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Automated Partial Discharge Data Evaluation During Monitoring of Stator Winding

Streszczenie. *W artykule opisano narzędzia do oceny stanu izolacji statora maszyny wirującej w czasie ciągłego monitorowania wyładowań niezupełnych. Wskazano na znaczenie systemu do automatycznej identyfikacji typu defektu w izolacji i do odróżnienia sygnałów wnz od sygnałów zakłóceniowych. Podano przykłady zastosowań gdzie pokazano, że defekty krytyczne mogą być wcześnie wykryte a ich ewolucja może być monitorowana w sposób ciągły.* ***(Automatyczne opracowanie danych z monitoringu wyładowań niezupełnych w izolacji statora).***

Abstract*. In this paper, the use of specific tools that enable the condition assessment of stator insulation in rotating electrical machines is described. The signal distinction between noise and PD defects is performed by means of a synchronous multi-channel evaluation technique. An automated PD defect classification system, which identifies the type of stator winding insulation defect and its location, has been developed and implemented in the continuous monitoring system described in this paper. The validation and evaluation of this system has been confirmed as successful by different case studies from real PD monitoring system installations.*

Słowa kluczowe: maszyny wirujące, izolacja statora, pomiar wyładowań niezupełnych, monitorowanie.
Keywords: rotating machines, stator insulation, partial discharge measurements, monitoring.

Introduction

Partial Discharge (PD) monitoring is nowadays a worldwide accepted method for the on-line condition-based assessment of stator insulation. Different solutions for sensors and acquisition techniques have been recommended, applied and lately acknowledged by international technical bodies [1-2]. Therefore, there is a strong need for a versatile PD monitoring system that can be applied to different types of rotating machines, and which can be connected to a wide range of PD sensors. Such a PD monitoring system is described in this paper. The advantage of having a fully digital system, whose settings can be easily remotely adjusted, is shown.

The sensitivity of the on-site PD measurements is strongly limited by the high noise level. The advanced features based on synchronous multi-channel techniques for noise and PD signal separation are presented [3], and the experience gathered from PD monitoring to automatically assess the condition of turbo generator stator winding insulation is shown.

Monitoring system description

The large part of insulation defects develops over lifetime of a machine. In order to detect such changes at an early stage, detailed information on the actual insulation condition is necessary. This information can be derived by PD monitoring during the operation of the equipment. Consequently, continuous monitoring is an essential tool for proper maintenance management to guarantee a high level of asset reliability [4].

Hardware

The PD signal is detected by capacitive sensors installed as close as possible to the stator end winding area. According to [2], coupling capacitors with capacitances between 1 nF and 9 nF have been successfully used for on-line PD measurements. Information coming from PD sensors is synchronously acquired by a multi-channel acquisition unit. The synchronicity between channels is mandatory for signal source separation. Further, the acquisition unit extracts the main characteristics of the PD signal and transfers them to a server that enables long-term data storage and further post-processing.

Software

The server receives data for analysis, display and storage. This allows operators to quickly react to detected problems and access the system data from any remote location. The software is a highly modular and scalable distributed system. Its architecture consists of a Windows-based core part and a Web-based control part (Fig. 1). The core part of the monitoring software is realized as Windows services and runs continuously without any direct user interactions. The core system includes: collection and persistence of measurement**,** data post-processing and analysis, security tasks for data access and system operations and external interfaces for data exchange over Ethernet or field bus.

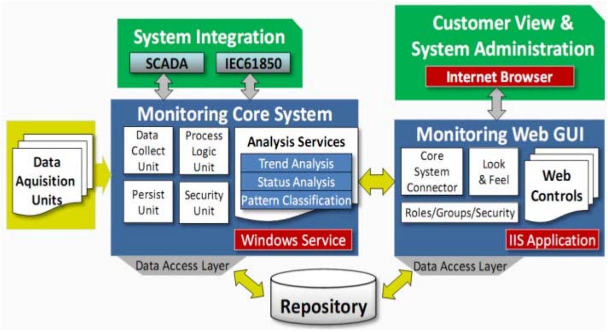


Fig.1. Monitoring software architecture

The monitoring system provides data from the acquisition unit in two modes: permanent and periodic mode. During the permanent mode, the data is acquired every second, compared with threshold values and displayed in the graphical user interface in real time. When this data is within normal margins, it will be colored in green. If the values exceed thresholds for "warning" or "alert", they are colored in yellow or red, accordingly.

The periodic measurements are initiated in equidistant time spans, e.g. every hour. The duration of the periodic measurement is normally one minute. During this time span, all relevant scalar values (charge, repetition rate, voltage phase, time stamp) are calculated and PRPD (Phase-Resolved PD) diagrams as well as 3PARD (3-Phase Amplitude Relation Diagram) are acquired. This data is saved for later post-processing and trend visualization. The monitoring system is configured for extended automated data evaluation - PD source separation and classification on a regular basis or triggered by alarm when one or more of the measured quantities exceed the threshold level.

Automated evaluation of PRPD patterns

For data evaluation, the software makes use of specific tools that enable the automated localization and assessment of the defect type. The result of defect detection and classification is influenced by different system setting parameters. One of the most important is the data acquisition time. It has to be sufficiently long to create clear PRPD pattern in cases of low PD pulse repetition rates. The automated evaluation of PRPD patterns is performed in five consecutive steps.

Step 1: Generation of 3PARD with separated clusters

3PARD generation is enabled by the synchronous data acquisition. It visualizes the relation among amplitudes of a single PD pulse in one phase (L1) and its crosstalk generated signals in the other two phases (L2 and L3) [3]. By repetition of this procedure for a large number of PD pulses, PD defects within the test object as well as external noise appear as a clearly distinguishable concentration of dots within the rectangular clusters in a 3PARD diagram (Fig. 2).

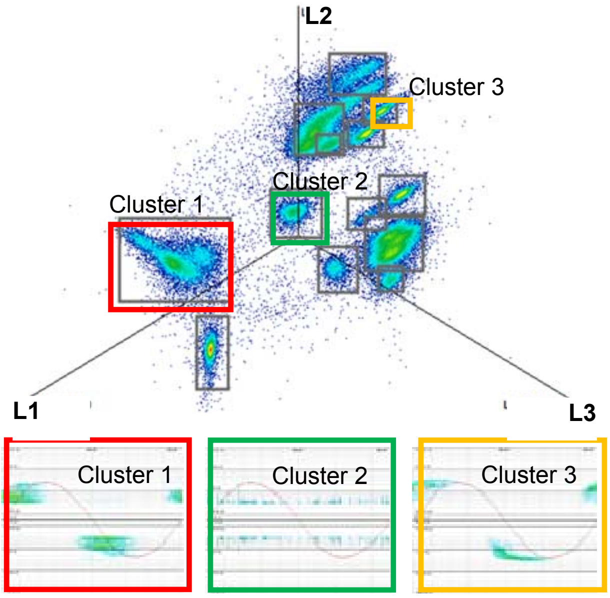


Fig.2. Example of automated cluster separation using 3PARD

The automated cluster separation is performed by OPTICS (Ordering Points to Identify the Clustering Structure), a highly efficient hierarchical density-based clustering algorithm. Only significant clusters are derived from the clustering structure. PRPDs coming from insignificant clusters (low repetition rate of pulses) are excluded from the analysis, since they contain insufficient data.

Step 2: Discrimination between noise and PD

For each cluster, the system automatically determines the phase of signal origin and identifies it either as noise or internal PD. The noise identification feature is designed as a sequential, statistical procedure capable of distinguishing several kinds of disturbances including asynchronous, synchronous and excitation/converter noise. Additionally, PRPD data has been improved through several iterations to include stochastic disturbances removal, PD charge level and PD pulse intensity. Finally, the PRPD is shifted in phase position to align the pattern to the zero crossing point.

Step 3: PD defects classification - knowledge based analysis

Automated PD defects classification is based on several sequential processing steps (Fig. 3). The PRPD data is the input for this classification. The output is a classification decision about the type of PD source.

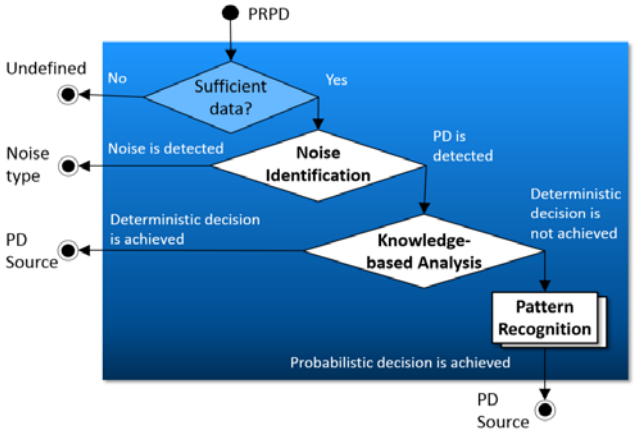


Fig.3. Automated PD defects classification

The PRPD data is processed for the knowledge-based analysis by means of categorical features (attributes). The key point is to generate a limited number of significant features that can differentiate the defects and describe the PD behavior in a convenient way for human interpretation. Descriptions of statistics of standard statistical distributions [5], shape and wavelet analysis [6] were utilized for feature generation and selection (Fig. 4).

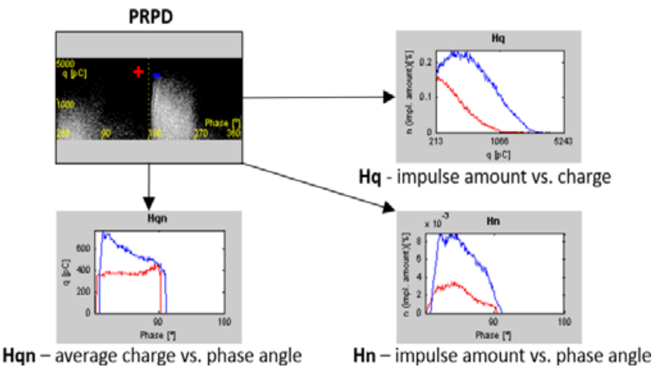


Fig.4. Statistical distributions derived from PRPDs

The knowledge-based analysis is designed as a decision tree. The decision tree construction is based on several iterations. The first iteration was an automated tree generation by the CART (Classification and Regression Tree) method. Following iterations were related to the manual tree adjustment procedure by PD experts. Each tree node and affected PD attributes were reviewed on the decision tree. An example of attributes for one PD defect type is presented in Table 1.

Table 1. Example of attributes for knowledge-based analysis

Attribute Name	Attribute Value
Pulse-charge variation on positive half	*Wide*
Pulse-charge symmetry on positive half	*Symmetric*
Pulse-charge behaviour on positive half	*Peaking*
Polarity ratio	*Equal polarity*
Pulse-phase symmetry on positive half	*Right-biased*
Charge-phase regularity on positive half	*Not flat*
Charge-phase symmetry on positive half	*Right-biased*

The decision tree provides a deterministic decision for clear cases. For unclear cases, where the PD signal can be assigned to more than one PD defect class, an additional pattern recognition procedure is applied to generate a probabilistic decision.

Step 4: PD defects classification - pattern recognition

There are several trained pattern recognition procedures specific to different groups of PD defect classes - each with unique statistical feature base. Each group is only limited to two or three PD defect classes. Pattern recognition procedures are implemented using the K-nearest neighbors algorithm. The results include class probabilities for specific PD defect classes, as well as a distances plot (Fig. 5 - 6).

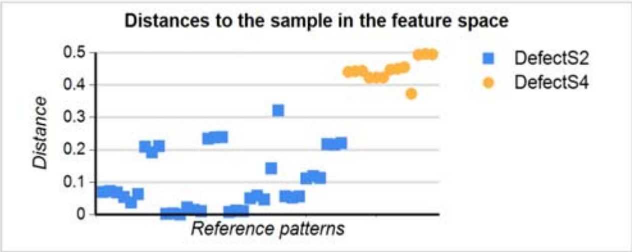


Fig. 5. Distance plot for a robust pattern recognition decision

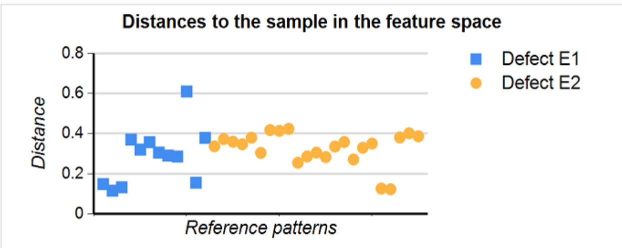


Fig. 6. Distance plot for an uncertain pattern recognition decision

The distances plot is an effective aid to judge how robust the probabilistic decision is. The plot visualizes the similarity of PRPD in comparison with the patterns from the reference database.

The probabilistic decision is robust when the distance is close to zero. It means that the PRPD is the most similar to reference patterns. The majority of points - closest to zero level on the distance plot - contributes to the probabilistic decision. Another criterion of the decision reliability is the relation between mean distance levels of specific classes on the distance plot. A larger difference of mean distance levels leads to a more robust probabilistic decision (Fig. 5).

Step 5: Generation of the report

According to [1], there are seven classes of PD defects that can be identified, as presented in Table 2 and Figure 7. At the end of the evaluation, a report including a detailed characterization of the PD defect is generated.

Table 2. Classification of PD defects [1]

Defect class	Defect class description
S1	Delamination of the insulation on the copper side
S2	Delamination of the insulation layers
S3	Delamination of the insulation on the core side
S4	Discharges in micro cavities
E1	End-winding surface discharge (tracking)
E2	End-winding discharges / sparking
E3	Discharge between corona protection and stress grading layers

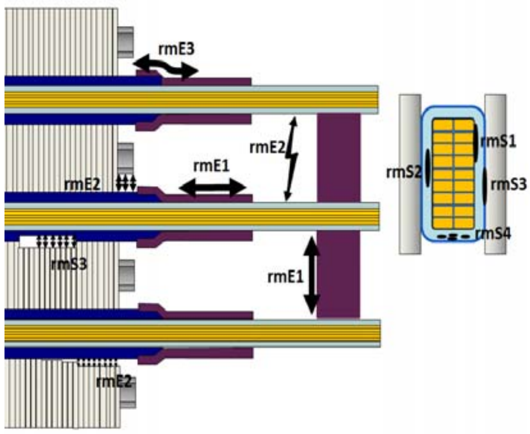


Fig. 7. Sources of PD defects

Case studies

The following case studies refer to one of the monitoring systems installed in Germany. The system is continuously monitoring a 1160 MW, 27 kV turbo generator. The PD monitoring system was installed and commissioned in 2012. PD data and the results of post-processing including clustering and pattern classification are stored in the database. The historical data was evaluated by a PD source behavior analysis over time.

Three representative case studies, corresponding to sequential time stamps (01/2017, 02/2017, 03/2017), are described. The case studies are evaluated by means of manual cluster tracking. Each cluster was analysed at different time stamps and compared with the other clusters. The analysis consists of a final decision regarding the PD origin by means of automated pattern classification.

The case studies are presented in Figures 8 - 9. The analyzed clusters for each case study are marked in red in the corresponding 3PARD.

Case study 1

The cluster marked in red in the 3PARD in Figure 8 is characterized by its similar position and size at different time stamps. The corresponding PRPDs are slightly different as they are influenced by the behaviour of surrounding clusters. Therefore the knowledge-based analysis returned different decisions, leading to two clear cases (01/2017, 03/2017) and to one unclear case (02/2017). The unclear case is solved by an additional pattern recognition procedure, which is designed particularly for such a case.

Case study 2

The size and position of the cluster indicated in Figure 9 is shown as stable in the 3PARD. The classification decision was defined between two similar PD sources. The system returned a probabilistic decision at all three time stamps. Further analysis by additional pattern recognition procedures was not as robust, due to the results from the distance plot analysis (e.g. Fig. 6).

Case study 3

The size and position of the cluster marked in red in Figure 10 is unstable in the 3PARD at different time stamps. The pulse repetition rate decreases over time. The cluster identified as PD activity in 01/2017 is large and covers both the PD source and the noise pulses. The cluster on 02/2017 is smaller. The corresponding PRPD is identified as typical noise. The PRPD of the cluster on 03/2017 has fewer pulses which were not enough to achieve a classification decision.

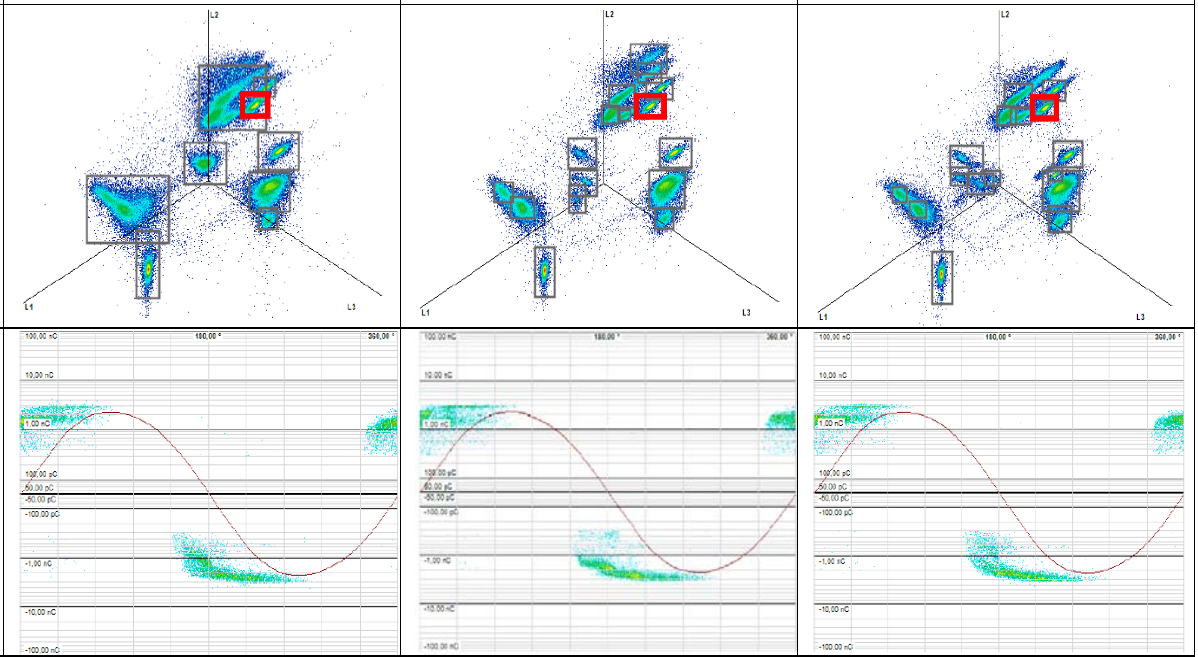
		01/2017	02/2017	03/2017
Case study 1	3PARD PRPD			
	Result	**End-winding surface discharge (tracking) – E1** Decision Path: Sufficient data → Not noise → Knowledge-based decision - clear case	**End-winding surface discharge (tracking) – E1** Decision Path: Sufficient data → Not noise → Knowledge-based decision - unclear case (between E1 and E2) → Probabilistic decision by Pattern Recognition (E1 100%)	**End-winding surface discharge (tracking) – E1** Decision Path: Sufficient data → Not noise → Knowledge-based decision - clear case

Fig. 8. Case study 1

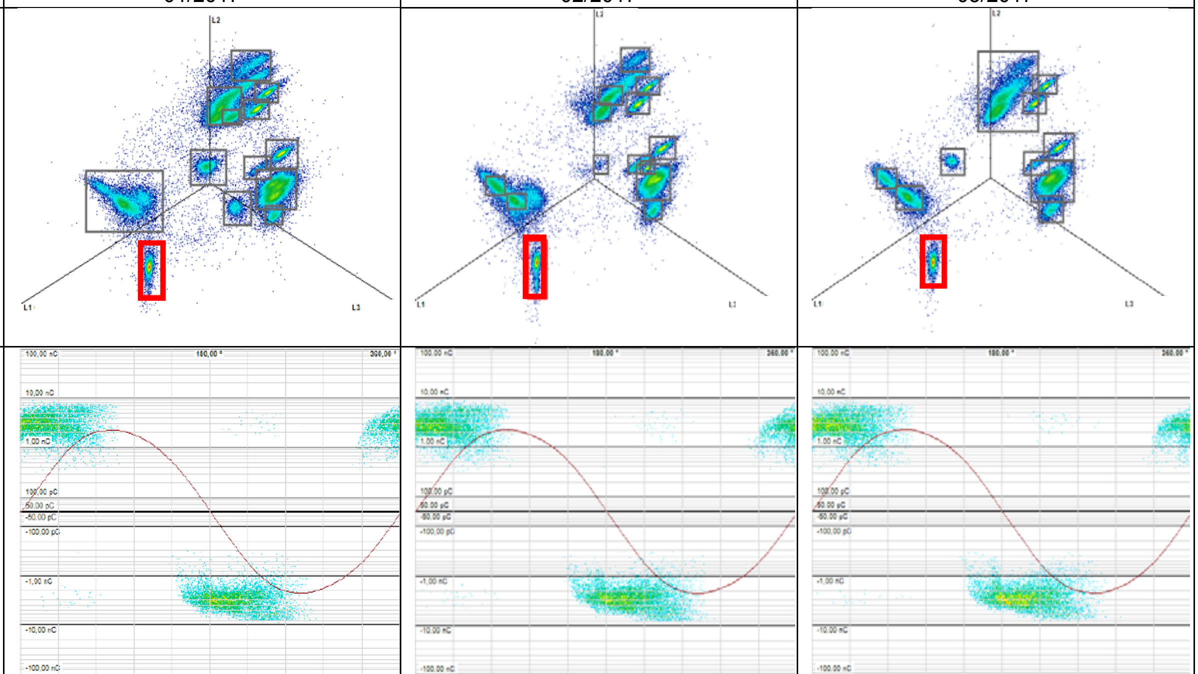
		01/2017	02/2017	03/2017
Case study 2	3PARD PRPD			
	Result	**End-winding surface discharge (tracking) – E1** Decision Path: Sufficient data → Not noise → Knowledge-based decision - unclear case (between E1 and E2) → Probabilistic decision by Pattern Recognition (E1 50%)	**End-winding surface discharge (tracking) – E1** Decision Path: Sufficient data → Not noise → Knowledge-based decision - unclear case (between E1 and E2) → Probabilistic decision by Pattern Recognition (E1 100%)	**End-winding surface discharge (tracking) – E1** Decision Path: Sufficient data → Not noise → Knowledge-based decision - unclear case (between E1 and E2) → Probabilistic decision by Pattern Recognition (E1 50%)

Fig. 9. Case study 2

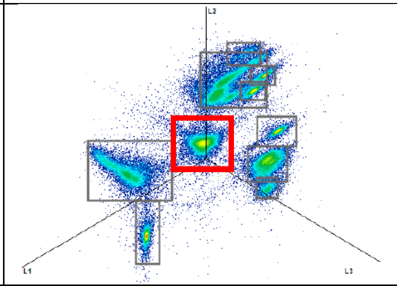
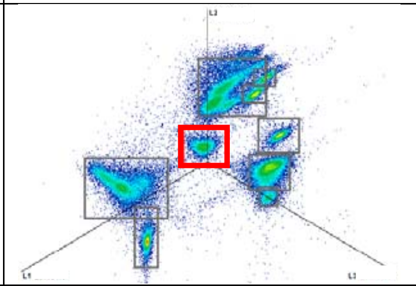
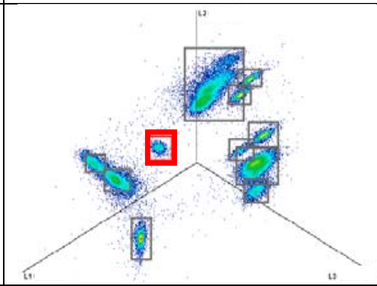
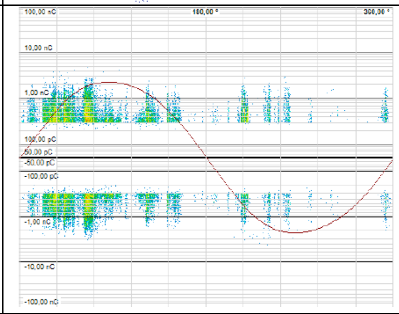
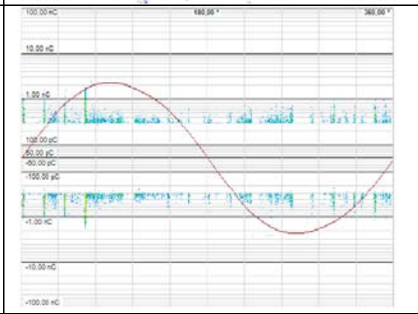
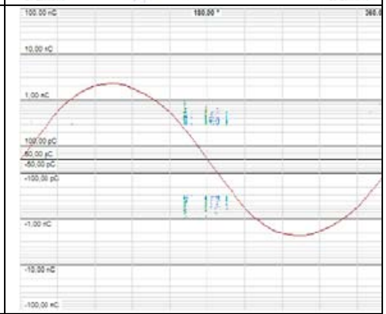
		01/2017	02/2017	03/2017
Case study 3	3PARD			
	PRPD			
	Result	**Delamination of the insulation on the copper side – S1** Decision Path: Sufficient data → Not noise → Knowledge-based decision - clear case	**Noise** Decision Path: Sufficient data → Noise	**Insufficient data for the analysis**

Fig. 10. Case study 3

Conclusions

A continuous monitoring system equipped with the automated PD defect classification tool can be applied to identify stator winding insulation defects.

The validation and evaluation of PRPD patterns has been successfully confirmed by different case studies from real PD monitoring system installations:

- For defects that generate stable clusters on 3PARD over time, the deterministic decision about the type of the defect is taken based on the knowledge-based analysis.
- For defects that generate unstable and unclear clusters on 3PARD with pulses changing in amplitude and repetition rate with load and temperature, the probabilistic decision is taken based on an additional pattern recognition procedure.

The PRPD Patterns related to PD and noise are well separated by means of the synchronous multi-channel technique.

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