Automatic Partial Discharge Pattern Recognition for Use in On-line Cable Condition Monitoring Systems

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ABSTRACT

For a growing number of utilities partial discharge (PD) based on-line condition monitoring systems are being used for Medium Voltage cables. Signal processing, including data denoising and feature extraction, is fundamental to obtaining useful data from the noisy raw signals. Because raw data in an on-line monitoring system emerges on a continuous basis, the ability to turn raw data into useful information is a significant challenge, requiring further data mining, to allow effective insulation condition assessment. Phase resolved PD patterns, ψ-q-n diagrams, are the most popular feature description method for identifying fault type in High Voltage systems. When the magnitude of the electric field is greater than the breakdown value, PDs are generated at the defect site(s). As the charge dynamics of a given type of defect are usually consistent there is a defined pattern of PD signals for each type of fault, e.g. internal discharge, surface discharge, etc. ψ-q-n diagrams are related to the applied voltage waveform but, in contrast to off-line monitoring, the phase of the applied voltage is missing in on-line measurements. As a result, neither 2 dimensional nor 3 dimensional Phase Resolved Pattern (PRP) have been adopted in on-line PD condition monitoring systems. This paper attempts to identify the most important features which can be extracted to describe the Q-N patterns, irrespective of the phase information. The paper presents in detail an automatic Q-N pattern recognition procedure which includes data denoising, signal classification, PD pattern comparisons. The automatic pattern recognition will contribute to PD based on-line cable condition monitoring systems and will also be applicable to on-line PD monitoring of other high voltage apparatus, e.g., transformer, motor, generator, etc.

INTRODUCTION

Phase Resolved Pattern (PRP) identification is the most popular method for partial discharge (PD) signal analysis, [1,2,3]. The PD pattern characteristics resulting from different types of fault, e.g. surface discharge, corona, internal discharge, differ from each other. For many years, with the development of computer technology and mathematical theory, PD pattern recognition ability has also developed. At the end of 1960s, CIGRE working group 21.03 published a classic summary of partial discharge recognition: this work addressed factors involved in recognition, diagnosis of origin of discharge and recognition of disturbance. 12 types of typical PD signals and 4 types of interference signals are described in term of distribution and variation magnitude with testing voltage and application time [2]. In 1990s, Krivda from Delft University of Technology introduced the procedure of automated recognition of partial discharge, which contains measurements of PD pattern, feature extraction, classification of the pattern and decision process [1]. Cluster analysis and neural network are discussed based on fundamental feature extraction and data base establishment work [1]. In 21th century, novel PD pattern recognition methods have continued to develop, i.e. inductive inference algorithm [3], neuro-fuzzy network [4], fractal image compression [5], genetic optimization [6], support vector machine [7], etc. Most of the methods cited above are applied in experimental situations, few methods are reported to be used in on-line cable PD monitoring systems. In practical, on-line situations there are lots of challenges to be overcome when attempting cable condition monitoring from PD pattern recognition.

The first challenge for on-line cable monitoring systems is that PD signals from cable faults are mixed with strong background noise and interference signals, e.g. sinusoidal RF noise, radio and power line carrier communication systems, switching pulses and PD from local plant, etc. Extracting the all pulsative signals from the interference, i.e. denoising, is not simple.

The second challenge is feature extraction to differentiate PD from cable from other pulsative signals discussed above. As the frequency bandwidths of other interference signals overlap with that of PD from cable, it is necessary to identify particular features to discriminate between them. After data denoising, further signal classification must be carried out based on the characteristics of signals from different sources.

A third challenge for applying PRP systems to on-line monitoring system is that phase information is difficult to obtain. For experimental testing in the laboratory, it is possible to set up high voltage coupling capacitor to obtain phase information on the applied voltage. For on-line application, however, it is difficult to obtain this phase information. There are two reasons why it is challenging to gain the correct voltage phase relationship. The first reason is that a phase shift may exist between voltage and current; as most sensors are current transformers, the reference phase will provide a relationship for current and not for voltage. Standard PRP systems require phase voltage information of measured cable. The second reason is that, due to cross bonding of the earth strap of three phases cables, PD from one phase will be coupled into another phase. For data acquisition from on-line monitoring systems, the trigger signal is significant to the phase information. Most of the commercial on-line monitoring systems use the phase voltage of the units power supply as trigger signal. Data acquisition will be triggered at the 0 degree of the low voltage power supply, not 0 degree of high voltage (HV) applied in the cable. Although this provides a fixed trigger position for data capture, a random phase shift will be generated between the set point and the applied HV.

A fourth challenge to pattern recognition in on-line systems is that, for some situations, it is difficult to distinguish the PRP in 3-phase data. Figure 1 (a) shows an example of one set of data from a piece of switchgear whilst Figure 1 (b) shows ten sets of data from the same plant overlaid. PRP is difficult to identify in Figure 1 (a), but clearer patterns can be identified from Figure 1 (b). In Figure 1 (b) a possible representation of the 3-phase voltage is overlaid for clarity.

A fifth challenge is that most pattern recognition systems have developed from situations where only 1 phase of the cable is energised. For many on-line monitoring systems, the PD generated is due to the influence of the 3 phase voltages. From Figure 1 (b), the challenge is to automatically extract recognisable patterns where the PD sources may be active on all 3 phase voltages.

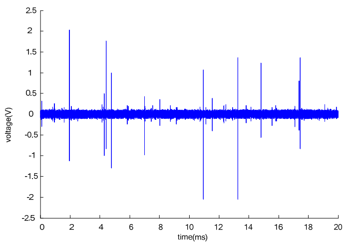

Figure 1(a): One set of data from switchgear

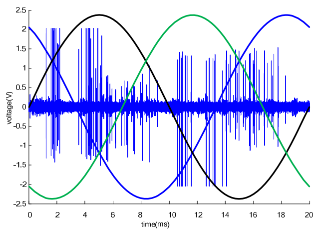

Figure 1(b): Ten sets of data from same switchgear

A sixth challenge is automatic PRP estimation for on-line PD monitoring data. Although many methods are reported to be effective for PD pattern recognition [1, 3, 4, 5, 6, 7], no method is reported to be universally effective for on-line PD monitoring system applied to MV cable, i.e. when signals are affected by strong noise, may contain PD from multiple sources, acquisition is triggered at random phase angle.

A novel signal processing method and knowledge based PRP diagnosis technique, aimed at overcoming these challenges, are presented in this paper. The method includes Adaptive Second Generation Wavelet Transform (ASGWT) based data denoising, feature extraction and decision tree based signals classification, phase area demarcation, knowledge rule table and PRP estimation procedure. Two example applications are introduced.

AUTOMATIC PD PRP ESTIMATION PROCEDURE

Figure 2 (a) shows the signal processing system flowchart. Input data are processed with ASGWT based data denoising algorithm [8, 9]. Then decision tree based classification [10] is carried out based on PD feature extraction [8]. Pattern comparison is carried out during signal classification. Candidate signals are compared with standard PD signal criteria and interference signal criteria, which are created during historical signal analysis. If none of the criteria matches with candidate signal, further signal analysis is carried out to determine whether it is PD signals or interference signal, of which the parameters will be added to each signal criteria.

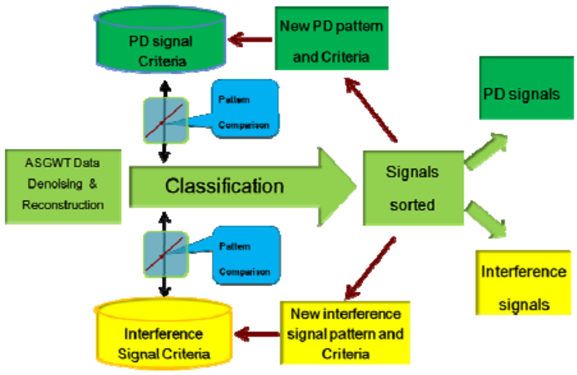

Figure 2 (a): Signal processing system flow chart

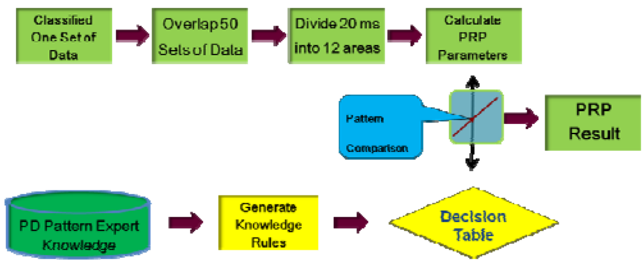

Figure 2 (b): PD pattern estimation system flow chart

The pattern estimation flow chart is shown in Figure 2 (b), the reasons for developing the system in this manner will be explained later in the paper. As shown, after data denoising and signal classification, input signals are classified into different types. Then 50 sets of data are overlapped. In addition, the data set is divided into 12 areas, as shown in Figure 3.

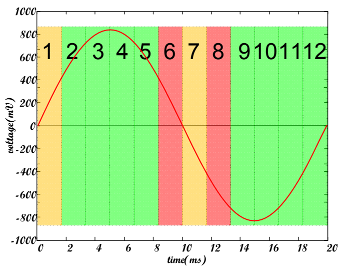

Figure 3: Divide data set into 12 areas, relating to voltage phase

PRP parameters are calculated in each area, i.e. PD number, PD magnitude, maximum magnitude. PD pattern knowledge rules and decision table are generated based on PD pattern expert knowledge. As most patterns relate discharge approximately 180 degrees apart, the PD pattern decision table compares PRP parameters in area 1 with those in areas 6, 7 and 8. Similarly, PRP parameters in area 2 will be compared with those in areas 7, 8 and 9, etc. PRP estimation result is made after all areas are compared with their corresponding three areas.

PD PRP KNOWLEDGE RULES AND DECISION TABLES

According to the CIGRE summary [2], PD signals can be divided into 12 types which are described in term of distribution and magnitude variation with testing voltage and application time. For on-line application, if the voltage phase shift is considered, 7 typical PRP can be identified: these are shown in Figure 4 (b) to Figure 4 (h). Figure 4 (a) is typical of interference signals. Figures 4 (b) and (c) are PRP of corona discharge; Figures 4 (d) and (e) are PRP of PD from external and dielectric surface; Figures 4 (f) and (g) are PRP of PD from internal insulation affected by 1 phase voltage; Figure 4 (h) is PRP of PD from internal faults affected by 3 phase voltages.

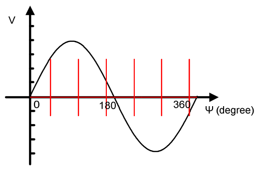

Figure 4 (a): PRP type 1

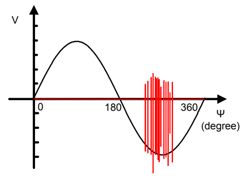

Figure 4 (b): PRP type 2

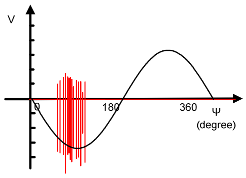

Figure 4 (c): PRP type 3

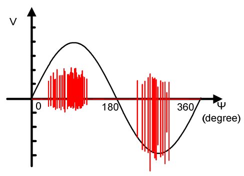

Figure 4 (d): PRP type 4

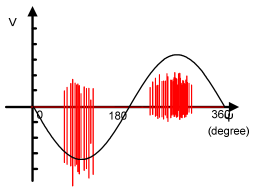

Figure 4 (e): PRP type 5

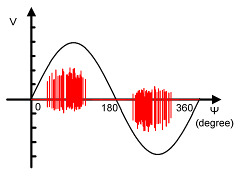

Figure 4 (f): PRP type 6

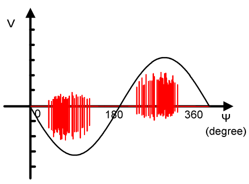

Figure 4 (g): PRP type 7

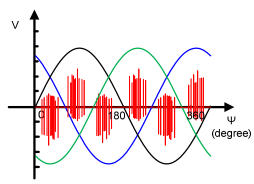

Figure 4 (h): PRP type 8

As introduced in Figure 3, each data set is divided into 12 areas. In each two corresponding areas, 6 parameters are computed, i.e. PD number, PD magnitude, PD maximum value of each area. In Table 1, data from regions 1 and 6 are entered. PD number in area 1 is named N1; PD number in area 6 is named N2; Total discharge magnitude in area 1 is named A1; Total discharge magnitude in area 6 is named A2; PD maximum value in area 1 is named M1; PD maximum value in area 6 is named M2. The PRP decision table developed for this set is shown in Table 1; parameters are all normalised.

Table 1 PRP decision table

Types	**N1**	**N2**	$\frac{N1}{N2}$	**A1**	**A2**	$\frac{A1}{A2}$	**M1**	**M2**	$\frac{M1}{M2}$
Type1	>1	>1	=1	>1	>1	=1	>1	>1	=1
Type2	=0	>1	=0	=0	<-1	=0	=0	<-1	=0
Type3	>1	=0	\	<-1	=0	\	<-1	=0	\
Type4	>1	>1	=1	>1	<-1	>-1	>1	<-1	>-1
Type5	>1	>1	=1	<-1	>1	<-1	<-1	>1	<-1
Type6	>1	>1	=1	>1	<-1	=-1	>1	<-1	=-1
Type7	>1	>1	=1	<-1	>1	=-1	<-1	>1	=-1
Type8	>1	>1	=1	<-1	>1	=-1	<-1	>1	=-1

When area 2 is investigated, corresponding areas are 7, 8 and 9, as shown in Figure 5. Similar comparisons are made across the full data set and a new decision table is built for each investigation.
The outcome of the analysis gives an indication of the most viable PRP for the cable under investigation. Two examples of investigations undertaken by the authors are presented in the following sections.

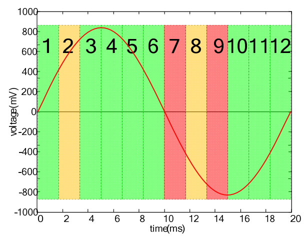

Figure 5: Area 2 and corresponding areas

EXAMPLE 1 OF APPLICATION TO ON-SITE TESTING DATA

The result of the application of the system to one set of on-site PD testing data is shown in Figure 6.
Figure 6 (a) shows the raw data in green and the output of the ASGWT data denoising in other colours, as discussed below. Peaks in dark blue are extracted PD signals; those in red are interference signals. Figure 6 (b) shows PD number in each area. Figure 6 (c) shows PD magnitude in each area. Figure 6 (d) shows maximum PD magnitude in each area. Histogram in blue is statistical value of PD signals with rise time less than 100 ns; histogram in green is statistical value of PD signals with rise time greater than 100 ns and less than 200 ns; histogram in yellow is statistical value of PD signals with rise time greater than 200 ns and less than 350 ns; histogram in pink is statistical value of PD signals with rise time greater than

350 ns.

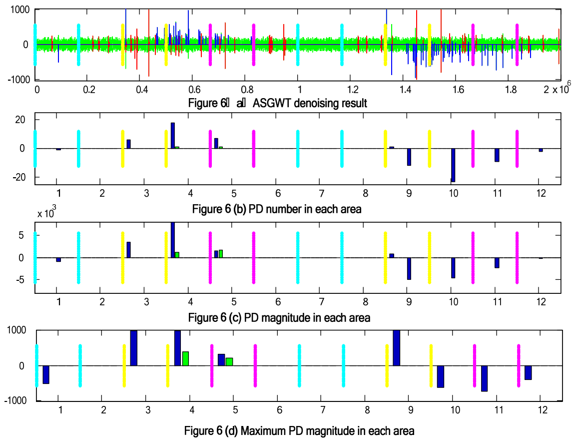

Figure 6: Application example of on-site PD testing data

According to PD PRP estimation procedure shown in Figure 2 and PRP decision rules in Table 1, this set of data is judged to be PRP type 6, as shown in Figure 4 (f).

EXAMPLE 2 OF APPLICATION TO ON-LINE MONITORING DATA

A second application example of on-line PD monitoring data is shown in Figure 7.

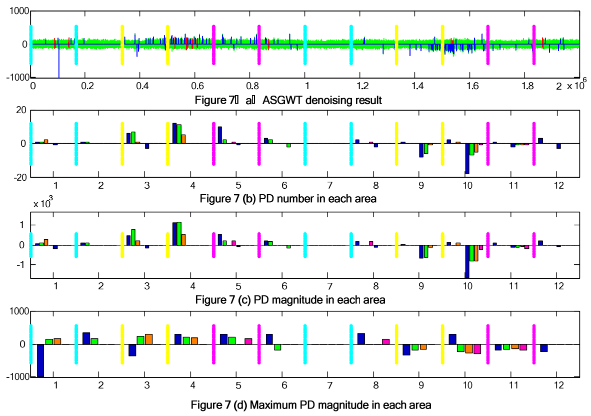

Figure 7: Application example of on-line PD monitoring data

The assignment of colours of the signal and the histogram are the same as Figure 6. According to the PD PRP estimation procedure, shown in Figure 2 and PRP decision rules in Table 1, the pattern of this set of data is judged to be PRP type 6, shown in Figure 4 (f).

CONCLUSION AND FUTURE WORK

In summary, the following conclusions can be drawn:

- Automatic PRP recognition requires data pre-processing, including data denosing and signal classification;
- ASGWT is an effective data denoising algorithm for on-site testing data and on-line monitoring data;
- Data stack processing will be significant for some of the case study;
- PD pattern knowledge rules are important for automatic PRP recognition;

Future work:

- Establish PD PRP knowledge rule decision table for on-line application system;
- Data mining from large scale on-line monitoring data should be undertaken to confirm the most effective parameters describing PRP;
- Application of system to on-line monitoring system to demonstrate robustness of system.

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