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Voltage - Difference Analysis, a Tool for Partial Discharge Source Identification

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Abstract: The application of the discharge parameter **'voltage difference between consecutive pulses'** is discussed as a physically based tool to identify the kind of defect that causes PD. Different kinds of model-defects are investigated and the '$\Delta u_n(\Delta u_{n-1})$-pattern' is introduced as a new pattern for a powerful classification of discharge sources.

It is demonstrated that an **identification** mainly **based on Δu** provides reliable classification results especially in cases where the accumulated phase of occurrence distributions include the risk of misclassification. When applying discharge parameters derived from the **Pulse-Sequence Analysis**, high recognition rates of the correct 'defect-class' and a reliable rejection of other defects can be obtained.

Introduction

Partial discharge measurement and subsequent analysis is a common method of performing non-destructive testing on HV equipment and represents a well-established tool for the diagnosis of different insulation systems. A reliable diagnostic decision is needed to assess of the actual stage of insulation deterioration and to take measures increasing the reliability of the equipment in service.

The growing application of modern computer technology to PD data collection and analysis has led to the development of sophisticated PD-pattern recognition procedures. New diagnostic techniques based on 'Multivariate Data Analysis', 'Artifical Neural Networks' as well as the use of 'Fuzzy Logic' are all discussed in the literature /1-4/, mainly with regard to the identification of discharge sources. PD-source identification is the first step towards the future aims of risk assessment and ultimately the evaluation of the remaining lifetime of the insulation system.

Regardless whether the recognition process is performed by a computer system or a 'human expert', standard PD-analyses usually apply phase resolved PD-pulse height and phase of occurrence distributions or so-called (ϕ-q-n)-patterns to extract information on the characteritics of defects as well as PD-induced ageing of the insulating materials /4-6/. The analyses of accumulated discharge data are mainly based on the parameter 'phase of occurrence' and hardly allow a physically meaningful interpretation of the local discharge phenomena, especially when solid dielectrics are involved. In this case **consecutive partial discharges** are not independent events because remaining space charges from preceding pulses modify the ignition conditions of subsequent pulses considerably /7-10/. A reliable identification of discharge sources is therefore likely to be most efficient when applying an analysis which provides information about the processes determining the correlation between consecutive discharge pulses.

Discharge parameter selection

It has been shown for electrical treeing /8/ that a pronounced scatter in the commonly used phase angle distributions can be found even during periods showing deterministic pulse sequences. This can be adequately explained by the field modifying influence of space charges.

Consequently, in spite of the encouraging results obtained by the PD-data analyses mainly based on the phase angle, the question of selecting characteristic PD-parameter sets to be analyzed has to be addressed more carefully. A meticulous selection of **physically meaningful input data** ought to allow further improvements in the powerful processing of digital information.

The purpose of this paper is to demonstrate that a reliable PD source identification with high recognition rates is possible, even if it is based on only one external discharge parameter, namely the **'voltage difference between consecutive pulses'**. This parameter is proportional to the local field change at the discharge site, which is necessary to compensate for the superposed space charge field and thus to reattain the inception field after a preceding discharge pulse.

The local distribution of space or surface charges, and therefore their field modifying influence, depends significantly on the discharge gap geometry as well as the local physical parameters of the insulating material. Consequently the external voltage difference between consecutive discharge pulses is sensitive to the type of insulation defect causing the PD signals.

$\Delta u_n(\Delta u_{n-1})$-pattern

A suitable diagram for a powerful classification of discharge sources is the '$\Delta u_n(\Delta u_{n-1})$-pattern', which can be derived from the sequence of discharge pulses as shown in **Fig.1**. Since each data point contains information on the sequence of three consecutive pulses, characteristic patterns can be expected for different PD sources.

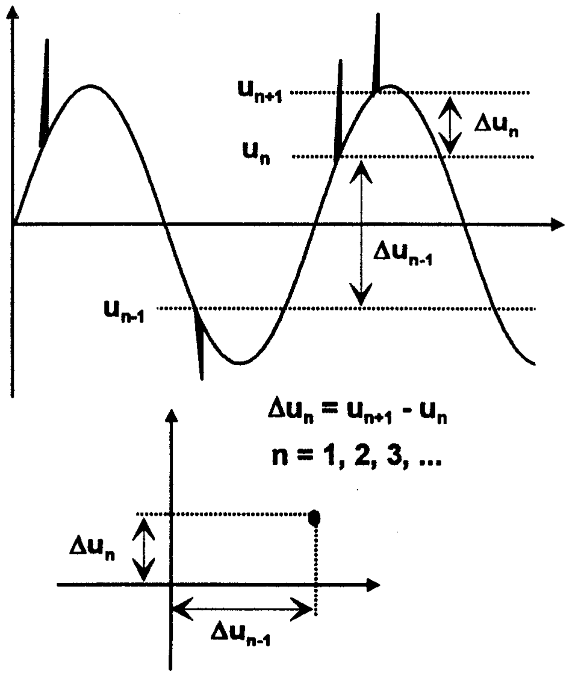

Fig. 1 : Transformation of a PD pulse sequence into the $\Delta u_n(\Delta u_{n-1})$-pattern

PD source identification

The insulation defects listed in **Table 1** have been investigated in order to demonstrate that the '$\Delta u_n(\Delta u_{n-1})$-pattern' can be efficiently used to identify different sources of PD activity.

defect no.	defect type
1	electrode bounded cavity at HV electrode
2	point-to-dielectric gap in air
3	surface discharge in air
4	electrical treeing in polyethylene
5	stochastic discharge sequence (noise pulses)

Table 1 : Defect types for PD source identification

Each defect tested includes gaseous and solid dielectrics in the vicinity of a metal electrode on high voltage potential, resulting in a pronounced influence of space charges on the pulse sequence characteristics. Defect no. 5 is an artificial PD source with a purely stochastic sequence of discharge pulses, produced with a random number generator.

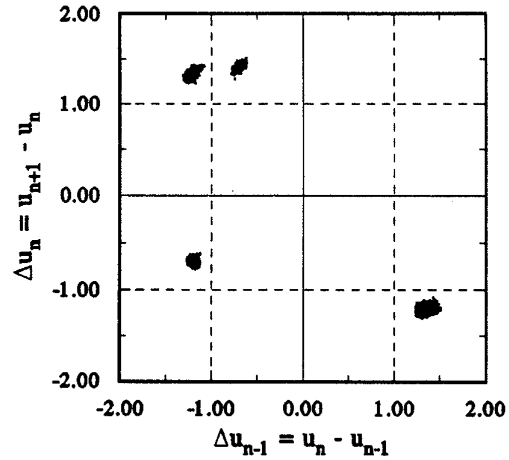

Fig. 2 : $\Delta u_n(\Delta u_{n-1})$-pattern for an electrode bounded cavity

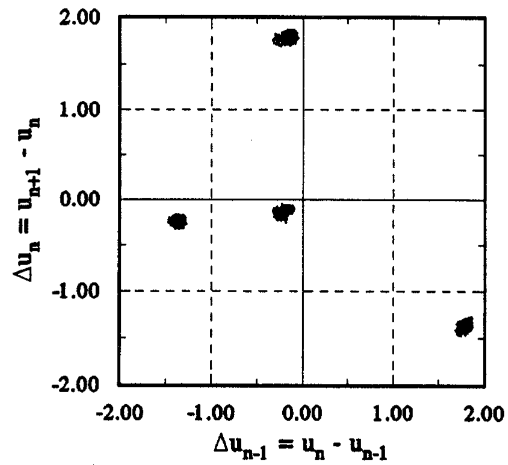

Fig. 3 : $\Delta u_n(\Delta u_{n-1})$-pattern for a point to dielectric gap

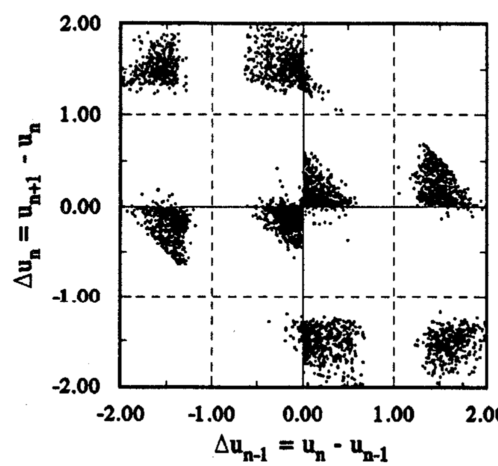

Fig. 4 : $\Delta u_n(\Delta u_{n-1})$-pattern for a surface discharge

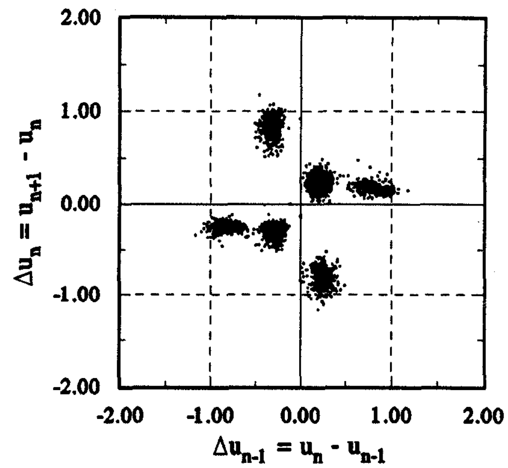

Fig. 5 : $\Delta u_n(\Delta u_{n-1})$-pattern for electrical treeing

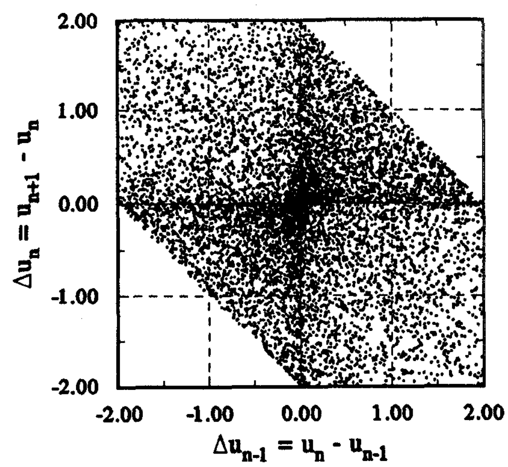

Fig. 6 : $\Delta u_n(\Delta u_{n-1})$-pattern for a stochastic PD sequence

Figs. 2 to 5 illustrate that there is a distinct grouping of '$\Delta u_n(\Delta u_{n-1})$-clusters' for each defect type. The number of groups, their specific location as well as the frequency within single groups correspond to characteristic consecutive changes in the local electric field at the discharge site and therefore depend on the specific properties of each discharge source. In contrast to the distinct formation of groups in Figs. 2 to 5, in the case of the stochastic discharge sequence in Fig. 6 every possible Δu value occurs, since no correlations between consecutive 'noise-pulses' exist.

The $\Delta u_n(\Delta u_{n-1})$-pattern enables a clear distinction and an identification of discharge sources by means of only one external parameter. A further improvement of the classification will be achieved if additional PD-quantities are taken into account. The decisive point in terms of a more physically based classification however is the application of quantities which represent the correlation between consecutive pulses.

Multiple discharge sites

In addition to the information obtained on the field modifying influence of space charges, significant information about multiple discharge sites can be derived from the $\Delta u_n(\Delta u_{n-1})$-pattern. In Figs. 2, 3 and 5 there are obviously no voltage differences $\Delta u=0$, whereas in Fig. 4 voltage differences $\Delta u=0$ occur.

In the case of the electrode bounded cavity as well as the needle plane arrangement with dielectric barrier, the area where the discharge process can start is strictly limited to the small cavity at the electrode and the needle electrode respectively. In both cases the ignition conditions of a discharge pulse are determined by remaining space charges from previous pulses. In the case of a surface discharge, electron avalanches may usually start from different positions on the electrode along the insulator surface. If there are simultaneously active discharge sites, pulses from these sites may occur nearly at the same time, causing external voltage differences $\Delta u=0$.

Hence an important conclusion can be drawn from Fig. 5 for electrical treeing in polyethylene. Since no voltage differences $\Delta u=0$ occur, the discharge activity at a given time is limited to only one tree channel. Simultaneous discharges within different channels of the tree obviously do not exit.

If space charge dominated PD sources are examined, $\Delta u=0$ will only be caused by multiple discharge sites. Even then special features of each defect are still present within the $\Delta u_n(\Delta u_{n-1})$-pattern. These can be used to identify the types of defects involved in the discharge activity. More detailed information with regard to multiple discharge site detection can be found in /11/.

Computer-aided PD source identification

The aim of a computer aided classification of a PD measurement is to obtain a 'recognition-rate' or a probability of membership within predefined defect classes of a reference database. Each defect class within the database comprises a set of parameter vectors belonging to that class, which correspond to a group of points distributed within some area of a n-dimensional Euclidean space. The n-dimensional PD parameter vector derived from the measurement of an unknown PD source is typically compared with each reference vector within the database. The test measurement is then assigned to the defect class its parameter vector fits best.

In order to achieve convincing classification results, a high recognition rate of the correct defect class and a reliable rejection of other defects are required. It is thus of utmost importance to extract a parameter vector which contains characteristic features providing a good discrimination of classes within the 'pattern-space'.

More than 130 measurements on the defect types 1-4 in Table 1 as well as 10 data files of the artificial defect no. 5

were divided in two groups. One group was used as a reference database, the other as a database to be classified. The diagnostic potential of the 'voltage difference' was examined using these PD data. In addition the 'voltage difference identification' was compared with an identification applying the usual 'phase of occurrence', in order to investigate which fundamental PD parameter a pattern recognition process should be generally based on.

The one-dimensional frequency distribution of the phase of occurrence was used as the parameter vector for the ϕ-identification. The identification based on Δu was performed with a one-dimensional frequency distribution derived from the $\Delta u_n(\Delta u_{n-1})$-pattern.

The 'unknown' measurements in the test-database can be assigned to a defect type by applying a special 'measure of similarity' which is computed for each vector in the reference database. The similarity of the test-vector to each defect class, i.e. the classification result, can then be expressed by a set of numbers which represent average recogniton rates of the corresponding defect classes. The relation of each n-dimensional reference vector to the test-vector, however, cannot be reconstructed.

The reference vectors are usually more or less distributed even within one particular defect class. A meaningful way of illustrating the identification of a PD measurement should therefore also display the influence of this distribution on the classification result.

A new method of performing an identification providing additional information is shown in **Figs. 7** and **8**. A single measurement on the defect **'electrode bounded cavity'** (defect no. 1) is classified by plotting the cumulative distribution of the similarity measure for each defect class.

When applying the phase of occurrence (**Fig. 7**) a correct identification of the measurement is not possible since the similarity measures for the reference vectors in the defect class no. 1 are scattered within a region between 0.8 and 0.15. In contrast the cumulative distribution for defect no. 3 (surface discharge) reveals a pronounced slope at higher values of the similarity measure, which may result in a misclassification of the measurement. When taking into account that none of the defect classes includes reference vectors with similarity measures close to 1, no decision regarding the class membership can be obtained.

The identification based on Δu (**Fig. 8**) however allows an unambiguous decision that the measurement belongs to defect class no. 1 because a steep increase of the curve corresponding to this defect class can be found close to the similarity measure 1. Other PD sources can be rejected since their cumulative distributions appear at considerably lower values.

The recognition rates derived from the cumulative probabilities in **Figs. 7** and **8** within each defect class are listed in **Table 2** for both parameters used to classify the measurement.

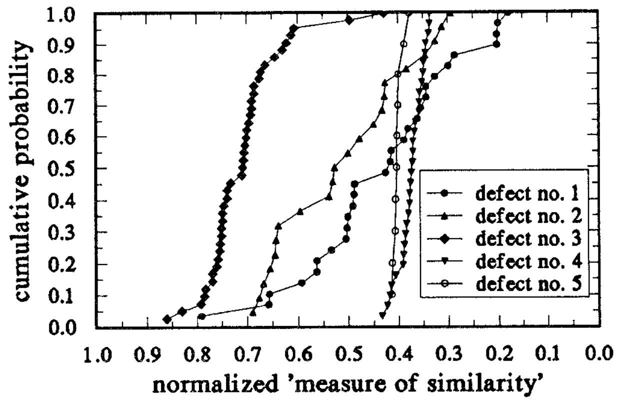

Fig. 7 : ϕ-identification of a measurement on defect no. 1

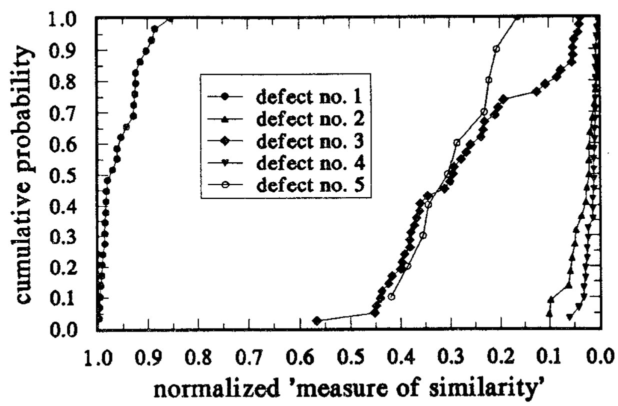

Fig. 8 : Δu-identification of a measurement on defect no. 1

defect no.	1	2	3	4	5
desired result	1	0	0	0	0
ϕ - identification	0.492	0.542	**0.716**	0.372	0.398
Δu - identification	**0.955**	0.057	0.348	0.029	0.337

Table 2 : Recognition rates for a measurement on the defect 'electrode bounded cavity' (defect no. 1)

In contrast to calculating a 'mean recognition rate' of each defect class (**Table 2**), the identification by means of the cumulative distribution of the applied similarity measure provides more detailed information because the similarity of each reference vector within the database to the 'unknown' measurement can be seen. In addition, the calculation of membership probabilities (e.g. Bayes classifier) is typically based on the assumption that the probability density function is multivariate normal, i.e. Gaussian. Thus the probabilities are difficult to calculate if only few reference vectors are available.

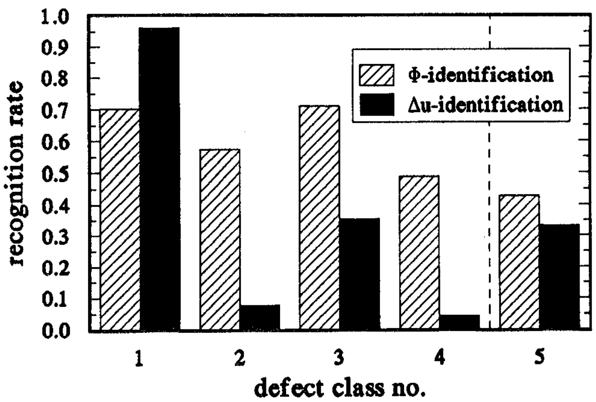

Fig. 9 : Mean recognition rates for **defect no. 1**

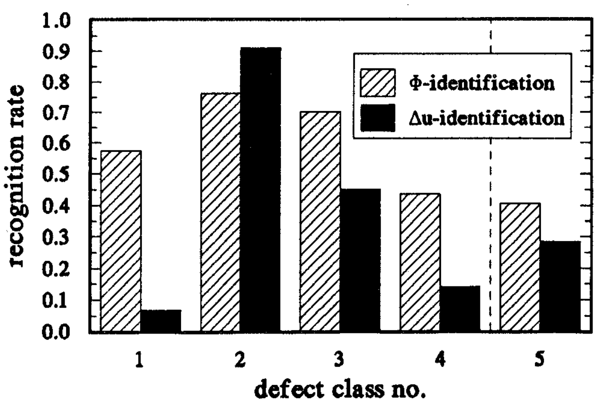

Fig. 10 : Mean recognition rates for **defect no. 2**

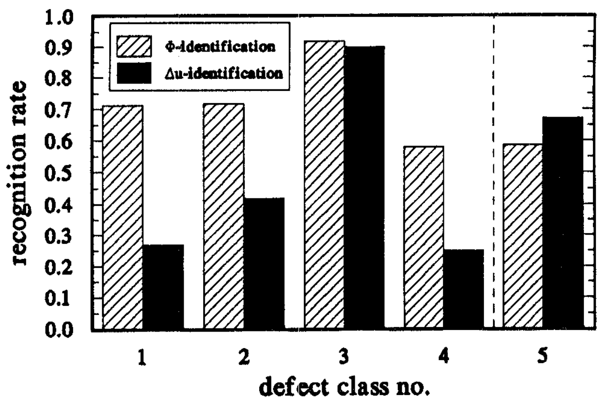

Fig. 11 : Mean recognition rates for **defect no. 3**

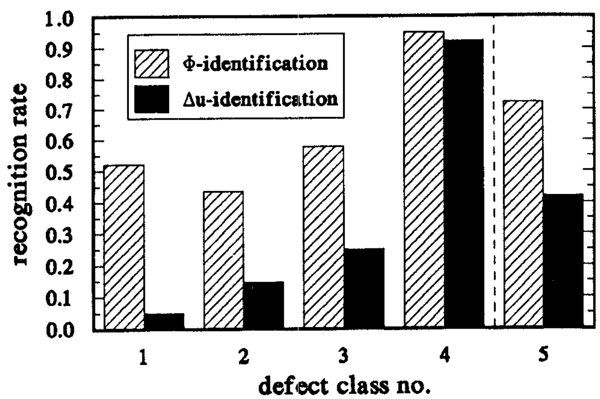

Fig. 12 : Mean recognition rates for **defect no. 4**

Mean recogniton rates for ϕ- and Δu-identification

For each measurement in the test database a 'recognition rate' was determined by calculating a weighted average of the measures of similarity between each reference vector in one defect class and the test vector. The weighted average emphasizes vectors which are close to the test vector more than outlying ones.

In **Figs. 9 to 12** the mean recognition rates for each defect class within the test database are shown, and the values for the ϕ- and Δu-identification are compared. The **electrode bounded cavity (Fig. 9)** as well as the **point to dielectric gap (Fig. 10)** cannot be identified by means of the phase of occurrence distribution. The recognition rates of the correct defect class are low and at least for one other class the value is nearly the same or even higher. In contrast the application of the **voltage difference** results in **high recognition rates** within the correct class and a reliable rejection of other defect classes.

The Δu-identification of **surface discharges (Fig. 11)** and **electrical trees (Fig. 12)** results also in a more differentiating classification than the ϕ-identification, even though the recognition rates of the correct defect classes are slightly higher for the phase of occurrence. The other classes, which should be rejected, however show considerably higher values when applying the phase angle. Thus a meaningful classification, especially of surface discharges, is hardly possible, whereas the decision concerning the class membership based on Δu can be easily obtained.

The artificial defect no. 5 can be used as a kind of threshold for a confident decision since the difference between the recognition rate of a defect class and that of the stochastic sequence indicates in how far deterministic physical mechanisms determine the discharge process.

Consequently defect classes with recognition rates below that of the stochastic sequence can be clearly rejected, whereas defect classes with recognition rates markedly above the 'noise class' indicate similar physical processes.

Conclusions

The analysis presented here has demonstrated that the **external voltage difference between consecutive discharge pulses** is a well-suited parameter for partial discharge source identification, especially because the field modifying influence of local space charges from preceding pulses is taken into account.

The **$\Delta u_n(\Delta u_{n-1})$-pattern** has been proposed as a new PD pattern which is sensitive to the physical mechanisms determining the correlation between consecutive pulses. Consequently it allows a powerful classification of discharge sources. Characteristic patterns for different types of insulation defects have been shown.

With regard to a computer aided PD source identification the application of the **cumulative distribution of an appropriate similarity measure** has been suggested to identify the type of defect. In contrast to the calculation of single numbers representing membership probabilities of predefined defect classes, the influence of the reference vector distribution on the classification result becomes obvious.

The diagnostic potential of the PD parameter 'voltage difference' has been examined by classifying measurements of different PD sources. The classification results have been compared with an identification based on the phase of occurrence. When applying a Δu-identification high recogniton rates of the correct defect classes can be obtained and other defects can be reliably excluded. In contrast the ϕ-identification results in numerous misclassifications and usually in a much less pronounced differentiation between defect classes.

Since it has emerged from this investigation that the diagnostic potential of the phase of occurrence is insufficient for a reliable classification of PD sources, the usual approach of analyzing phase resolved PD patterns has to be questioned. The basic parameter phase angle, these analyses are based on, does not seem to contain all relevant information regarding the physics of the PD processes.

It can thus be concluded that a powerful analysis of PD data, aiming at the identification of PD sources, will be considerably improved when applying **quantities describing the correlation between consecutive discharge pulses** rather than making use of only accumulated discharge data.

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