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Partial Discharge Detection and Recognition in Random Matrix Theory Paradigm

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ABSTRACT The detection and recognition of partial discharge (PD) is an important topic in insulation tests and diagnoses. Take advantage of the affluent results from random matrix theory (RMT), such as eigenvalue analysis, M-P law, the ring law, and so on, a novel methodology in RMT paradigm is proposed for fast PD pulse detection in this paper. Furthermore, a scheme of time series modeling as random matrix is also proposed to extend RMT for applications with non-Gaussian noise context. Based on that, the eigenvalue distribution property is used for PD pattern recognition, which is completely new compared with traditional phase resolved PD and time-resolved PD methods. The simulation and experimental results show that the proposed methods are efficient, reliable, and feasible for PD detection and recognition especially for online applications.

INDEX TERMS Partial discharges, detection algorithms, pattern recognition, random matrix theory, time series analysis.

I. INTRODUCTION

Even a minor insulation defect can be disastrous in electrical equipment operations. This may cause insulation failure of an entire equipment and result in large scale power system blackout, inflicting damages to the national economy [1]. Partial Discharge (PD) detection and pattern recognition is of great significance to insulation defects detection of power equipment.

One key challenge of PD signal detection and analysis is effective suppression of field noise interference including white Gaussian noises, frequency-modulated (FM) radio signals, and wireless communication signals [2]. Many works have been done about the de-noising techniques for a data window containing PD signals [3]–[5]. For reducing the computation burden and improving the effectiveness, there is a requirement of pre-processing tool to deliver sub-windows containing PD pulses [6].

Nowadays, the algorithm for separating PD sources are mainly based on phase resolved partial discharge (PRPD) pattern [7], time resolved partial discharge (TRPD) [8], [9], and time frequency (TF) analysis [10], [11]. Much researches have been done about PD recognition including neural network, wavelet transform, fractal theories, and the hidden Markov model [12]. Recently, new algorithms and recognition parameters for PD classification are proposed [13], [14] which enriched the existing solutions and ideas. However, there are some limitations with the existing recognition methods. In the DC power transmission system, there is no information on the phase due to the existence of DC equipment which means the PRPD methods are no longer useful in DC power system [15], [16]. Otherwise, periodical narrowband interference makes it very difficult to extract waveform characteristic of PD pulses. Therefore, the methods based on TRPD are not easy to perform. Moreover, TF methods are only suitable for suppression of narrowband periodical noises and have no effect on white noise distributed in the entire frequency domain.

Random matrix theory provides a series of methods for wireless channel estimation, neural networks, network capacity analysis, and cognitive radio networks [17]–[20] and recently has been applied for electrical equipment status evaluation and anomaly detection [21], [22]. In this paper we would like to propose a novel fast PD pulse detection algorithm based on RMT. A simulated PD signal seriously contaminated is used to verify the proposed method. In the meantime, this paper also proposes an approach to recognize PD pattern using the time domain signal along with random matrix spectrum distribution. The PD signals are generated by the high voltage laboratory measurement system and PD models. Based on the spectral analysis of the time domain PD signals, we define the eigenvalue distribution features of the matrix assembled by each type of discharge signals as the patterns recognition parameters. Based on these recognition features, the K-nearest neighbor (KNN), BP neural network and comprehensive decision strategy are used to verify the effectiveness of our proposed method for PD pattern recognition.

The remainder of this paper is organized as following: the mathematic formulas of RMT are introduced in section 2. Section 3 gives the PD data processing procedure used in this paper. Section 4 describes the proposed fast PD pulse detection method and corresponding case study. Then the PD pattern recognition method based on RMT is explained in section 5. Section 6 highlights the key findings of this paper and draws conclusions.

II. MATHEMATICAL FORMULA

A. MARCHENKO-PASTUR LAW (M-P LAW)

Let $X = \{x_{ij}\}_{1\leq i\leq N, 1\leq j\leq T}$ be a random $N \times T$ matrix whose entries with the mean $\mu\ (x) = 0$ and the variance $\sigma^2(x) < \infty$, are independent identically distributed (i.i.d.). N is an integer such that $N/T = c \in (0, 1]$. Then the ESD of the corresponding sample covariance matrix $S = 1/N(XX^H)$ converges to M-P law with distribution density function [23]:

$$f_{MP}(x) = \begin{cases} \dfrac{\sqrt{(b-x)(x-a)}}{2\pi x c \sigma^2}, & a \leq x \leq b \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where $a = \sigma^2(1-\sqrt{c})^2, b = \sigma^2(1+\sqrt{c})^2$.

M-P law gives the asymptotic behavior of singular values of large rectangular random matrices. More interesting thing is that when there is no signal in $\boldsymbol{X}$, the support of the eigenvalues of its covariance matrix $\boldsymbol{S}$ is finite, whatever the distribution of the noise. However, deviations from this theoretical limit in the eigenvalue distribution (as shown by the arrow in Fig. 1) should indicate non-noisy components such as information in the matrix $\boldsymbol{X}$ [24]. Our proposed PD detection algorithm was based on this feature.

B. THE RING LAW

Considering the matrix product $Z = \sum_{i=1}^{\alpha} \tilde{X}_i$, where $\tilde{X}_i \in \mathbb{C}^{N\times N}$ is the singular value equivalent [25] of rectangular $N \times T$ non-Hermitian random matrix X_i, whose entries are i.i.d. variables with the mean $\mu\ (x) = 0$ and the variance $\sigma^2(x) = 1$. The empirical eigenvalue distribution of $\boldsymbol{Z}$ converges almost surely to limit given by [23]:

$$f_Z\,(z) = \begin{cases} \dfrac{1}{\pi x \alpha} |z|^{\frac{2}{\alpha}-2}, & (1-c)^{\frac{\alpha}{2}} \leq |z| \leq 1 \\ 0, & \textit{elsewhere} \end{cases} \tag{2}$$

as $N, T \rightarrow \infty$ with the ratio $N/T = c \in (0, 1]$. On the complex plane of the eigenvalues, the inner circle radius is $(1-c)^{\alpha/2}$ and outer circle radius is unity. And the singular value equivalent matrix $\tilde{X}$ is calculated by:

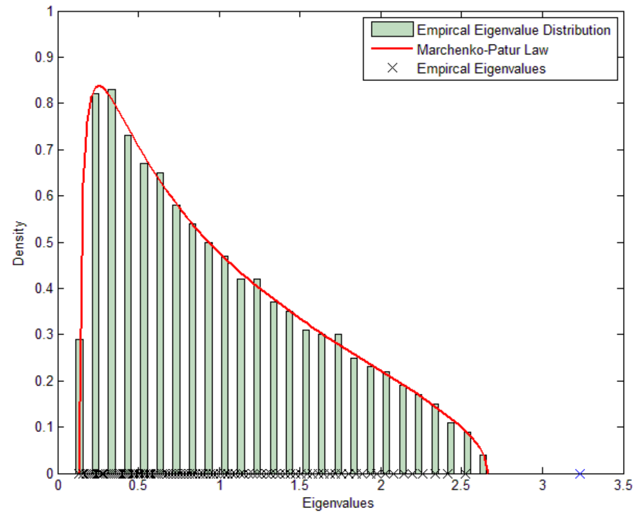

FIGURE 1. Empirical eigenvalues distribution of a 250 × 1000 random matrix in case of a signal present.

$$\tilde{X} = \sqrt{XX^H}\,U \tag{3}$$

where $U \in \mathbb{C}^{N\times N}$ is a Haar Unitary matrix.

The Ring Law extends the RMT to large non-Hermitian random matrices and is one of the most remarkable developments in the modern probability. Moreover, this product $\boldsymbol{Z}$ allows us to study the streaming datasets generated as a function of both space and time as presented in [21] and [22]. The eigenvalue distribution of matrix produce $\boldsymbol{Z}$ would be used as the PD pattern recognition feature in this paper.

C. M-P TYPE THEOREM OF TIME SERIES

A significant difficulty in the application of RMT in solving power system problems is that the ambient noise may be absent of white Gaussian. The observations of signal may not be independent, even they may be correlated in space or time so may not be white Gaussian. Some researchers have tried to extend the M-P type theorem to time series observations instead of a pure Gaussian constraint for a more general situation [26], [27].

Let $\{y_t : t = 0, \pm 1, \ldots\}$ be a sequence of a real random variables and $\{\varepsilon_t : t = 0, \pm 1, \ldots\}$ be a sequence of white noise with mean 0 and variance σ^2. Considering a stationary and invertible ARMA(p,q) modeling time series [28]:

$$\phi(B)y_t = \theta(B)\varepsilon_t \tag{4}$$

where $\phi\ (B) = 1 - \phi_1 B - \ldots - \phi_p B^p$ and $\theta\ (B) = 1 - \theta_1 B + \ldots + \theta_p B^p$ are real polynomials in B which is a backshift operator $B^j y_t = y_{t-j}, j = 0, 1, \ldots$.

Let y $= (y_1, y_1, \ldots y_T)$. Assuming $X_1 = (X_{11}, X_{21}, \ldots X_{T1}), \ldots, X_N = (X_{1N}, X_{2N}, \ldots X_{TN})$ are N independent copies of y, then we can write:

$$X = \begin{pmatrix} X_{11} & X_{21} & \cdots & X_{T1} \\ X_{12} & X_{22} & \cdots & X_{T2} \\ \vdots & \vdots & \cdots & \vdots \\ X_{1N} & X_{2N} & \cdots & X_{TN} \end{pmatrix}_{N\times T} = (X_1, X_2, \ldots, X_{\mathrm{N}})' \tag{5}$$

We assume that $c = T/N \in (0, \infty)$, then the ESD of $S = 1/N(XX^H)$ tends to a non-random probability distribution F. Moreover, the Stieltjes transform $s = s_F(z)$ of $\boldsymbol{F}$ satisfies the equation [26]:

$$z = -\frac{1}{s} + \frac{1}{2\pi}\int_0^{2\pi} \frac{1}{cs + \{2\pi f(\lambda)\}^{-1}} d\lambda \tag{6}$$

where $s_F(z) = \int \frac{1}{x-z} F(dx)$, $z \in \mathbb{C}^+$, and $f(\lambda)$ is the spectral density of the ARMA(p,q) process:

$$f(\lambda) = \frac{\sigma^2}{2\pi}\left|\frac{\theta\left(e^{-i\lambda}\right)}{\phi\left(e^{-i\lambda}\right)}\right|^2, \quad \lambda \in [0, 2\pi)$$

Equation (6) gives an implicit solution which could be solved explicitly in some special cases that have been considered in [26]. Furthermore, a numerical solution could be applied to get the solution [29].

The M-P type theorem of time series extends RMT from pure Gaussian noise to non-Gaussian context which greatly improves its application in power systems. As described before the PD signals always polluted by not only Gaussian noise but also pulse and fix-frequency interference. Therefore, the M-P type theorem is more suitable for PD analysis. From this theorem we know that there is a definite asymptotically convergent empirical spectrum distribution of a time series which could be used as the PD recognition pattern parameters in this paper.

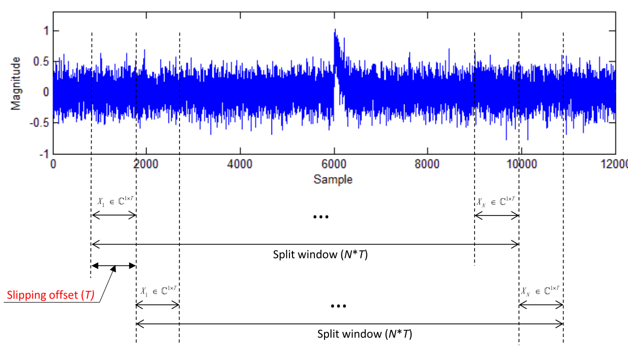

FIGURE 2. A real-time data processing framework.

III. PD DATA PROCESSING

Given a continuous sampling vector x, we can assemble it as a matrix by chronological order. As shown in Fig.2, the PD signal is continuously sampled and a split window truncates the measured data to form a raw matrix $X \in \mathbb{C}^{N\times T}$ for further analysis. It is worthy to denote that the split-window length for assembling the matrix $\boldsymbol{X}$ is $N \times T$ and T is also defined as the slipping offset for continuous real-time processing. Then, T becomes a control parameter to determine the matrix size ($N \times T$, and $N/T = c$, where $0 < c < 1$) of $\boldsymbol{X}$ which decides the computation speed. Therefore, the parameters T could be adjusted according to the real-time processing requirement.

To keep in accordance with the M-P law, etc. the normalized non-Hermitian matrix $\overline{X} \in \mathbb{C}^{N\times T}$ is obtained by:

$$\overline{X}_{i,j} = \frac{X_{i,j} - MEAN(X_i)}{stdDEV(X_i)} \tag{7}$$

where $MEAN(X_i)$ denotes the average of vector X_i and $stdDEV(X_i)$ means the standard deviation of vector X_i.

It should be note that in this paper we set L equal to 1 for simplicity and the PD signal data analyzed later will be processed according to this procedure.

IV. FAST PULSE DETECTION

Inspired by the signal detection through RMT presented in Fig. 1, we proposed a maximum eigenvalue observation method for fast PD pulse detection.

Here the double exponential decay oscillation function is used to simulate PD signals of power equipment [30] for our analysis:

$$f(t) = A(e^{-\tau_1(t-t_d)} - e^{-\tau_2(t-t_d)})\sin(2\pi f_c t) \tag{8}$$

where A is the amplitude, τ_1 and τ_2 are the attenuation coefficient, f_c is the center oscillation frequency, t_d represents the starting moment of the PD pulse. Fig.3 (a) gives the simulated PD pulse whose A is 0.7 V, τ_1 and τ_2 are 2 us and 0.2 us respectively, t_d is 6000 us and the sample rate (f_c) is 1 MHz. The SNR of Gaussian noise superimposed is -10 dB. Besides, two sinusoidal signals whose amplitudes are 0.2 V, 0.6 V and frequencies are 0.1 MHz, 1.5 MHz are added to simulate narrow-band interference. Fig.3 (b) shows the contaminated signal. The data length in Fig.3 (b) is 12000 points would be as the raw data set for verification of our proposed algorithm.

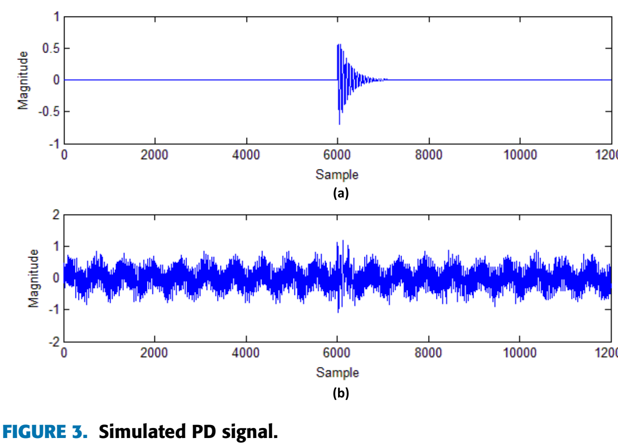

FIGURE 3. Simulated PD signal.

The proposed fast PD detection procedure based on maximum eigenvalue observation is depicted as Algorithm 1.

Algorithm 1 Steps of PD Pattern Recognition Features Extraction

1) Obtain the matrix $\boldsymbol{X}$ by equation (5)
2) Convert matrix $\boldsymbol{X}$ to standard non-Hermitian matrix $\overline{X}$ by equation (7)
3) Obtain corresponding sample covariance matrix $\boldsymbol{S}$
4) Get the singular value equivalent matrix $\widetilde{X}$ of $\overline{X}$ by Eq. (3) and Haar Unitary matrix
5) Obtain the matrix product $\boldsymbol{Z}$
6) Calculate the eigenvalues of matrix $\boldsymbol{Z}$ and $\boldsymbol{S}$

As addressed before, we have 12000 points simulated signal for analysis. We choose 100 as the sliding offset length T and 4000 as the split window length. The assembled matrix would be 40×100 and denoted as $\boldsymbol{X}$. The M-P law ESD of its corresponding covariance matrix $S = 1/40(XX^H)$ could be obtain by equation (1).

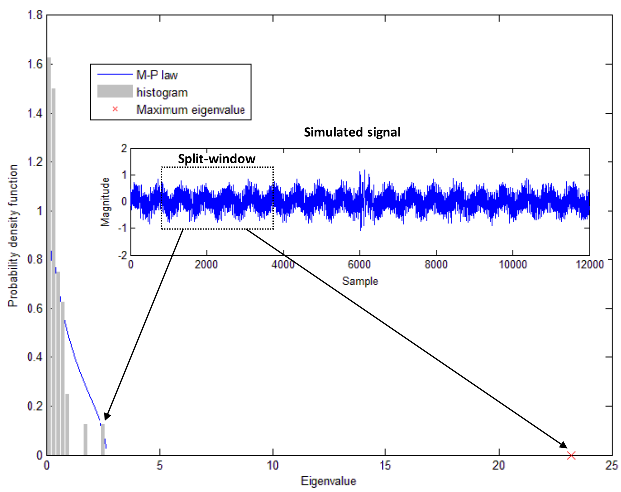

FIGURE 4. Comparison between the M-P law and eigenvalue distribution of simulated PD signal (without PD pulse).

Fig. 4 gives the eigenvalue distribution (histogram) of $\boldsymbol{X}$ generated by the split window as shown in the subgraph where without PD pulse. We can observe that the eigenvalue distribution of matrix $\boldsymbol{S}$ follows the M-P law (blue curve) in principle except for the maximum eigenvalue in Fig. 4. It's reasonable because the waveform in the split window contains two sinusoidal signals which means not pure Gaussian noise.

When we slide the split window gradually to the right with split window length N as 4000 and offset T as 100, the PD pulse is approaching. The maximum eigenvalues observation procedure is performed and the results are shown in Fig. 5. From Fig. 5 we can see that there is a synchronous emergence of maximum eigenvalue (red dots in black box) and the PD pulse: the PD pulse appears at 6000 point and the maximum eigenvalue disturbance appears at about 22 offset units which means the split window at this moment contains the points from 2200 ($T \times 22$) to 6200 ($T \times 22 + N$). Therefore, we can

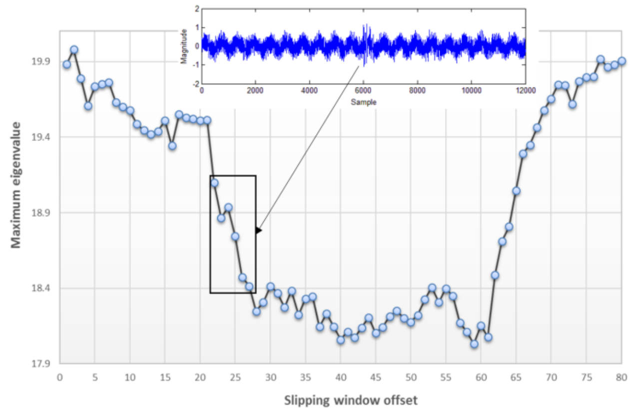

FIGURE 5. The maximum eigenvalue evolution according to the sliding split window for PD pulse detection.

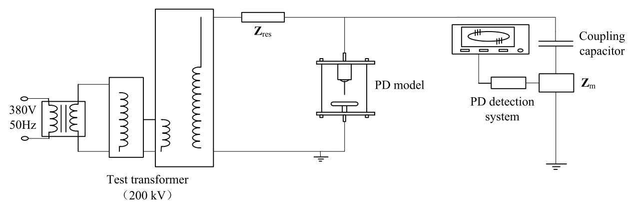

FIGURE 6. PD measurement system in laboratory.

be aware of the PD pulse under non-Gaussian (Gaussian noise plus fix-frequency interference) noise instantly with the evolution of the maximum eigenvalue of matrix $\boldsymbol{S}$.

Some significant advantages of our proposed method can be summarized as: firstly, the algorithm is robust for complex noise and low SNR environment PD signals processing. Secondly, the proposed method is straight to be understood and the computation burden is reduced under manageable value (in this case, only the eigenvalue calculation of a 40×100 matrix is needed).

V. PD PATTERN RECOGNITION

A. LABORATORY MEASUREMENT SETUP

The high voltage laboratory measurement system is setup and shown in Fig. 6 which includes a PD free 380V/200kV high-voltage transformer, a protection resistor $\boldsymbol{Z}_{res}$, the PD models, a coupling capacitor installed in parallel with the HV side of the transformer, a detection impedance $\boldsymbol{Z}_m$ and the PD detection system based on pulse current method.

Four typical PD models are designed and established in this paper. The corona discharge is measured by needle-plane electrodes in air as shown in Fig. 7 (a). The radius of the plane and needle are 40 mm and 0.25 mm. The metal particle model is shown in Fig. 7 (b). the radius of the copper ball, high voltage electrode and ground electrode are 1 mm, 30 mm and 30 mm respectively. The HV surface discharge model is shown in Fig. 7 (c). The medium is epoxy resin pillar whose height is 20 mm and radius is 15 mm. The radius of high voltage electrode is 10 mm. the floating potential discharge model is illustrated in Fig. 7 (d) where the radius of high

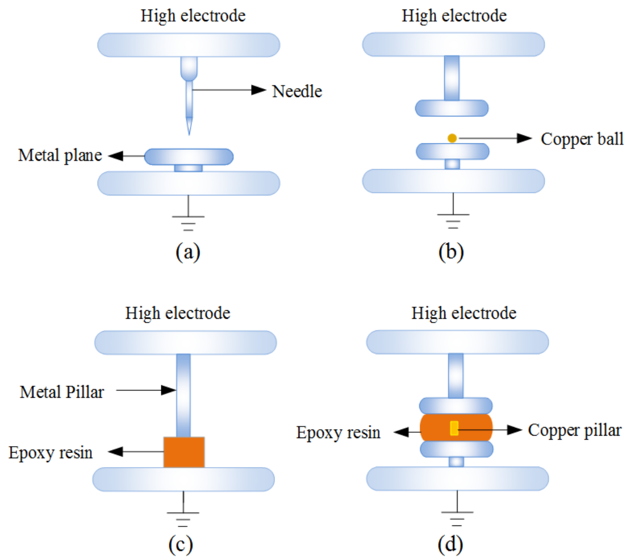

FIGURE 7. PD models: (a) needle plane, (b) metal particle, (c) HV surface, (d) floating potential.

voltage electrode, ground electrode and resin are 30 mm. The height of resin pillar is 20 mm. The height and radius of copper pillar are 10 mm and 1 mm respectively.

PD amplitude series extracted from the experiment of four models are shown in Fig. 8. The sampling rate is 5M/s, and corresponding data points is 600000.

B. FEATURES FOR PD PATTERN RECOGNITION

We would apply RMT to PD pattern recognition based on the PD time series illustrated in Fig. 8. By doing this, we can construct a 600×1000 (total 600000 points) random matrix $\boldsymbol{X}$. Then we calculated the corresponding sample covariance matrix by $S = 1/600(XX^H)$ and matrix product $\boldsymbol{Z}$ according to the procedure as Algorithm 2.

Algorithm 2 Steps of maximum eigenvalue observation

1) Obtain the matrix $\boldsymbol{X}$ according to the method proposed in section 3 by the chosen offset length T and split window length $N \times T$
2) Convert matrix $\boldsymbol{X}$ to standard non-Hermitian matrix $\overline{X}$ by equation (7)
3) Obtain corresponding sample covariance matrix $\boldsymbol{S}$
4) Calculate the eigenvalues of $\boldsymbol{S}$
5) Sort the eigenvalues by descending order to get the maximum eigenvalue
6) Shift the split window by offset T to generate next matrix and then go to step 1 until to the end of raw data set

It is theoretically proven that the empirical spectrum distribution of matrix $\boldsymbol{S}$ follows a M-P type theorem. On the other side, the eigenvalues of $\boldsymbol{Z}$ would exhibit a circular distribution. Therefore, in this paper we consider the empirical spectrum distribution of $\boldsymbol{S}$ and the eigenvalue distribution of $\boldsymbol{Z}$ as PD pattern recognition features.

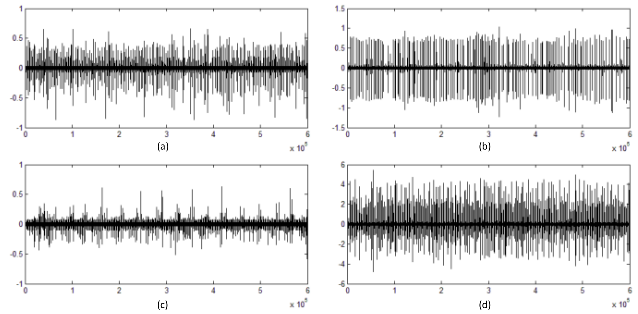

FIGURE 8. PD time series by laboratory measurement: (a) needle plane, (b) metal particle, (c) HV surface, (d) floating potential.

For further explanation of these two features, we collected 10 sets of PD time series of each PD model shown in Fig. 7. The random matrix $\boldsymbol{X}$, covariance matrix $\boldsymbol{S}$ and product $\boldsymbol{Z}$ are calculated as the training inputs of recognition algorithm.

1) SPECTRAL DISTRIBUTION OF COVARIANCE MATRIX *S*

The eigenvalues of 40 matrices $\boldsymbol{S}$ (600×600) are calculated and sorted by ascending order to generate its spectral distribution and shown in Fig. 9. There are four types of PD signal and 10 sets data for each type. Therefore, totally 40 curves are reported in Fig. 9. Because the eigenvalues in the field 550-600 are too large to be shown together with another 550 eigenvalues, the last 50 eigenvalues are shown in the subgraph of Fig. 9.

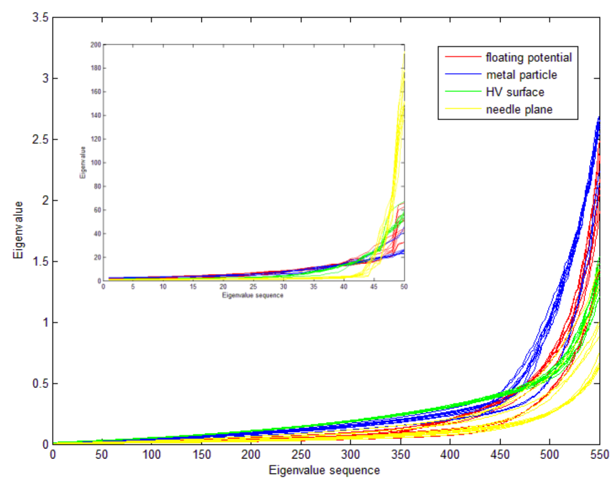

FIGURE 9. Spectral distribution of matrix *S* of each type of PD signal.

From Fig. 9, it can be observed that although there are some intersects among each curve, a clustering for each type of PD is obvious which make the spectral distribution of $\boldsymbol{S}$ as the PD pattern reorganization features feasible.

2) EIGENVALUE DISTRIBUTION OF MATRIX PRODUCT *Z*

Fig. 10 gives the eigenvalue distribution of product matrix $\boldsymbol{Z}$ generated by a set of four type PD signals. It's clearly noticed that the eigenvalues follow a circular ring distribution.

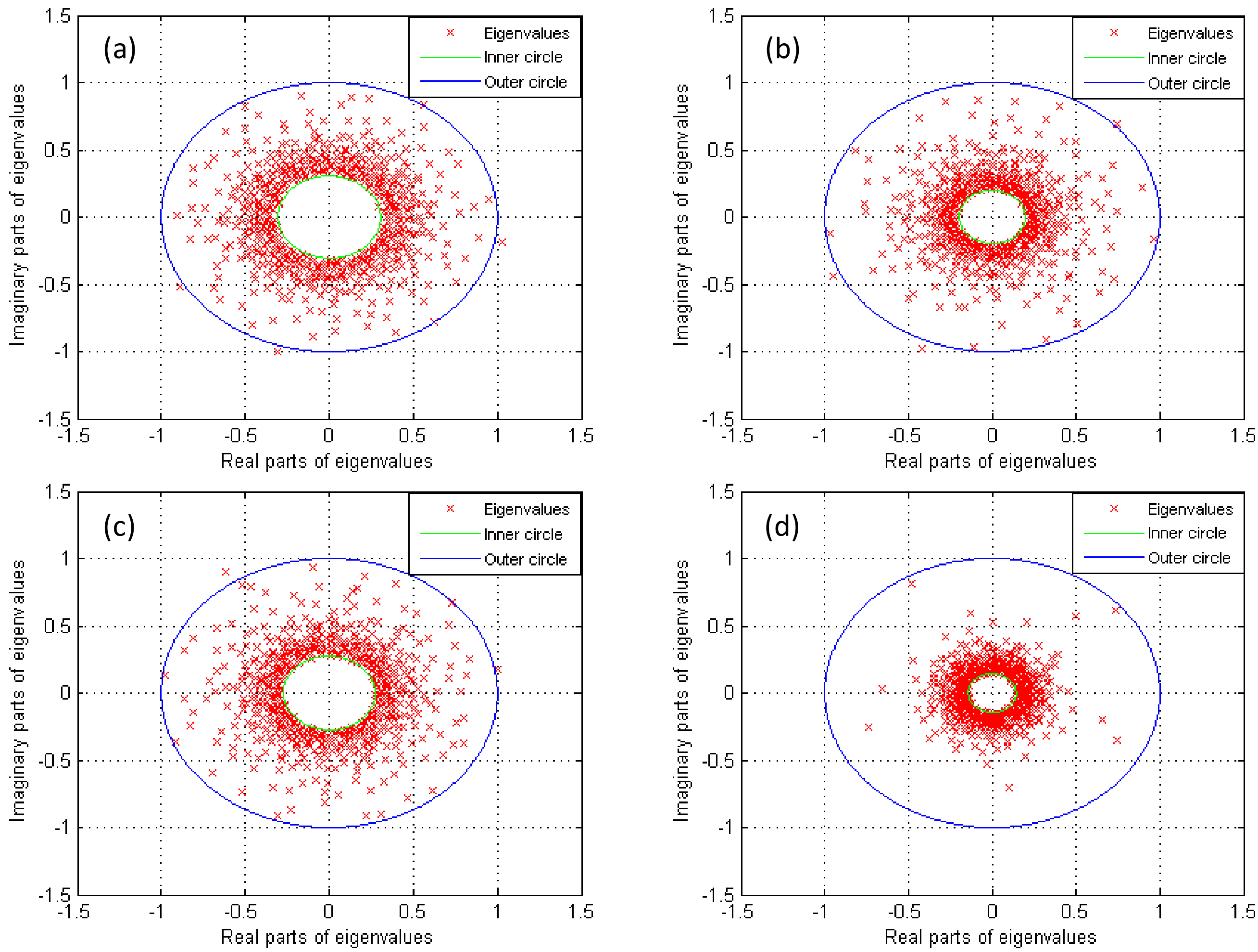

FIGURE 10. **Eigenvalues distribution of product matrix *Z* generated by the PD series: (a) needle plane, (b) metal particle, (c) HV surface, (d) floating potential.**

The sparseness and the inner radius of eigenvalues distribution for each type of PD series varies uniquely. Therefore, we also take the eigenvalues of $\mathbf{Z}$ into consideration as the PD reorganization features which could also be quantified by the mean spectral radius (MSR) [22]:

$$k_{MSR} = \frac{1}{N}\sum_{i=1}^{N}\left|\lambda_{Z,i}\right| \tag{9}$$

where $\lambda_{Z,i}$ is the eigenvalues of matrix $\mathbf{Z}$, $\left|\lambda_{Z,i}\right|$ denotes the radius of λ_Z in the complex plane.

C. PD PATTERN RECOGNITION ALGORITHM

This paper proposed a BP neural network based spectral distribution recognition method and a KNN based MSR recognition method respectively.

1) RECOGNITION METHOD BASED ON THE BP NEURAL NETWORK AND SPECTRAL DISTRIBUTION OF MATRIX *S*

The BP neural network supports linear inseparability highly tolerant to errors which make it suitable and widely used for PD pattern recognition [12]. In the practical application, the transmission function of the hidden layer is "*tansig*", the output layer is "*purelin*", and the LM algorithm is used as the training function.

From Fig. 9 we also observed that the clustering effect is most obvious during 451-550 region. Thus the inputs of BP neural network are the 100 eigenvalues from 451 to 550. The outputs are the type of PD pattern = {needle plane, metal particle, HV surface, floating potential}.

2) RECOGNITION METHODS BASED ON KNN AND MSR

KNN is a simple machine learning algorithm [31], [32]. For a given set of training samples and a new input, KNN finds the K nearest samples to this new input, and allocates this new input to the class where most of the K samples belong. The choice of K, distance measurement, and the classification of decision criterion constitutes the three elements of this algorithm. Euclidean distance is used as the measure of distance in this paper. That is, for the circular ring spectral distribution of the 10 wave-forms across the two types of signals, the Euclidean distance of MSR is:

$$d(k_{MSR1}, k_{MSR2}) = \sqrt{\sum_{i=1}^{N} (k_{MSR1i}, k_{MSR2i})^2} \tag{10}$$

The classification decision criterion in this paper is as follows. For the MSR of the newly input waveform, we choose the K MSRs nearest to it from the spectral distribution of each type of PD signals. Then, we allocate the new waveform to the class where the K ones belong. The experimental results in this paper show that the optimal value for K is 3.

3) COMPREHENSIVE DECISION

The recognition algorithm aforementioned relies only on one feature which make it unreliable and lead to misclassification. Therefore, to improve the recognition accuracy this paper would uses two features to make a comprehensive decision.

Let P(A|BP), P(B|BP), P(C|BP), P(D|BP) denote the recognition rate of the BP method, while P(A|KNN), P(B|KNN), P(C|KNN), P(D|KNN) denote the recognition rate of KNN method for four types of PD respectively where A is needle plan, B is metal particle, C is HV surface and D is floating potential. The criterion for comprehensive decision is that if the two algorithms allocate an unknown PD signal to the same type, then the signal belongs to this type of PD. Otherwise, the signal belongs to the type allocated by the method whose recognition rate is higher.

For example, assuming KNN allocates an unknown signal to type A and the BP allocates it to type B. If P(B|BP)>P(A|KNN), then the signal belongs to type B.

4) RECOGNITION RESULTS AND DISCUSSION

We collected another 50 discharge waveforms for each type of PD model to construct the high-dimensional random matrix for PD pattern recognition verification. The extracted features as presented before were input to the trained KNN and BP neural network to get the classification results and corresponding recognition rates are reported in TABLE I. According to the recognition rates of BP and KNN methods, the comprehensive decision is performed and also reported in the "Comp." columns of TABLE I.

TABLE 1. The result of PD recognition.

PD	Correct/Undetermined/Fault			Recognition Rate (%)		
Type	BP	KNN	Comp.	BP	KNN	Comp.
A	41/3/6	44/3/3	47/0/3	82	88	94
B	43/5/2	44/2/4	48/1/1	86	88	96
C	42/3/5	43/4/3	47/1/2	84	86	94
D	40/4/6	43/5/2	45/0/5	80	86	90
Avg.	-	-	-	83	87	93.5

A: needle plan; B: metal particle; C: HV surface; D: floating potential

The results in TABLE I show that the proposed methods can both achieve an average accuracy of 83% for the four classes of discharge signals. Comparatively, the KNN algorithm together with the eigenvalue distribution of matrix

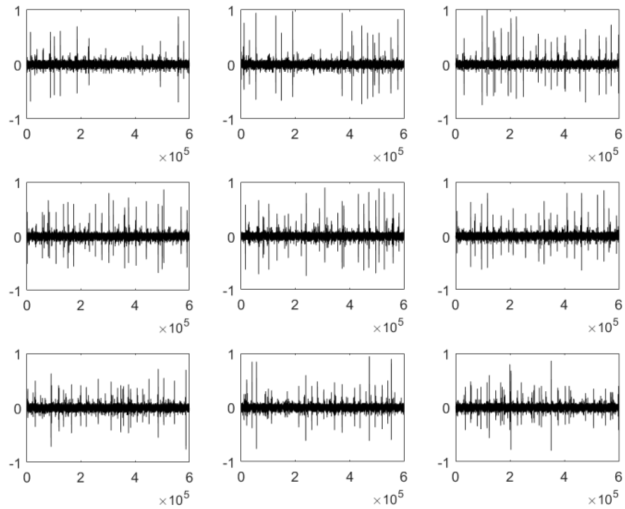

FIGURE 11. PD time series sampled by HV surface model.

product **Z** is more effective at an average accuracy of 87%. Improved by comprehensive decision strategy, the average recognition rate could approach up to 93.5%. In short, two pattern recognition methods to verify the PD recognition features based on the eigenvalues distribution from RMT are used in this section. The results proved the effectiveness of our proposed algorithm.

It's worthy to denoted that the advantages of our proposed methods: firstly, the algorithm is very easy to perform, only two matrix needed to be assemble and corresponding eigenvalues need to be calculated. Secondly, it is observed that the PD signals vary greatly according to different triggering time. This can be seen in Fig. 11 from the 9 waveforms of the HV surface discharges. However, the proposed method can still find the clustering feature of the eigenvalue generated by these waveforms clearly, as is shown by the green curves in Fig. 9. It demonstrates the remarkable robustness and anti-interference performance of the proposed algorithm which make it more suitable for practical applications.

VI. CONCLUSIONS

From the analysis above, we can see that RMT based data modelling together with the related theoretical deductions and conclusions can provide an effective analysis method for partial discharge. With the results of the applications, we can conclude that with M-P type theorem of time series, the RMT based data models can also be used for unknown noise patterns, and thus be more applicable for PD signal processing, which are always conducted with field test data, containing complex environment noise.

To conclude, this paper introduced the modern statistic mathematic tool of random matrix theory into partial discharge detection and pattern recognition analysis.

Firstly, key theoretical findings based on RMT are described. The most important contribution is a M-P type theorem of time series which extends the RMT to non-Gaussian noise environment and more suitable for PD signals.

Secondly, a novel maximum eigenvalue observation method is proposed for fast PD pulse detection. The simulation results revealed that the proposed algorithm is capable of locating the PD pulse through the slipping data window with high robustness and calculation speed.

Thirdly, we defined the eigenvalue distribution property of high-dimensional random matrix constructed by the PD signal as time series for the pattern recognition features. Compared with the traditional methods, the proposed method adopts a different analysis strategy which is robust to environmental variations in both time and frequency domain, and is efficient, reliable and feasible in the practical applications.

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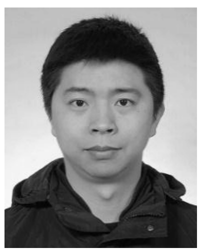

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