t$ (input value): number of the temporal instants where all components are equal to zero; iv) $C_l$ (output value): aging index using a range from 1 to 3. A value for $C_l$ equal to 1 identifies a spark or rapid rise time pulse state, while a value equal to 2 identifies an intermediate state, and a value equal to 3 a glow discharge state.

Intermediate values can be considered as an evolutionary trend of the system between two different phases. Twenty different transient shapes have been simulated in the Matlab environment to train the system. The parameters adopted as inputs for the fuzzy system are automatically calculated by another Matlab procedure. These data have then been employed for the fuzzy system training phase; the results of the training phase have been tested in the same environment, using the following test procedure: 1) first, the system has been tested by applying waveforms very similar to those used for the training phase; 2) then, the discharge trigger and time constant have been changed in order to evaluate the sensitivity of the fuzzy function. The system has been observed to behave satisfactorily. In the following paragraphs, some interesting cases are described. A rapid rise time pulse (spark discharge) waveform has been analyzed under two different conditions: 1) delay of the starting instant in the same sampling windows; 2) changing of the time constant characterizing time evolution. The first test has been realized by applying a set of signals with the same time evolution (same decay time constant) but characterized with a different trigger instant. The most interesting result is that the clustering function has been found to be insensitive. In fact, the same value obtained for the training pattern with index of 1.12 has been confirmed under modified conditions. This value indicates that the signal has been classified as a spark-type discharge with a good confidence level.

Also, the analysis using a fixed trigger and a modified time constant gave the expected results. The classification coefficient $C_l$ moves toward 2 when the time constant increases. In this situation, the phenomenon interests the whole observation window, which is the first indication that the material is aged. It is possible to observe that if the time constant does not permit the extinction of the exponential decay before the end of the window, the phenomenon will appear very similar to that of the following phase (cf. Fig. 5). The related level diagram for this event is illustrated in Fig. 6. The system has been tested even with actual PD pulse shapes, which were different from those used in the training stage. A great number of fault cavities can coexist, and, for this reason, it is possible to have different discharges in the same sampling window. The window used for the rapid rise time pulse or spark discharge must be large enough to be used with a slow rise time pulse discharge, and then it is possible to have in the same data acquisition more than one spark-type discharge. For this reason, the system has been tested with multiple transient pulse form discharges without affecting the shape of the single waveform.

After the analysis with simulated data, a second phase in the validation has been conducted using data acquired with actual PD pulses. In the following, two examples are reported. Fig. 7 shows the pulse form of the first test. These sets of data were processed by Matlab, using the following procedure: (i) The number of samples has been reduced in order to apply the wavelet transform. To be precise, just one sample in every ten
has been considered for the transformation. (ii) The input parameters for the fuzzy system have then been automatically extracted. (iii) The fuzzy algorithm for classification has been applied. The result of this first test identified the pulse form of a spark type discharge with an extremely high level of confidence, having as index $C_l = 1.12$. The second example considered concerns the signal in Fig. 8. This example is a little more complicated, having more transients within the same window.

Applying the same procedure described above, an index of 2.2 has been obtained. This result is extremely interesting from two different points of view: (i) the transient was acquired with an aged specimen for which an index greater than 2 confirms its aged state, and (ii) the system has been able to extract correct information from an actual PD pulse form even though it has not been trained or designed to identify exactly the same PD pulse form.

VI. CONCLUSION

The method described allows the automatic analysis of the aging process of a dielectric exposed to PD pulses. This approach combines the advantages of the wavelet transform with fuzzy logic. In particular, fuzzy logic is shown to define a model when it cannot be defined with mathematical modeling. Furthermore, the application of the wavelet transform allows the easy identification of the parameters for the quantitative analysis of the PD aging phenomenon. The combination of these two algorithmic approaches has allowed the definition of a single index for the classification of the aging of the sample under analysis. Other authors have proposed classification methods based on neural networks. The main advantage of using the fuzzy system is the possibility for the users to introduce their experience into the mathematical description: the rules keep a stricter connection with the physical phenomenon in comparison with the weights of a neural network. Furthermore, the application of a neuro algorithm limits the number of degrees of freedom for the system designer, who can optimize many fuzzy parameters automatically, and gives the designer the possibility of precisely tuning them. The results, obtained for both simulated and actual PD pulses, confirm the capability of the present approach. Also, the correct classification of transients not utilized in the training phase represents a most encouraging result in the application of the wavelet transformation technique, in combination with the neural network and fuzzy logic technique, to partial discharge pulse measurements.

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REFERENCES


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