# KNOWLEDGE BASED INTERFERENCE SIGNAL REJECTION AND PARTIAL DISCHARGE IDENTIFICATION FROM MULTI-PD SOURCES FOR CONDITION MONITORING OF CABLE SYSTEMS

Xiaosheng PENG
Glasgow Caledonian University – UK
Xiaosheng.Peng@gcu.ac.uk

Donald M HEPBURN
Glasgow Caledonian University – UK
D.M.Hepburn@gcu.ac.uk

Chengke ZHOU
Glasgow Caledonian University - UK
C.Zhou@gcu.ac.uk

## *ABSTRACT*

*Autonomous partial discharge (PD) identification is not only key to the success of, but also one of the major challenges in, PD based condition monitoring of cable systems. In industrial applications, two challenges restrict the implementation of autonomous PD identification. The first challenge is that interference signals are of different shapes and the frequency bandwidths of some interference signals are similar to that of PD signals. The second challenge is that, as PD signals originate from different sources, their characteristics also vary. Sources of PD include cable and cable termination, switch-gear enclosures, motors connected at the end of the cable being monitored, etc. The ability of identifying PDs from the multiplicity of PD sources is therefore in great demand.*

*To overcome the above two challenges, this paper demonstrates a knowledge based method for interference signals rejection and autonomous PD signal identification. The fingerprints of typical interference signals and PD signals emanating from various sources are defined and differentiated in the time domain. Based on the fingerprints, a decision tree based recognition method and a knowledge base has been developed.*

*The method was based on PD on-site testing data collected from more than 300 cables in one power system. It was then applied to another two systems and proved to be effective.*

## INTRODUCTION

Autonomous partial discharge (PD) identification would be a key component in the uptake of PD based, on-line condition monitoring of cable systems [1-4]. Developing reliable methods for autonomous operation is also one of the major challenges. In recent years, on-line PD monitoring systems were reported to be applied in industrial applications, however, due to different sources of strong interference few on-line monitoring systems could identify PD from multiple sources autonomously [4]. Efforts have been made to differentiate PD signals generated in different power equipment from random noise and pulsative signals from other sources, including data denoising techniques, feature extraction techniques and knowledge based system [5-6].

Knowledge based systems have following advantages: firstly, knowledge based systems use computer analysis to mimic human learning, which can be directly used for on-line monitoring systems or on-site testing systems; secondly, knowledge based systems can describe complex situations, which is ideal for interpretation of PD signals are they are affected by different factors and are difficult to describe; thirdly knowledge based systems have self-study ability, to allow knowledge rules to adapt to new information and to increase with the application.

This paper proposes a knowledge based method for rejecting interference signals and autonomously identifying PD signals. It contains a training process stage and an application process stage, as shown in Figure 1. In the training process, PD knowledge rules and interference signal knowledge rules are built based on on-site testing data from 300 cables from one site; in the application stage, the established knowledge rules are applied to another two power systems. The results show that the knowledge based method is effective for PD signal identification from multiple PD sources and effective for autonomous interference signal rejection when the fingerprints of different signals are established.

## KNOWLEDGE BASED SYSTEM FOR PD CONDITION MONITION

Figure 1 shows the flowchart of the proposed PD condition monitoring knowledge based system, containing a training process stage and a practical application.

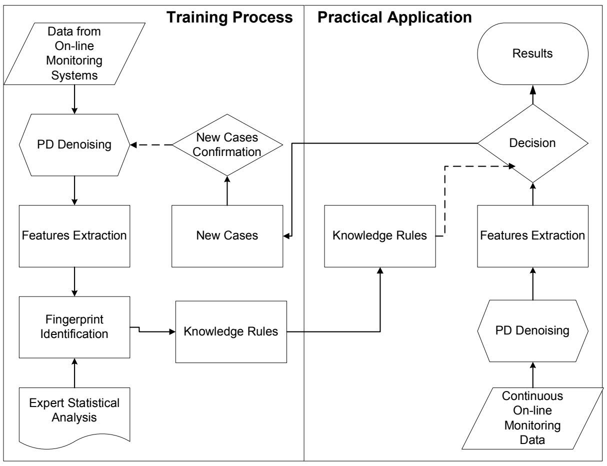



Figure 1 Flowchart of knowledge based system for PD condition monitoring

As shown, the stages in the training process are: data are obtained from on-line monitoring system or on-site testing experiments; data denoising is carried out to generate high signal noise ratio information; feature extraction is applied to describe signals in terms of specific characterstics, described in the following section; based on the expert knowledge and statistical analysis, fingerprints of typical PD signals and typical interference signals are identified, which are described in terms of different knowledge rules. These knowledge rules are applied in the practical application, which is shown on the right hand part of Figure 1.

In practical application, continuous on-line monitoring data are detected using High Frequency Current Transformers (HFCT) attached to the earth strap of cables. The first two steps of practical application are the same as training process, i.e. data denoising and feature extraction, then decision process is made based on PD features and knowledge rules which are generated in training process. If the features of the PD detected do not match any of the existing knowledge rules, a new case is discovered. A feedback route is input into training process, which allows generation of new knowledge rules and modified existing knowledge rules.

## PD FEATURES ADOPTED

6 PD features are adopted for knowledge rules generation, i.e. rise time, pulse width, maximum magnitude, pulse interval, pulse repetition rate and phase resolved PD pattern. The first three features describe characteristics of individual PD pulses; pulse interval and pulse repetition rate describe PD signals in terms of short time statistical distribution; phase resolved PD pattern describes PD signal in terms of clustered signal relationships.

The definition of rise time ($t_r$) (10% to 90% of peak value) and pulse width ($t_w$) of PD pulses are from reference [2, 7].

The maximum magnitude of individual PD pulse is defined as:

$$V_{\max} = \max\{V_1 \cdots V_n\} \qquad (1)$$

$V_1$ … $V_n$ are magnitude values of n samples of an individual PD pulse.

Pulse interval $t_I$ is defined as:

$$t_I = \frac{1}{N}\sum_{i=1}^{n} t_i \qquad (2)$$

Where N is the total number of PD pulse in one power cycle, $t_i$ is the time interval between two neighboring PD pulses.

According to IEC 60270 standard, pulse repetition rate $N_r$ is the total number of PD pulses recorded in a selected time interval [7].

Phase resolved pattern (PRP) providing information on when during an AC cycle discharge activity is occurring, is one of the most effective methods for PD signal interpretation. From analysis of the various PRP constructs which can be gathered during analysis of 3-phase MV cables, the authors have grouped the signals into 6 types, which are shown in figure 2.

PRP type 1, a random distribution, is a typical pattern of interference signals. PRP type 2, a regular distribution, signifies those signals emanating from periodic interference source, such as electronic signals from certain equipment. PRP type 3 is typical of the pattern expected of corona from a single phase. PRP type 4 illustrates a typical discharge between external metal and dielectric surface on a single phase. PRP type 5 is typical internal insulation PD pattern for a defect affected by one phase in a 3-phase system. PRP type 6 shows the pattern expected of sources influenced by three phase voltages.

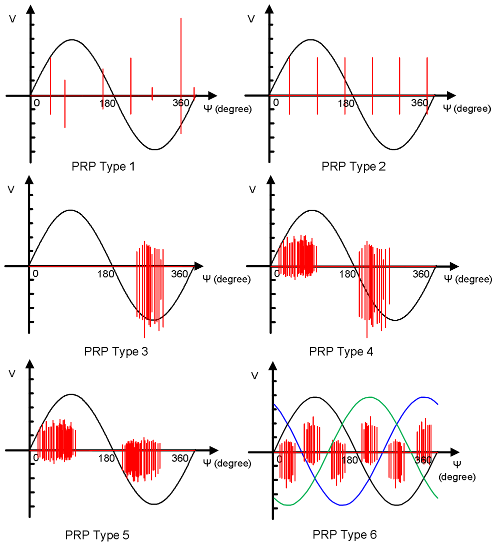



Figure 2 Six types of PRP

## KNOWLEDGE RULES IDENTIFICATION METHODS

There are three kinds of methods for knowledge rules identification, which are shown in figure 3.

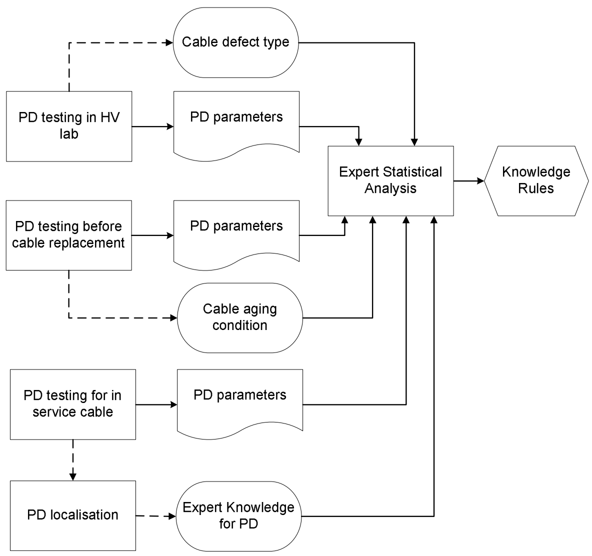



Figure 3 Three methods for knowledge rules identification

PD testing in a High Voltage (HV) laboratory is ideal method for PD knowledge rules identification, as cable defect types and testing voltage are easily controlled.

Comparison of PD test data before cable replacement with analysis of identified faults after replacement is an effective method for PD knowledge rules identification,

i.e. knowledge rules of relationships between PD activities and cable defect types can be verified.
In service cable PD testing is not an effective method for PD knowledge rules identification unless PD localisation can be carried. After PD localisation, PD knowledge rules for corresponding equipment could be identified.

## IDENTIFICATION OF KNOWLEDGE RULES FROM PD TESTING IN HV LAB

In [8], analysis of experimental PD testing of ethylene-propylene rubber (EPR) cable with artificial defects identified knowledge rules for classifying PD. Typical PD signal identified in the experiments, which is name as PD1, is shown in figure 4.

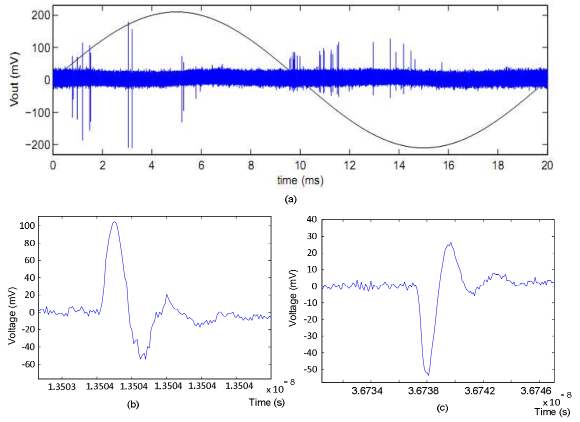



Figure 4 (a) PD from EPR cable with artificial defect in 20ms AC cycle (b) Positive pulse (c) Negative pulse *The signals are amplified 25dB.

Characteristics of the pulses and the PRP which have been used to develop knowledge rules for these signals are shown in Table 1.

Table 1 Knowledge rules of PD from EPR cable

| $t_r(\mu s)$ | $t_w(\mu s)$ | $V_{max}(V)$ | $t_l(ms)$ | $N_r(/s)$ | $PRP$ | Decision |
|---|---|---|---|---|---|---|
| 0.06-0.08 | 0.16-0.2 | 0.001-0.03 | 0.25-0.9 | 100-1500 | PRP type5 | PD1 |

## KNOWLEDGE RULES IDENTIFICATION FROM ONE POWER SYSTEM

During on-site testing in one power system containing 300 cables, 85 Gigabytes of signal information were collected. After expert analysis and PD localisation, 4 types of typical interference signals and 3 types of typical PD signals knowledge rules were established.

After considerable analysis and investigation, knowledge rules of signals, expressed in term of characteristics discussed, and used in Table 1, are shown in Table 2.

A typical signal for the interference signal designated as INT3 is shown in Figure 5. Figure 6 shows a second typical interference signal, from power electronic device, designated as INT4. Figure 7 shows a typical PD signal identified from switchgear box after PD localisation, designated as PD2. Figure 8 shows a typical PD signal identified from motor after PD localisation, designated as PD3.

Table 2 Knowledge rules of interference signals and PD signals

| $t_r(\mu s)$ | $t_w(\mu s)$ | $V_{max}(V)$ | $t_l(ms)$ | $N_r(/s)$ | $PRP$ | Decision |
|---|---|---|---|---|---|---|
| 0.8-2.5 | 5-6 | 0.08-0.1 | 1-5 | 200-1000 | PRP type1 | INT1 |
| 0.015-0.020 | 0.04-0.06 | 0.005-0.5 | 0.012-0.015 | 25000-40000 | PRP type3 | INT2 |
| 0.5-0.6 | 14-17 | 0.05-0.18 | 0.4-0.8 | 1250-2500 | PRP type2 | INT3 |
| 50-80 | 500-600 | 0.8-1.5 | 5.9-6.5 | 150-200 | PRP type2 | INT4 |
| 0.01-0.03 | 0.02-0.07 | 1-2 | 0.2-0.5 | 650-850 | PRP type6 | PD2 |
| 0.2-0.4 | 0.5-0.9 | 0.01-0.04 | 0.2-0.35 | 2000-3500 | PRP type5 | PD3 |
| 0.02-0.04 | 0.04-0.08 | 0.1-0.15 | 0.05-0.08 | 7000-9000 | PRP type3 | PD4 |

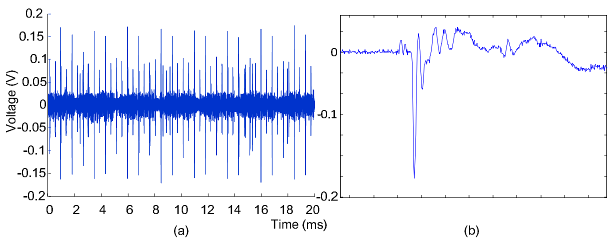



Figure 5 (a) Typical regular interference signal (b) Original pulse

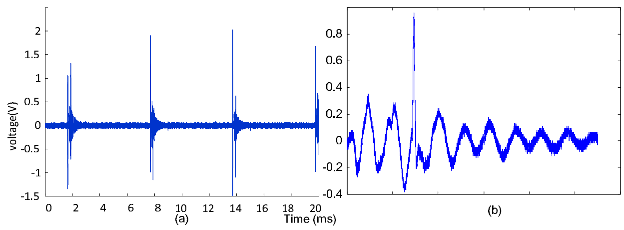



Figure 6 (a) Interference from power electronic device (b) Original pulse

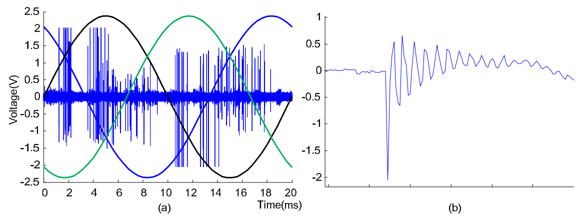



Figure 7 (a) PD from switchgear box (b) Original pulse

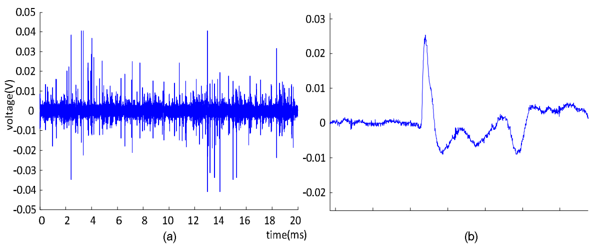
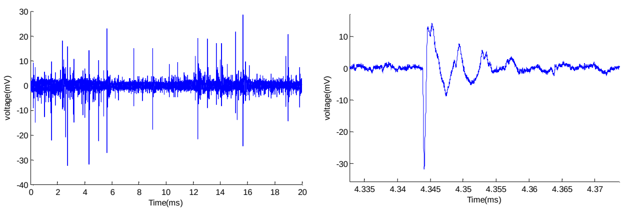



Figure 8 (a) PD from motor (b) Original pulse

## KNOWLEDGE RULES APPLICATION IN TWO OTHER POWER SYSTEMS

Based on the PD signal knowledge rules and interference signal knowledge rules identified, further on-site testing experiments were carried out on two other power systems. The results show that the established knowledge rules are effective for further interference signals rejection and PD signals identification. Two case studies are presented here.

Case 1: PD from motor
One set of on-site testing data is shown in Figure 9, the corresponding signal parameters are shown in Table 3. According to the PD knowledge rules, the signals are judged to be PD2, i.e. signals from motor. After PD localisation, the signals are confirmed as coming from far end of the cable which is connected to a motor.



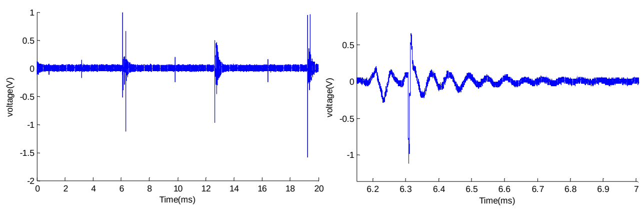

(a) (b)

Figure 9 (a) Raw data (b) Original pulse

Table 3 Parameters of the signal

| $t_r(\mu s)$ | $t_w(\mu s)$ | $V_{\max}(V)$ | $t_l(ms)$ | $N_r(/s)$ | $PRP$ | Decision |
|---|---|---|---|---|---|---|
| 0.23-0.25 | 0.52-0.6 | 0.015-0.035 | 0.15 | 2300 | PRP type5 | PD2 |

Case 2: Interference from power electronic devices
One set of on-site testing data is shown in Figure 10, the corresponding signal parameters are shown in Table 4. According to the interference signal knowledge rules, the signals are judged to be interference signal INT4.




(a) (b)

Figure 12 (a) Raw data (b) Original pulse

Table 4 Parameters of the signal

| $t_r(\mu s)$ | $t_w(\mu s)$ | $V_{\max}(V)$ | $t_l(ms)$ | $N_r(/s)$ | $PRP$ | Decision |
|---|---|---|---|---|---|---|
| 60-70 | 550-600 | 1.2 | 6.1 | 150 | PRP type2 | INT4 |

During the application, new cases of signal characteristics are found. Another 3 knowledge rules for interference signals and another 2 knowledge rules for PD signal are identified. The proposed method is also proved to be effective for PD identification from different sources when different PD knowledge rules are established.

## CONCLUSION AND FUTURE WORK

In summary, the following conclusions can be drawn on the knowledge based analysis system:

- Transfer of testing results into decision rules, which can be directly used for on-line monitoring systems or on-site testing systems, is possible;
- The system is effective for interference signal identification and rejection;
- The system is effective for PD signal interpretation;
- The system can describe PD signal from different sources.
- The system has self-study ability and will increase and be modified with the application.

Future work:

- Further testing experiments in HV lab is required to establish knowledge rules for other PD sources;
- PD characteristics and knowledge rules need to be established for different types of cables;
- Additional practical experience to improve PD knowledge rules and interference signal knowledge.

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