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Partial Discharge Monitoring of Medium Voltage Switchgears: Self-condition Assessment using an Embedded Bushing Sensor

G.C. Montanari, *Fellow, IEEE*, R. Ghosh, *Member, IEEE*, L. Cirioni, G. Galvagno and S. Mastroeni

***Abstract*— Condition assessment of Medium Voltage switchgears requires effective, but inexpensive solutions to become a common practice. On the other hand, failure of a switchgear component can cause cascade effects and outage of other apparatus, in addition to significant economic losses due, e.g., to lack of energy availability. A major diagnostic property to evaluate switchgear health and reliability is partial discharges, being a direct cause of failure of organic insulation systems. A new approach to automatic, self-assessment of switchgear reliability based on partial discharge, PD, acquisition and processing, as well as a new type of PD sensor solution are presented in this paper. The sensor is based on the capacitive divider existing in most bushings to indicate the presence or absence of voltage. The innovative automatic software is able to provide automatic noise and PD separation, noise rejection and type of PD-source identification. The embedded bushing sensor has been tested on switchgears in the presence of defective components as cable terminations and bushings. Results show that the sensor, coupled with the automatic software, is able to provide good sensitivity compared to other sensors, and good capability to locate the cabinet and identify the type of source generating partial discharges.**

***Index Terms*— Bushings, MV switchgear, partial discharge, sensors, automatic diagnostics, noise rejection, PD recognition, PD identification.**

I. Introduction

MEDIUM voltage (MV) switchgears are a fundamental component in any electrical assets, from electrified transportation to industrial plants and renewable generation. However, because they are inherently a low-cost component, there is not too much stimulus to invest in condition maintenance and monitoring. Actually, failure of MV switchgears could be catastrophic for safety, especially in electrified transportation applications, and cause significant economic damage, much higher than the cost of switchgears themselves (e.g. in industrial plants and renewable generation).

Focusing on partial discharges (PD), which are undoubtedly one of the most frequent cause of premature breakdown of any organic electrical insulation system, it can be speculated that the major driver for the implementations of PD monitoring and condition assessment systems are cost and the complex interpretation of measurements, that needs most often the use of experts. This constitutes a further expense, it implies the availability of real experts, and may cause significant delay times involved in expert quest and data (often a huge amount) interpretation.

Harmful PD phenomena are e.g. discharges in cable terminations and in cavities embedded in bushings, while discharges on bushing surface are much less harmful because they may take much longer time, compared to internal discharges, to cause insulation breakdown and, on the other hand, maintenance can be very simple and cheap [1], [2]. Corona discharges, that together with surface discharges are well detectable also by acoustic systems, are often more a curiosity and a driver for PD detector sales than a reliability issue. Eventually, before approaching to breakdown, corona discharges would turn into surface/interface/internal phenomena that may not be anymore well detectable by acoustic systems (but well identifiable by the approach presented in the following).

This premise raises major issues to be addressed in order to promote PD monitoring as an useful tool for condition assessment and Condition-Based Maintenance, CBM:

1. Sensors and detectors must be as less expensive as possible, compared to a switchgear cost, but effective in terms of capability to sense the most harmful PD source typologies.
2. PD acquisition, denoising, and interpretation must be automatic, providing alerts which are not based on expert interpretation.

This paper addresses the two items, first assessing and characterizing the performance of a new PD sensor, that uses insulator components already existing in switchgear (thus it does not introduce additional costs for PD monitoring) and then proposing an automatic approach to noise rejection and PD typology identification, where automatic means that there is not any need of experts both in carrying out measurements or monitoring, and in interpreting the data flow originated by PD

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monitoring. Of course, the cost paradigm is taken into account, in a discussion that is corroborated by PD measurements carried out on switchgear cabinets, with artificial defects created in cable terminations and bushings.

II. An Embedded-Bushing PD Sensor

A. Principle of Operation

Typical sensors used in switchgears couple electromagnetically conducted or irradiated signals. Among the former, high frequency current transformers (HFCT), capacitive couplers and transient earth voltage sensors (TEV) are widely known sensors. The latter include various types of antennas located externally where electromagnetic flux can be irradiated through dielectric windows and holes, or internally. All these are valid and effective ways to extract PD signal from switchgear insulation defects. Eventually, acoustic sensors are broadly used, being perhaps the most popular solution, but, as mentioned above, generally they are sensitive mostly to corona and surface discharges, [3], [4], which have lower harmfulness than internal discharges for insulation reliability [1], [2]. New developments for partial discharge monitoring in MV switches have also been reported in recent times [5]-[7], with particular focus on low-cost solutions.

A major issue of all electromagnetic measurement methods is noise, that must be recognized and rejected to enable trend-based PD inference. Hence, a sensor should be immune to noise as much as possible. Also, a sensor should be selective, meaning that it should help identifying which cabinet is affected by PD. Indeed, PD signals can propagate from the source (e.g., bushings, cable terminations) to the ground and to the MV leads, with limited attenuation between one cabinet and those in proximity (due to the very small distance between them) [8], [9].

Most switchgears have an embedded sensor in some of the bushings which has the purpose of providing an indication of the presence or absence of voltage in a cabinet, and it is based on a voltage divider [10], [11]. A scheme of a bushing with its capacitive divider is displayed in Fig. 1. This divider, designed to transduce voltage, has been proved to work also to detect PD, using an adapter which can be designed in order to be able to provide not only PD signals, but also the synchronization signal for PD pulse acquisition (referring to zero voltage). This is fundamental to achieve a correct phase-resolved PD (PRPD) pattern representation [12].

B. Sensitivity of the bushing PD sensor

In principle, such sensor can be sensitive mostly to conducted and irradiated signals generated inside a cabinet, thus quite well shielded from external noise, but also to conducted signals coming e.g. from defective cable termination, which flows towards the bushing. Experiments were done to check the sensitivity of the embedded bushing sensor compared to commonly used sensors, such as TEV or HFCT. Fig. 2 displays the sensitivity test arrangement for HFCT, where PD pulses are generated either by a test object having an artificial internal cavity or by a calibrator. Fig. 3 reports the mean values of the signal magnitude detected by the new bushing sensor and a classic HFCT (bandwidth 10 kHz-50 MHz). As can be seen, for signal generated near the location of both sensors, the devised bushing sensor might be even more sensitive than a HFCT. It is noteworthy that such measurements were performed using a broadband PD detector, covering the same frequency range as the HFCT and, thus, very sensitive to signal attenuation along the coupling circuit [8], [13], [14]. Calibration according to IEC 60270 was also done, [15], but the whole UHF bandwidth allowed by the measurement chain was exploited (as an example, TEV sensors have a low frequency cut that does not allow to calibrate them according to [15]).

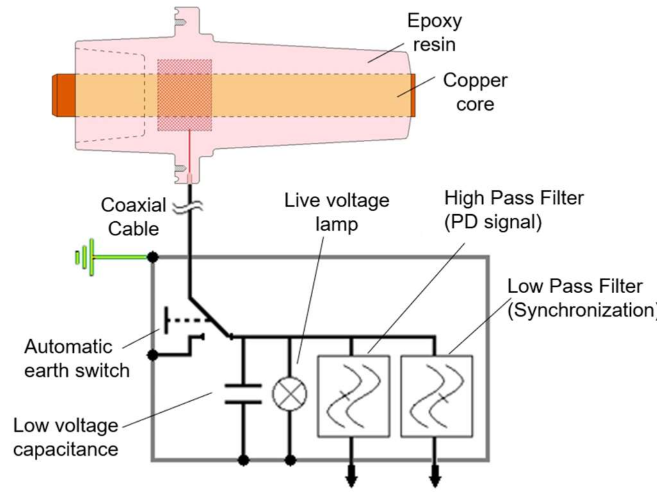

Fig. 1. Scheme of the bishing and of the sensor, able to provide both synchronization signal (with the supply voltage) and PD pulses.

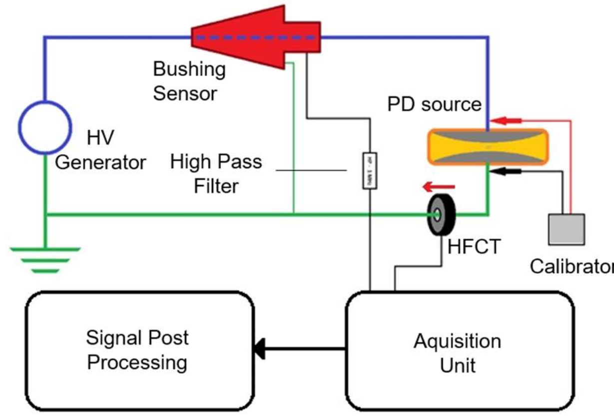

Fig. 2. Circuit for sensitivity validation of the PD bushing sensor.

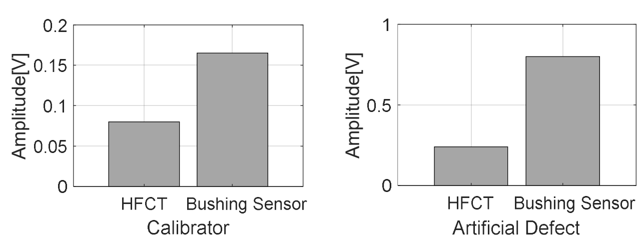

Fig. 3. Sensitivity for bushing sensor and HFCT to calibration pulses and PD pulses from the defective test object of Fig. 2.

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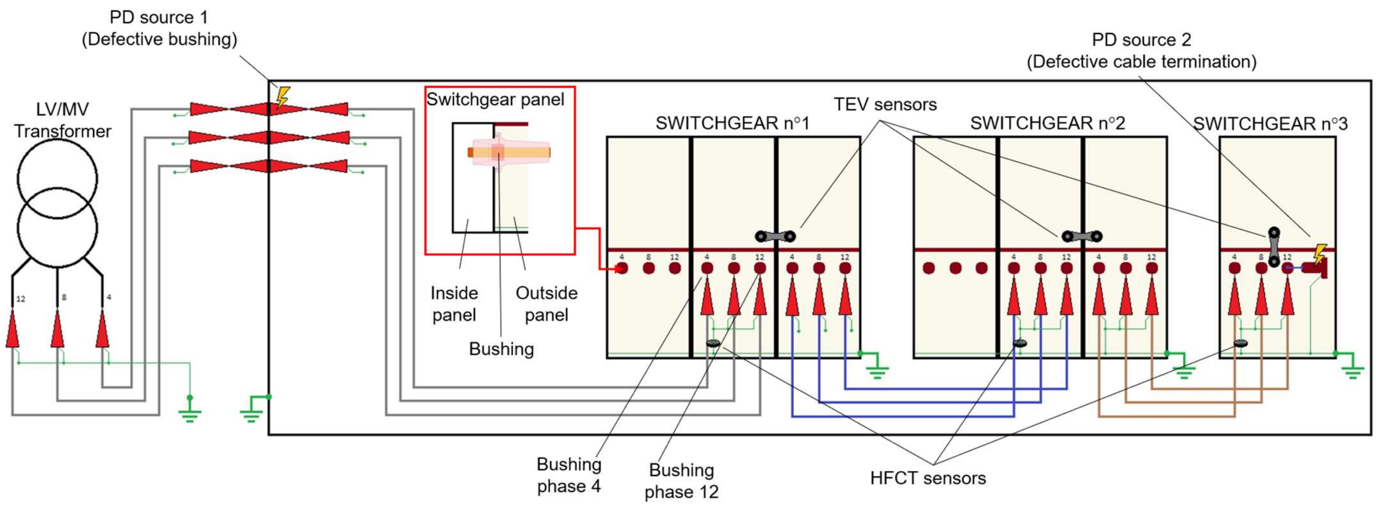

Fig. 4. Switchgear PD test circuit layout. Note the defective busing and cable termination, that could be located, as the PD monitoring point, in different cabinets of different switchgears.

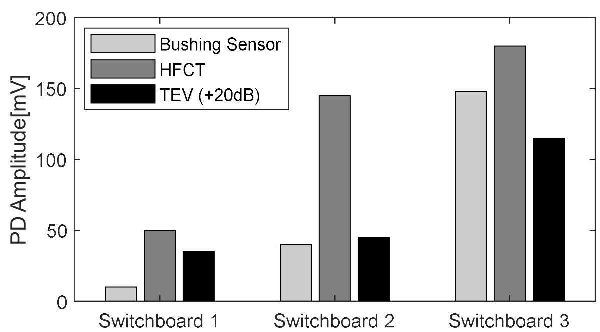

Fig. 5. Comparison of the sensitivity of the three types of sensors as a function of the distance from the defect generating PD (defective termination connected to the cabinet of switchboard 3), see Fig. 4.

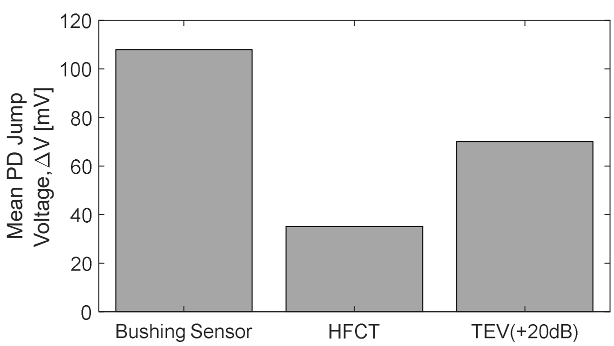

Fig. 6. Values of the mean PD magnitude jump (ΔV) from the cabinet where the cable termination generates PD and the nearest cabinet, for the three types of sensors of Fig. 5.

C. *Attenuation and localization*

A testing circuit, consisting of a variable number of cabinets was assembled in factory. Artificial defects were created both in bushings, that were displaced in various cabinets to be closer or farther from the PD measurement point, and in cable termination, see Fig. 4. Besides the embedded bushing sensor, HFCT and TEV sensors were used to detect PD. A comparison of PD measurement results, among many obtained varying the PD test and defect locations, are shown in Fig. 5 and Fig. 6. As can be seen, the new bushing sensor has, in general, the feature to be quite selective, showing the most significant jump in PD magnitude from the cabinet where PD are located to the near ones. To support this finding, Fig. 6 reports the values of the mean PD magnitude jump (ΔV) from the cabinet where the defective bushing or the cable termination generate PD and the nearest cabinet for the three types of sensors.

On the whole, it appears that the bushing sensor has better capability to locate PD in the cabinet where they are generated, as PD coming from near cabinets seem to be more attenuated than with the other two types of sensors. This comes also as a consequence of using broadband PD detectors, with high upper band frequency, since the signal spectra energy becomes very sensitive to the distance from detection and PD location points [9].

It is noteworthy that such experiments were carried out in factory environment, with significant amount of any type of noise, thus the issue of noise rejection and PD identification had to be addressed properly [16], [17]. This is, indeed, what is expected to occur on-field. The next Section will describe how automatic PD acquisition, denoising, and interpretation as mentioned in section I can be addressed for the purpose of factory PD testing and, broadly, on-line PD monitoring.

III. PD Monitoring: An Advanced Automatic Approach

Separation of signals having different typology, thus being generated by different type of sources, recognition whether a cluster contains PD pulses or noise and then identification of the type of source generating PD, on the basis of its harmfulness, is the rationale behind the automatic PD data processing approach discussed here, but valid in general for any type of electrical apparatus. Knowing only the type(s) of PD source(s), an effective CBM action can be implemented.

Separation can be based on extraction of multiple parameters from each signal recorded during PD measurements, such as equivalent time length, equivalent frequency, entropy, skewness and kurtosis of the magnitude and repetition rate distributions. Relying upon multiple parameters increases the

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possibility of identifying characteristics that can provide good discrimination between groups of signals belonging to different sources [16]. The use of dimensionality reduction techniques can then allow to view the projection of the high dimensional data into a two-dimensional subspace. This, as well as the removal of redundant features, can be achieved through Principal Component Analysis (PCA). Hierarchical clustering or similar techniques can be then used for automatically clustering the data [17], [18].

Recognition of the type of signals, whether consisting of PD or some kind of noise or cross-talk, that belong to each cluster can be performed automatically on the basis of the information collected for each sub-pattern. This can be achieved through various statistical and mathematical techniques, such as the fitting to the two-parameter Weibull distribution of PD-pulse magnitude, q, calculating the second and higher-order moments of the signal repetition rate distribution, as well as carrying out a linear prediction (LP) analysis applied to each signal belonging to a sub-pattern. The last is based on the concept that PD signals are inherently more structured compared to noise signals, the latter being mostly random and, thus, lacking a well-defined structure [19].

Eventually, identification can rely upon simple markers as the shape parameter of the two-parameter Weibull distribution of charge magnitude [19], [20]:

$$F(q) = 1 - \exp\left[-\left(\frac{q}{\alpha}\right)^{\beta}\right] \tag{1}$$

where q is charge amplitude from the detected pulses, α and β are the scale and shape parameters (the latter is the slope of the regression line in the so-called Weibull paper). β has identifiable ranges of values that can allow an artificial intelligence algorithm, as fuzzy logic, to indicate whether e.g. detected PD come from internal or surface defects, or from corona discharges (having in mind, as mentioned above, that their harmfulness, thus the need to plan maintenance, is of descending importance from internal to corona discharges [20], [21]).

The use of the mathematical, statistical and artificial intelligence algorithms just described will allow to carry out the whole PD processing stage, from separation to identification, automatically and without any need of experts, and it can be applied successfully also to switchgears, as shown in the following.

Examples of the application of this three-step procedure on PD measurements performed on switchgears, using the configuration of Fig. 4, are reported in Figs. 7 to 9.

Figure 7 shows how automatic separation is carried out based on the global PRPD pattern of Fig. 7(a), which is populated by peak and phase values of the signal pulses that are clustered in the multi-dimensional map, and projected in a 2-dimensional plane in Fig. 7(b) (the plane, obtained from PCA decomposition, showing the maximum distance among the cluster centroids). Figure 7(c) displays how the automatic hierarchical clustering works, and Fig. 7(d) highlights the contribution to the global pattern by each cluster singled out in Fig. 7(c).

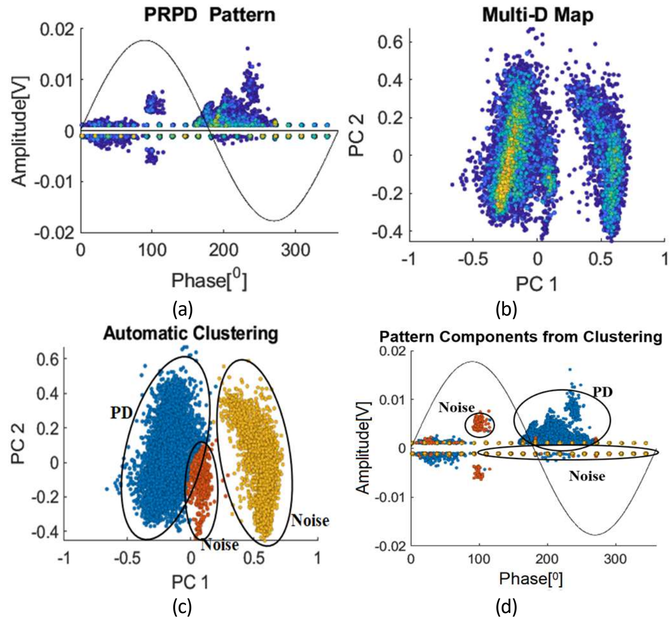

Fig. 7. (a) Global PRPD pattern measured by the new bushing sensor, (b) relevant signal pulse clusters in the multi-dimensional map projected in a 2-dimensionall plane, (c) result of automatic hierarchical clustering and (d) the representation of automatically clustered sub-patterns in the global pattern.The recognition of the cluster nature reported in the figure comes from the processing in Fig.8.

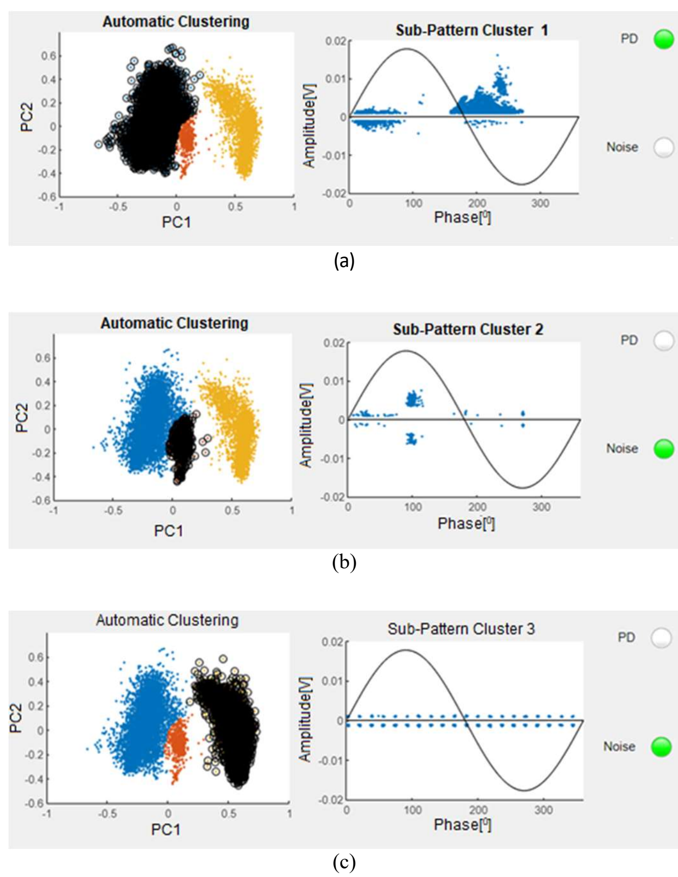

Fig. 8. Recognition from the three clusters of Fig. 7(b) and 7(c) of those clusters populated by signals generated by PD or noise. The cluster colored by black is that under examination in each case. The relevant sub-patterns (that all together compose the global pattern of Fig. 7(a)) are also reported.

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The next step is to recognize which clusters are populated by PD and which by noise or disturbance, as shown by Fig. 8. Among the three clusters separated in Fig. 7(c), only one contains PD, the inference being based on the combination of the various markers which are obtained from each sub-pattern (also reported in Fig. 8). The quality of fitting to Weibull distribution of charge amplitude is considered to be an indicator for differentiating a PD cluster from noise: a good fitting likely indicates PD, while poor fitting can be associated to noise clusters. This is evaluated through the R^2 goodness of fit test of each cluster to Weibull distribution. Figure 9 shows the Weibull plots for the three clusters in Fig. 7(c), along with the R^2 values and β values. Other markers that help in recognition of PD and noise are those representing the pulse structure: PD being inherently more structured than noise, which are more random. The use of markers such as pulse entropy and the skewness of the linear prediction residual of pulses give a good estimate of the pulse structure [22]. Recognition is done using a fuzzy logic (automatic) approach (see the traffic light representation of Fig.8).

The last step is to identify the type of defect generating PD, which is based on typical PD magnitude and phase distribution markers addressed by fuzzy logic, as explained in [18]. Fuzzy logic inference is based on linguistic expressions (rules) which are applied to the fuzzification of the information provided by the statistical parameters extracted from PRPD pattern, pulse shape analysis and so on, as summarized in Fig. 10 (the markers used and their values for the cluster and sub-pattern of Fig. 8(a) are reported in Table I). As can be seen, the identification is internal PD with likelihood 100% (indeed, PD were generated by the defective bushing with internal cavity), which would already alert switchboard operators. A traffic-light alerting logic could then be implemented trending PD amplitude and repetition rate over time only for those clusters and sub-pattern recognized as due to PD. The alert can be based on type of PD (harmfulness) and appropriate thresholds on amplitude and repetition rate (of different values depending on the PD source typology, thus harmfulness): see Fig. 11.

IV. Examples of PD Switchgear Monitoring

Partial discharge measurements were performed (and monitored for times up to a few hours) in several locations of the assembly of switchboards of Fig. 4. Various types of defects, inside and outside the switchgears, were considered. Here, those relevant to defective MV bushing (having an internal cavity) and defective cable termination are presented.

PD monitoring was carried out using all the three types of sensors indicated in Fig. 4, that is, transient earth voltage, TEV, placed on the outer part of the cabinet enclosure, high-frequency current transformer, HFCT, connected on the ground lead of cable terminations entering into a switchgear cabinet, and the new bushing sensor.

PD measurements were performed farther and farther from the PD sources, and also moving HFCT and TEV along the switchboard cabinets, in order to compare, at least in qualitative way, the sensitivity of the sensors as a function of the distance from the PD source.

TABLE I
Markers for Fuzzy Logic Identification of PD Type from the PD Sub-pattern of Fig. 8a (Phi is phase angle)

Markers	Positive Pulses	Negative Pulses
Beta	1.6	2.9
Skewness	2.4	2.4
Symmetry	0.07	0.07
Minimum Phi	151.0	4.0
Delta Phi	117.0	83.0

Fuzzy Inference Output: Surface → 0 / Internal → 100%

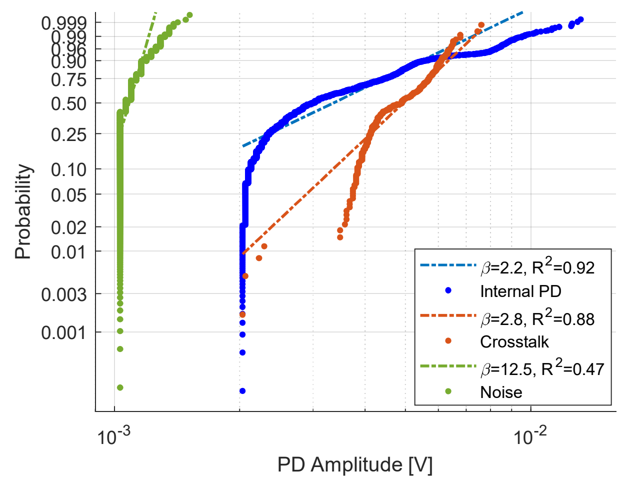

Fig. 9. Weibull plots of charge amplitude from the data provided by the three clusters of Fig. 7(c) (or sub-patterns of Fig. 8). The values of the shaope paramenter, β, and correlation coefficienrt R^2 are reported.

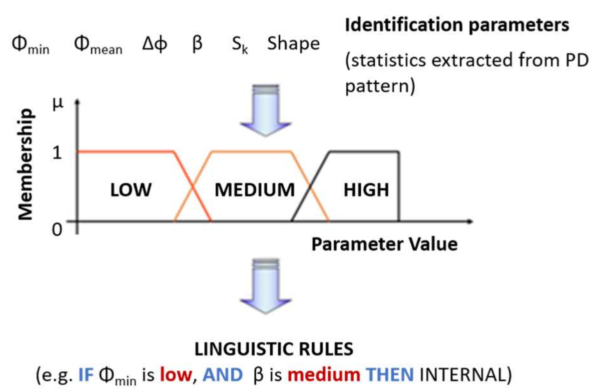

Fig. 10. Identification of the type of PD source providing the data of Cluster 1 and relevant sub-pattern (Fig. 8 a).

A summary of a few interesting results is condensed in the Figs. 12 to 14, having the purpose to show how the new bushing sensor is effective in capturing PD from defective parts of the switchgear and how the proposed automatic algorithm is able to separate, recognize and identify PD and noise sources.

Figure 12 and 13 report examples of PRPD patterns obtained by the bushing sensor for the two defects shown in Fig. 4, i.e., for the defective bushing and the cable termination respectively. The separation and identification of clusters as noise and PD are indicated in the figures. In both cases, the diagnostic markers indicate internal defects in bushing and cable termination, see Table II.

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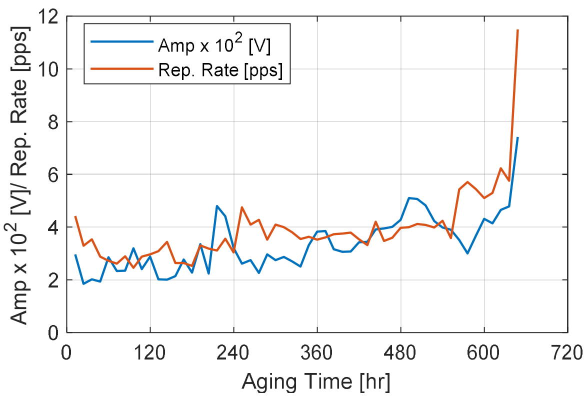
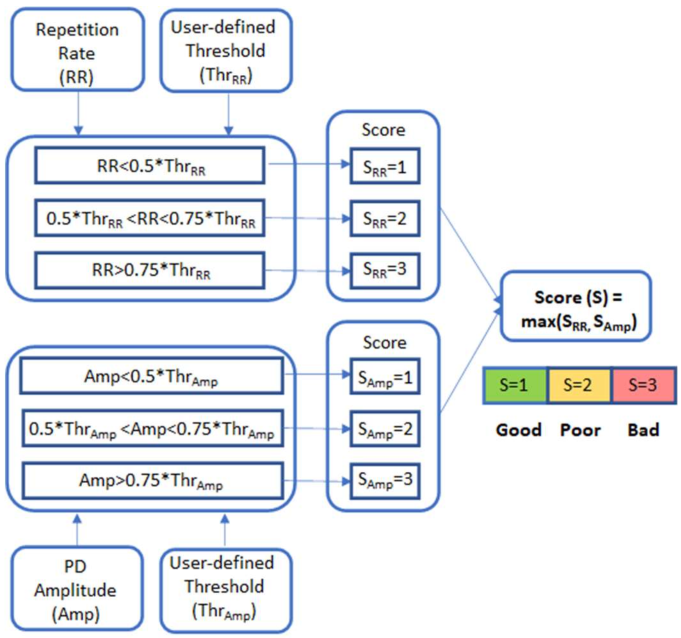


(a)

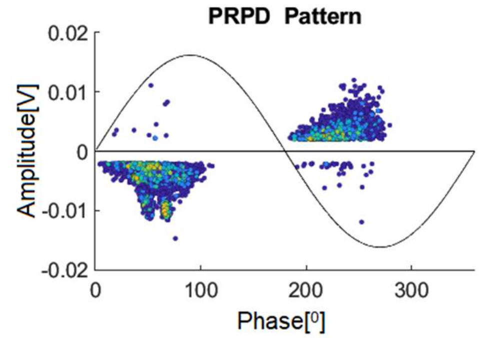


(b)

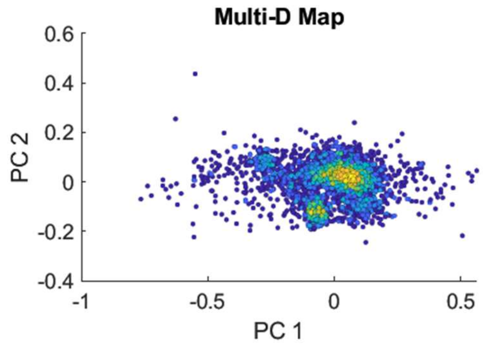
Fig. 11. Example of PD magnitude and repetition rate trend for a cluster of internal PD (a) and relevant alert logic (b).

TABLE II
MARKERS FOR IDENTIFICATION OF PD TYPE FROM THE PD SUB-PATTERNS OF FIGS. 12 & 13

Markers	Defective Bushing (Fig. 12)		Cable Termination (Fig. 13)	
	Positive Pulses	Negative Pulses	Positive Pulses	Negative Pulses
Beta	2.5	2.9	1.5	2.2
Skewness	1.8	1.6	2.8	6.7
Symmetry	0.8	0.8	0.3	0.3
Minimum Phi	178.0	4.0	153.0	6.0
Delta Phi	97.0	109.0	122.0	92.0
Fuzzy Inf.	Surface → 2.5% / Internal → 97.5%		Surface → 11% / Internal → 89%	



(a)



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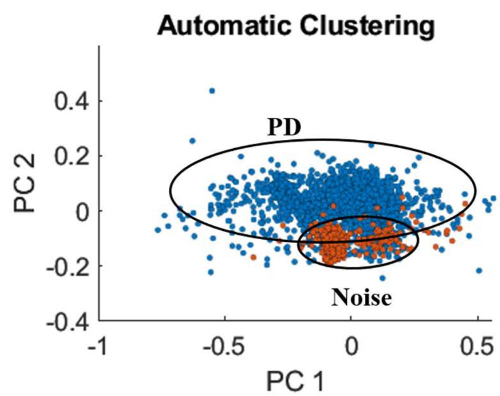

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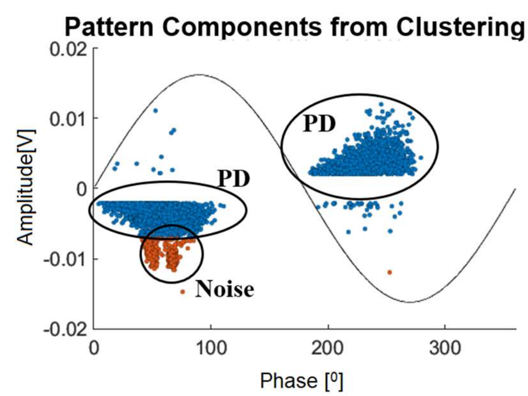

(d)

Fig. 12. (a) Global PRPD pattern measured in switchgear 1 for the defective bushing (Fig.4) using the bushing sensor, (b) relevant signal pulse clusters in the multi-dimensional map projected in a 2-dimensional plane, (c) result of automatic hierarchical clustering with recognition and (d) the representation of automatically clustered sub-patterns of the global pattern.

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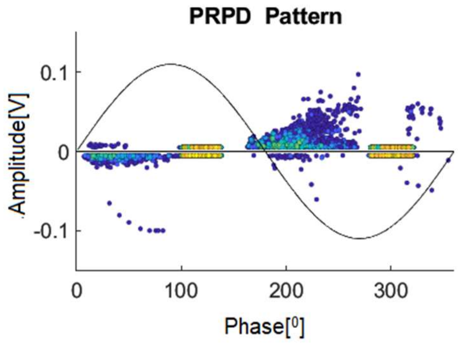
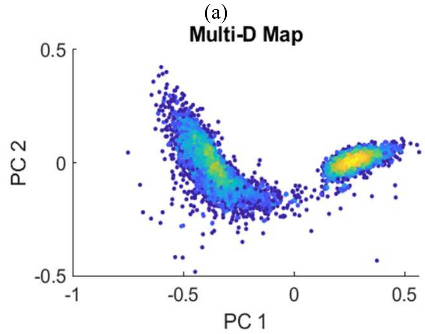


(a)



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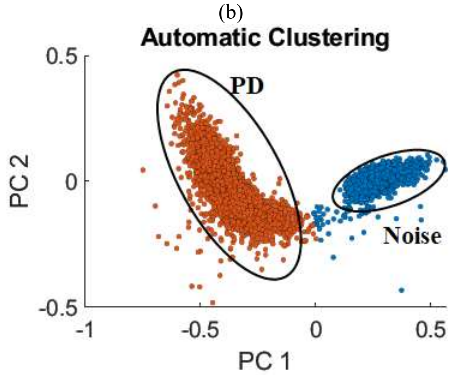
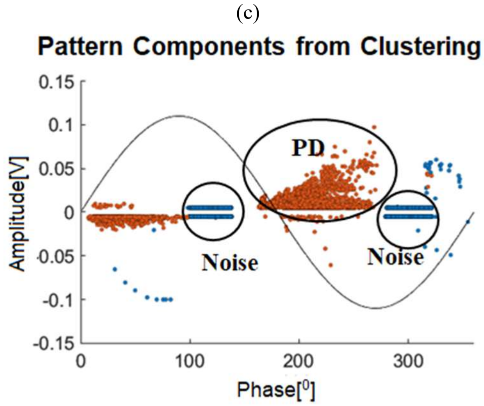


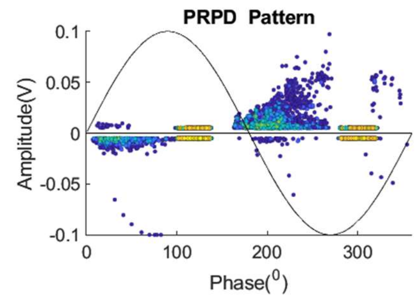
(c)



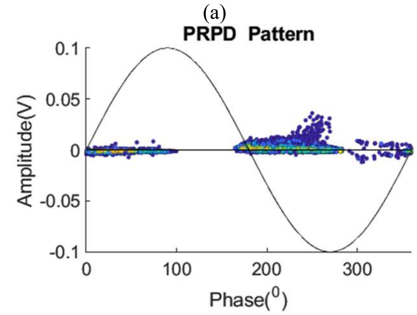
(d)

Fig.13. (a) Global PRPD pattern measured in switchgear 3 for the internal defect in cable termination (Fig. 4) using the bushing sensor, (b) relevant signal pulse clusters in the multi-dimensional map projected in a 2-dimensional plane, (c) result of automatic hierarchical clustering with recognition and (d) the representation of automatically clustered sub-patterns in the global pattern.

Figure 14 depicts the PRPD patterns obtained from the bushing sensor for the defect in the cable termination in switchgear 3, already shown in Fig. 13, and measured at two different points: switchgear 3 where the defect is located (Fig. 14(a)) and switchgear 1 which is the farthest from the defect location (Fig. 14(b)). A significant signal attenuation is clearly visible comparing Fig. 14(b) and Fig. 14(a). This is due to the distance of the sensor from the defect location. Figure 15 displays the PRPD patterns for the same defect and same location (cable termination in switchgear 3) but measured by a HFCT connected at switchgear 3 (Fig. 15(a)) and switchgear 1 (Fig. 15(b)). A quick comparison between Figs. 14 and 15 indicates that the bushing sensor has higher signal attenuation, thus selectivity, than the HFCT. This indicates that the bushing sensor may be more suitable to discriminate between PD occurring within the cabinet and those coming from outside.

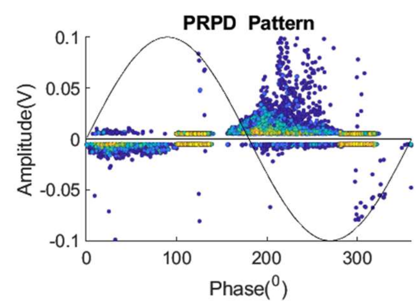


(a)

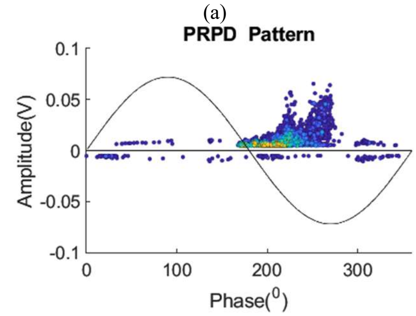


(b)

Fig.14. Comparison of PRPD patterns obtained from the new bushing sensor for a defect located in the cable termination of switchgear 3. Measurement carried out on (a) switchgear 3 and (b) switchgear 1.



(a)



(b)

Fig. 15.Comparison of PRPD patterns obtained from the HFCT for the same defect locations as in Fig. 14 (cable termination of switchgear 3). Measurement results from HFCT located at (a) switchgear 3 and (b) switchgear 1.

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V. Conclusions

Relying upon expert-driven, or on automatic, unsupervised separation and identification algorithm, as that proposed here, a time trend of the most significant PD quantities (primarily magnitude at a given probability and mean repetition rate) can be built up referring to the PD clusters and sub-patterns, that is, after having cleaned up the global PRPD pattern from the contribution of noise and disturbances. In this way, an effective alerting system can be set, and the contribution of PD degradation rate to a more general heath index for switchgears can be devised. It is evident that the use of automatic procedures can be a game changer because expert support is often not economically sustainable in MV switchgears and, sometimes, too delayed compared to maintenance exigences.

Monitoring on a few cabinets, alerting and on-site assessment of the cabinet affected by PD, and subsequent maintenance actions could be the drivers of a low-cost, but effective, PD monitoring system for a switchgear. The automatic software described above should be able to minimize Type I and II errors (false negative and false positive), thus reducing maintenance cost and increasing the return of the investment (ROI).

It has to be underlined again that this automatic PD detection and processing approach holds for any component of an electrical asset, so that it can be applied to e.g. cables and loads (motors) connected to a switchgear, in order to obtain a global, unique, diagnostic tool to allow condition based maintenance to be carried out reliably and profitably on the whole asset.

The sensor investigated in this paper fits to the requirements of sensitivity and selectivity, allowing the switchgear cabinet(s) where PD are present to be singled out. Also, it constitutes a low-cost solution being, in principle, already embedded in bushings for the purpose of voltage detection. In addition, its gain can be amplified by redesigning the coupling capacitance in order to improve detection bandwidth and sensitivity to PD detection. Also, it can provide the synchronization signal (with the supply voltage), which is an important add up for the identification of the type of defect generating PD, which is based on the shape of the PD pattern.

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