Electric Signature Detection and Analysis for Power Equipment Failure Monitoring in Smart Grid

Shunfan He, Yan Zhang Fellow, IEEE, Rongbo Zhu, Member, IEEE, and Wei Tian

Abstract—Power equipment is one kind of basic element in smart grid, and how to design an efficient detection and analysis scheme of electric signature (ES) for power equipment failure (PEF) monitoring is a key and challenge issue. This paper proposes an ES detection and analysis method which can monitor multi-kinds of PEF in smart substation. The bottleneck of ES analysis is explored in the view of Heisenberg uncertainty, and an optimal time-frequency analysis method is designed to solve the problems. The proposed method (PM) is based on union of time and frequency bases whose decomposition is realized by Bayesian compressive sensing using Laplace prior. Simulated and field ESs are employed to test PM with comparisons of existing methods. Also, PM is applied in a smart substation of China. Several typical PEFs and measurement soft failures caused by electromagnetic interference are discussed. The results indicate that the PM can accurately monitor PEFs whose mechanism can be revealed by time-frequency features of ESs, if the required sampling rate and sampling time are satisfied because of its immunity of the uncertainty principle restriction. The robustness in noise environment and optimal time-frequency representation of ESs make the PM an efficient general-purpose power equipment failure monitoring in smart grid by time-frequency analysis.

Index Terms—Failure monitoring, Heisenberg uncertainty, power equipment, smart grid, time-frequency analysis.

I. INTRODUCTION

S MART grid is now the foundation for a modern society, and its reliability is very important. It is reported that nearly half of power outages result from power equipment failures (PEFs) [1]. Power equipment such as cable, power line, transformer and capacitor bank are pillars of power systems, and the reliability of smart grid cannot be without PEF monitoring. Recently, nonintrusive PEF monitoring is developed to avoid high monitoring instrument cost and power interruption required by traditional PEF monitoring, which relies on advanced signal processing technology for analysis of electric disturbances caused by PEFs. These disturbances are called as electric signatures (ESs) of PEFs.

The ES has diverse time scale, some of which can only be identified from the waveforms (short-time scale) while some of which are more visible from a longer-time scale such as root mean square (RMS) value variations in minutes. The waveform type, disturbance related data contain unique information about the behavior and characteristics of power system and equipment involved [2]. Hence, many effective target shooting methods (TSMs) use waveform ESs to monitor various PEFs. Nonintrusive inductive coupling method that integrates with spread spectrum time domain reflectometry for cable diagnosis is proposed in [3]. Incipient underground cable fault location algorithm based on arc voltage and current analysis is proposed in [4], [5]. The ES is also used to diagnose the fault of capacitor banks [6]. Compressive sensing and morphology singular entropy method is designed to deal with distorted voltage signals for faults discovery [7]. Neutral current is used for interturn fault detection of transformers [8]. Disturbed current signals are used for fault classification in transmission lines [9].

High frequency transient power disturbances are used for vacuum interrupters [10]. The TSMs prove many kinds of PEFs can be viewed from waveform ESs, however, general-purpose condition monitoring method is still urged in [2]. One possible reason is that not every power equipment can have its own waveform sensors in the grid. In many cases, the disturbed waveforms which can reflect mechanism of various equipment failure are sensed in a hub or center such as power substation. Another reason is that there are still PEFs not well understood and a general study method can help the development of TSMs. The schemes of nonintrusive PEF monitoring in smart substation and general-purpose power equipment condition monitoring method are presented in Fig. 1(a) and Fig. 1(b) respectively.

In Fig. 1(a), smart substation can get electric waveforms of all feeders and has strong information processing capability, which makes the substations probably the most feasible location for nonintrusive PEF monitoring [2], [11]. However, there are multi-kinds of power equipment connected with smart substations whose waveform ESs are totally different from each other. The efficiency of monitoring will be very low if only TSMs are used, because many TSMs should work simultaneously to monitor all possible PEFs. While the general-purpose method (GPM) can detect and analyze the waveform ESs of various PEFs, then give analytic results of the PEF on grid, which is of high efficiency in this situation. The representation of ES feature is one of the main challenges for...
GPMs. Only when the representation can reflect the PEF mechanism clearly, the PEF characterization will be accurate. Noise and resolution are two important factors controlling the representation of ES feature, which will be explained by taking Fig. 1(b) for the instance.

The strong computation capability and massive power equipment connection of smart substation provide an opportunity to develop an efficient and effective power equipment failure monitoring in general-purpose. Optimal representation of ES features is the foundation of general-purpose PEF monitoring. Union of bases (UB) decomposition can provide optimal signal representation in different bases with respect to Heisenberg uncertainty [19]. And the main contributions of this paper are:

1) To solve the bottle neck of waveform ES, lack of resolution, a UB method is proposed. And a real UB is designed to provide representation of each power disturbance of the ES with optimal resolution in time-frequency domain. Then faithful representation and accurate analysis of waveform ES are acquired with respect to Heisenberg uncertainty.

2) Bayesian compressive sensing (BCS) using Laplace prior is employed for a fast and robust UB decomposition in noise varying environment, which guarantees a reliable power disturbance detection for the trigger of waveform ES analysis.

Electrical waveforms are the most granular data [2], and the long-time scale ESs are derived from electrical waveforms analysis. Hence, this paper focuses on waveform ES detection and analysis for PEFs monitoring. In the following parts, ES is used for brief description of waveform ES. The remainder is organized as follows: Section II describes the new ES detection and analysis method based on optimal time-frequency analysis, Section III validates the noise tolerance capability and analysis accuracy of ES by simulations, Section IV tests the proposed method with field ESs in real applications, Section V discusses the generality and application of the method and Section VI summarizes the whole work.

II. THE PROPOSED METHOD

In this Section, the electric signature modeling is presented, the effect of Heisenberg uncertainty on GPMs is discussed, and then a union of time and Hartley bases is designed for the optimal time-frequency representation of ESs. Then the application conditions of the proposed method (PM) is presented. The highlighted contribution of the new method is the idea to solve bottle neck problem, unfaithful representation of waveform electric signature analysis in time-frequency by union of time and frequency bases decomposition.

A. Electric Signature Modeling

The mechanism of PEF decides what kind of ES is. In turn, by faithful representation and accurate analysis of ES, the mechanism can be known, and the kind of PEF will be identified. ES is a distorted electric waveform which contains different power disturbances. Different PEFs which have different failure mechanisms result in the power disturbance waveforms with different time-frequency features. To reflect the features of ES in both time and frequency, it should be taken into consideration of transient disturbances (such as impulse, oscillation), steady disturbances (such as harmonic and interharmonics) and short duration disturbances (such as sag, swell and interruption). To our best knowledge, many ESs contain one or multiple of these disturbances. In Table I, the


Disturbances are modeled by three basic signal components: $\delta(t)$, $\cos(\omega t)$ and $e^{-\alpha t}$, where $\delta(t) = \int_0^\infty \delta(t) \, dt$, $\omega$ is the angular frequency, $\alpha$ is the amplitude and $d$ is the damping factor.

### TABLE I 

<table>
<thead>
<tr>
<th>Disturbances type</th>
<th>Disturbances model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impulsive transient: (D1)</td>
<td>$a[\delta(t-t_{start}) + \exp(-(t-t_{start})/d)]$</td>
</tr>
<tr>
<td>Oscillatory transient: (D2)</td>
<td>$a[\delta(t-t_{start})+\exp(-(t-t_{start})/d)\cos(\omega(t-t_{start}))]$</td>
</tr>
<tr>
<td>Short duration: (D3)</td>
<td>$a[\delta(t-t_{start})-\delta(t-t_{end})]\cos(\omega t)$</td>
</tr>
<tr>
<td>Steady: (D4)</td>
<td>$\sum a_i \cos(\omega_i t)$, $i=1,2,3,\ldots$</td>
</tr>
</tbody>
</table>

The ES signal model can be expressed as:

$$ES = D1 + D2 + D3 + D4 + \text{noise}.$$  

(1)

### B. Influence of Uncertainty Principle on Electric Signature Representation and Analysis

There are many kinds of power equipment and each of them may have several kinds of failures. Many of the failures generate ESs as Eq. (1) describes. The time-frequency features of ESs are most concerned to reveal the corresponding PEFs. Hence, the bottle neck problem of ES representation and analysis in time-frequency should be explained first.

Denote $u_I$ and $u_F$ are time uncertainty and frequency uncertainty respectively. When an analog signal is sampled and processed in digital form, smaller uncertainty brings more accurate and faithful representation of the signal waveform, which is essential for ES analysis. The smallest time uncertainty is time resolution and the smallest frequency uncertainty is frequency resolution. Then we have:

$$\text{Minimum}(u_I) = 1/F_s, \quad \text{Minimum}(u_F) = 1/T_s$$  

(2)

where $F_s$ is sampling rate and $T_s$ is sampling time. According to Heisenberg uncertainty, if the ES is represented in one basis, then [20]

$$u_I \times u_F \geq 1/4\pi,$$  

(3)

which means no matter how to increase $F_s$ and $T_s$, the $u_I$ and $u_F$ cannot be minimized simultaneously. The bottle neck problem is, consequently, the ES representation cannot be faithful and the analysis cannot be accurate, if which domain (time or frequency) the features of ES belongs to is unknown or time features and frequency features of the ES are both important (arc voltage for example).

### C. Union of Bases Design for Faithful Representation of Electric Signatures of Power Equipment Failure in Time-frequency

Faithful representation of ES in time-frequency is the premise of accurate ES analysis in time-frequency.

Time domain gives faithful representation for transient disturbances and frequency domain gives faithful representation for steady disturbances representation. To minimize time uncertainty and frequency uncertainty simultaneously for the faithful time-frequency representation of power disturbances, one practical way is to represent transient power disturbance in time domain or basis only, and to represent steady power disturbance in frequency domain or basis only. Hence, PM represents the ES in the union of time and frequency bases. Define $I$ is the identity matrix and $F$ is the Fourier matrix, the union of $I$ and $F$, $[I, F]$, can be used for faithful representation of ES in time-frequency. However, $F$ is a complex matrix which raises the computation cost of the method in real applications.

Hartley transform is a real transform for periodical signal analysis and has close relationship with Fourier transform [20]. The discrete Hartley transform is:

$$Y_h(k) = \sum_{i=0}^{N-1} y(i) \cos(\frac{2\pi k i}{N}), \quad k = 0, 1, \ldots, N-1$$  

(4)

where $\cos(\frac{2\pi k i}{N}) = \cos(\frac{2\pi k i}{N}) + \sin(\frac{2\pi k i}{N})$. Define $Y_F(k)$ as the Fourier transform of $y$, and

$$Y_F = Y_h + Y_{he}$$  

(5)

where $Y_{he}$ and $Y_{he}$ are the odd part and even part of $Y_h(k)$ respectively, then the relation of Hartley transform and Fourier transform can be described as:

$$\begin{align*}
Y_F &= \text{Re}(Y_F) - \text{Im}(Y_F) \\
Y_F &= Y_{he} - jY_{he}
\end{align*}$$  

(6)

where $\text{Re}()$ and $\text{Im}()$ return the real and imaginary part of “.” respectively and $j$ is the imaginary unit.

Then Hartley basis can be derived from Hartley transform as:

$$H = N^{1/2} \begin{bmatrix}
1 & 1 & \ldots & 1 \\
1 & \cos(\frac{2\pi}{N}) & \ldots & \cos(\frac{2\pi}{N}(N-1)) \\
\vdots & \vdots & \ddots & \vdots \\
1 & \cos(\frac{2\pi}{N}(N-1)) & \ldots & \cos(\frac{2\pi}{N}(N-1)^2)
\end{bmatrix}$$  

(7)

Cross correlation, $\xi$, is used to evaluate the relevance of two bases. Supposing y is a N dimension ES, the cross correlation of two bases $\Psi$ and $\Phi$ is calculated as:

$$\xi(\Psi, \Phi) = \max_{i,j \in \mathbb{R}} \left| \overline{\psi_i} \phi_j \right|$$  

(8)

where $\overline{\psi_i}$ and $\phi_j$ are the atoms of $\Psi$ and $\Phi$ respectively. The $\xi$ ranges from $\sqrt{1/N}$ to 1. To represent a power disturbance in the corresponding domain only (to keep solution uniqueness [21]), the $\xi$ should be as small as possible. The $\sqrt{1/N} \leq \xi(I, H) \leq \sqrt{2/N}$. When $N>2$, the $\xi(I, H)$ can be equal to $\sqrt{1/N}$ approximately for machine computing. In our experiment, when $N>100$, the UB $[I, H]$ can work as nearly the same as UB $[I, F]$. In fact, in real application, the sampling rate is several kHz (6.4 kHz for example at least) [25]. N of one cycle of power signal waveform is several hundreds. In the aspect of time-frequency analysis, several cycles of power signal waveform are needed at least, and $N$ is about 1000 or above. Therefore, it is rational to use UB $[I, H]$ for the substitution of UB $[I, F]$.

### D. Solution for Union of Bases Decomposition

When $A=[I, H]$, the sparse representation of $y$ in the UB, $x$, is...
with noise \( \mathbf{n} \) is

\[
\mathbf{y} = \mathbf{A} \mathbf{x} + \mathbf{n}. \tag{9}
\]

Because \( \mathbf{A} \) is a \( N \) by \( 2N \) dimension matrix, the Eq. (9) is an underdetermined group of linear equations, and the estimated \( \hat{\mathbf{x}} \) is

\[
\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \{ \| \mathbf{y} - \mathbf{A} \mathbf{x} \|^p + \tau \| \mathbf{x} \|^p \} \tag{10}
\]

where \( \| \cdot \|^p \) is the \( p \) norm of "\( \cdot \)" and \( \tau \) controls the relative importance applied to Euclidian error and the sparseness term. Solving Eq. (10) can be approximated to:

\[
\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \{ \| \mathbf{y} - \mathbf{A} \mathbf{x} \| + \tau \| \mathbf{x} \| \}. \tag{11}
\]

There are three kinds of methods to solve Eq. (8): greedy algorithm, convex relaxation and nonconvex optimization\,[22]. In these methods, Bayesian compressive sensing (BCS) using Laplace prior is employed because:

(1) A general-purpose method is supposed to monitor multi-kinds of power equipment failures, and electric signatures of these failures are quite different from each other. The initialization of BCS using Laplace prior relies on no priori-knowledge of ESs, which leads to no failure preference.

(2) In BCS, noise is modeled in Gaussian distribution (complying with real applications) and independent from signal components. The iteration process provides an accurate noise variance estimation which ensures a strong noise tolerance in harsh environment\,[23].

The process of BCS using Laplace prior is briefly described as the following:

The noise \( \mathbf{n} \) is with Gaussian distribution (\( \mathcal{N}(0, \sigma^2) \)) and denote \( \beta = \sigma^{-2} \). The BCS deems that each \( y(i) \) of \( \mathbf{y} \) is with Gaussian distribution, then

\[
p(\mathbf{y} | \mathbf{x}, \beta) = \mathcal{N}(\mathbf{y} | \mathbf{A} \mathbf{x}, \beta^{-1}) \tag{12}
\]

with a Gamma prior placed on \( \beta \) as follows

\[
p(\beta | a^\beta, b^\beta) = \Gamma(\beta | a^\beta, b^\beta) \tag{13}
\]

where \( a \) and \( b \) are constant parameters of Gamma distribution, and the Gaussian likelihood model of measurement \( \mathbf{y} \) can be expressed as:

\[
p(\mathbf{y} | \mathbf{x}, \beta) = (2\pi\beta)^{-N/2} \exp(-\beta/2 \| \mathbf{y} - \mathbf{A} \mathbf{x} \|^2). \tag{14}
\]

In Bayesian theory, priors of \( \mathbf{x} \) and \( \beta \) should be assumed for the estimation of \( \mathbf{x} \) and \( \beta \). Because \( \mathbf{x} \) is a sparse vector when projected in the UB, Laplace prior can be used on \( \mathbf{x} \). However, because the Laplace prior is not conjugate to the condition distribution in Eq. (12), hierarchical priors are employed, then

\[
p(\mathbf{x} | \gamma) = \prod_{i=1}^{N} \mathcal{N}(x_i | 0, \gamma), \tag{15}
\]

\[
p(\gamma, \lambda) = \frac{\lambda^{\gamma/2}}{2^{\gamma/2}} \exp(-\lambda/2 \gamma). \tag{16}
\]

The Laplace prior of \( \mathbf{x} \) is

\[
p(\mathbf{x} | \lambda) = \frac{\lambda^{\gamma/2}}{2^N} \exp(-\sqrt{\lambda} \| \mathbf{x} \|). \tag{17}
\]

where \( \lambda \) is with Gamma hyperprior. Then the Bayesian inference is

\[
p(\mathbf{x}, \gamma, \lambda, \beta, \mathbf{y}) = p(\mathbf{x}, \gamma, \lambda, \beta | \mathbf{y})p(\mathbf{y}). \tag{18}
\]

Eq. (18) means that using \( \mathbf{y} \), the \( \mathbf{x} \) and \( \beta \) can be estimated. However, \( p(\mathbf{x}, \gamma, \lambda, \beta | \mathbf{y}) \) is intractable, and type II maximum likelihood approach is used to perform the Bayesian inference:

\[
p(\mathbf{x}, \gamma, \lambda, \beta | \mathbf{y}) = p(\mathbf{x} | \gamma, \lambda, \beta)p(\gamma, \lambda, \beta | \mathbf{y}). \tag{19}
\]

The \( p(\mathbf{x} | \gamma, \lambda, \beta) \) of Eq. (19) is with multi-variance Gaussian distribution \( \mathcal{N}(\mathbf{x} | \mu, \Sigma) \) where

\[
\mu = \Sigma \beta \mathbf{A}^T \mathbf{y}, \tag{20}
\]

\[
\Sigma = (\beta \mathbf{A}^T \mathbf{A} + \Lambda)^{-1}. \tag{21}
\]

with

\[
\Lambda = \text{diag}(1/\gamma_i). \tag{22}
\]

The \( p(\gamma, \beta, \lambda, \beta | \mathbf{y}) \) of Eq. (14) can be used for the estimation of hyperparameters \( \gamma \), \( \beta \), and \( \lambda \). In type-II maximum likelihood procedure, the hyperparameters are estimated by the maxima of the following equivalent function:

\[
\mathcal{L} = -\frac{1}{2} \log |\mathbf{C}| - \frac{1}{2} \gamma^T \mathbf{C}^{-1} \gamma + N \log (\lambda/2) - \frac{1}{2} \sum_i \gamma_i + \frac{1}{2} \log \nu_2 - \frac{1}{2} \log \Gamma(\nu/2) + (\nu/2 - 1) \log \lambda - (\nu/2 + a^\beta - 1) \log \beta - \nu \beta \tag{23}
\]

where \( \mathbf{C} = (\beta^{-1} \mathbf{I} + \mathbf{A} \Lambda^{-1} \mathbf{A}^T) \). By taking the derivation of Eq. (23) with respect to \( \gamma \), \( \beta \), \( \lambda \), and \( \nu \), the estimations can be known respectively.

\[
\gamma_i = \frac{1}{2\lambda} + \frac{1}{4\lambda^2} \left< x_i^2 \right> \tag{24}
\]

where \( \left< \cdot \right> \) returns the mean value of "\( \cdot \)», \( \left< x_i^2 \right> = \mu_i^2 + \Sigma_{ii} \), and \( \Sigma_{ii} \) is the \( i \)-th diagonal element of \( \Sigma \).

\[
\lambda = \sum_i \gamma_i/2 + \nu/2 \tag{25}
\]

\[
\beta = (N/2 + a^\beta) \left( \| \mathbf{y} - \mathbf{A} \mathbf{x} \|^2 / 2 + b^\beta \right) \tag{26}
\]

\[
\log \frac{\nu}{2} + 1 - \psi\left( \frac{\nu}{2} \right) + \log \lambda - \lambda = 0 \tag{27}
\]

where \( \psi(\nu/2) \) is the derivation of \( \log \Gamma(\nu/2) \). The Eq. (27) can be solved numerically.

Initialize \( \gamma \), \( \beta \), \( \lambda \), and \( \nu \), then \( \mu \) and \( \Sigma \) can be obtained.

And by \( \mu \) and \( \Sigma \), new \( \gamma \), \( \beta \), \( \lambda \), and \( \nu \) are obtained. The iteration is stopped when the signal reconstructed error is within the demanded one. The estimated \( \hat{\mathbf{x}} \) is derived from \( \mu \), and estimated noise variance is derived from \( \beta \) when the iterative procedure is over. The fast algorithm of BCS using Laplace prior is presented in [23], which is not described in our paper.

E. Electric Signature Detection in Noise and Analysis Method

The detection of electric signature based on the difference detection of two successive power waveforms. Equation (11) is
used to estimate \( \mathbf{x} \) by \( \hat{\mathbf{x}} \). The difference of \( \mathbf{x} \) and \( \hat{\mathbf{x}} \) is the demanded representation accuracy or the sensitivity of ES detection. The robustness of ES monitoring is the accurate estimation of \( \mathbf{x} \) in noise environment.

According to IEEE 1159-2009 [25], the measured power waveform is with independent Gaussian noise with which Eq. (9) complies. In Eq. (9), \( \mathbf{n} \) is a Gaussian noise which is independent from \( \mathbf{x} \). By Eq. (26), the variance of noise is estimated as accurate as possible to keep the difference within the demand accuracy by the iteration. Then the difference of two successive power waveforms can be certain from \( \mathbf{x} \) rather than \( \mathbf{n} \), which guarantees a reliable power disturbance detection in noise environment.

The \( \hat{\mathbf{x}} \) is UB decomposition coefficients of \( \mathbf{y} \), which is a 2N dimension sparse vector. The first \( N \) dimension part, \( \hat{\mathbf{x}}_1 \), is the transient disturbances represented in time basis and the rest part, \( \hat{\mathbf{x}}_H \), is the steady disturbances represented in Hartley basis. The transient disturbance can be directly obtained by \( \hat{\mathbf{x}}_1 \) which is the time samples. Supposing \( \hat{\mathbf{x}}_y \) is the Fourier coefficients of \( \mathbf{y} \), because \( \hat{\mathbf{x}}_{1H} \) and \( \hat{\mathbf{x}}_{1L} \) are the real part and imaginary part of \( \hat{\mathbf{x}}_1 \) respectively. The frequency spectrum of \( \mathbf{y} \) can be obtained by Hartley coefficients as:

\[
\mathbf{y}_H = \sqrt{\hat{\mathbf{x}}_{1H}^2 + \hat{\mathbf{x}}_{1L}^2}
\]

where \( \hat{\mathbf{x}}_{1H} \) and \( \hat{\mathbf{x}}_{1L} \) are the odd part and even part of \( \hat{\mathbf{x}}_1 \) respectively.

Supposing \( \mathbf{y}_1 \) and \( \mathbf{y}_L \) are the two consecutive electric data frames, and \( \hat{\mathbf{x}}_{1} \) and \( \hat{\mathbf{x}}_{1L} \) are the optimal time-frequency representations of \( \mathbf{y}_1 \) and \( \mathbf{y}_L \) respectively, PM is working as the following steps:

**Step 1:** Initialization. There are two parameters are needed to be set. The threshold for the iteration stop and the noise variance \( \beta \). The \( \gamma \), \( \lambda \), and \( \nu \) can be initialized as 0.

**Step 2:** Abnormality detection. If \( |\hat{\mathbf{x}}_1 - \hat{\mathbf{x}}_{1L}| > \text{Threshold} \), the abnormality is detected.

**Step 3:** Signature analysis. Get features of the abnormality. Measure the amplitude, time index and duration of transient disturbances from nonzero coefficients of \( \hat{\mathbf{x}}_1 \), and measure the amplitude and frequency of steady disturbances from nonzero coefficients of \( \mathbf{y}_H \). Then the estimated fundamental component is obtained by

\[
\hat{\mathbf{y}}_F = H \hat{\mathbf{x}}_F
\]

where \( \hat{\mathbf{x}}_F \in \hat{\mathbf{x}}_H \) is the fundamental coefficient in Hartley spectrum. The root mean square (RMS) of \( \hat{\mathbf{y}}_F \) can be obtained by sliding window RMS calculation [23]. Then, use the features to identify the ES.

**Step 4:** Failure characterization. By the connection of ES and mechanism of PEF, the equipment failure can be characterized.

**F. Applied Range of the Proposed Method**

Equation (3) is the bottleneck condition that \( u_1 \) and \( u_2 \) cannot be minimized simultaneously, which confines the accuracy of PEF mechanism revealing by many time-frequency methods such as Gabor methods, discrete wavelet transform methods, continuous wavelet methods, S-transform methods, Hilbert transform methods and so on.

On the contrary, when the ES is represented in UB \([I, H]\), only time features are represented in \( I \) and only frequency features are represented in \( H \), which means both \( u_1 \) and \( u_2 \) can reach the minimum value simultaneously without the Eq. (3) restriction.

Hence, what PEF the PM can monitor is clear now. If the required sampling frequency and sampling time are satisfied for representation of time-frequency features of the ESs, and the mechanism of the PEFs can be discovered from the ESs, the PM can be applied to monitor the corresponding PEFs. No uncertainty principle influence is suffered and no parameter tuning of PM is needed.

**III. SIMULATION RESULTS**

In this section, the noise tolerance for abnormality detection and analysis accuracy of ES by PM are tested. The results with comparisons of traditional methods are also discussed. The threshold is \( 10^{-4} \) p.u and the initial noise variance is \( 10^{-2} \) p.u. The \( F_s \) and \( T_s \) of simulations are 6.4 kHz and 0.2s respectively.

**A. Noise Tolerance for Abnormality Detection**

In an electromagnetic environment, varying noise is inevitable for the sensing transformer measurement. Because the abnormality detection depends on the difference of two successive waveforms, noise should be taken into consideration.

Define an electric signal \( s \) is contaminated by noise \( n \) and is measured as \( y \) which is 0.2s duration. The signal to noise ratio (SNR) is \( 10\log(P(s)/P(n)) \), where \( P(.) \) return the power of “.”. The main noise in the waveform is Gaussian noise and the magnitude is within 0.01 p.u [25]. The noise tolerance test is as:

Simulate the measured signal with noise as:

\[
\hat{\mathbf{y}} = \mathbf{s} + \mathbf{n}
\]

where \( s = \sin(2\pi t) \). Suppose that \( s \) is with three different noise levels and SNR \( \rho_1 \) of \( y_1 \) is 35 dB, SNR \( \rho_2 \) of \( y_2 \) is 40 dB, and SNR \( \rho_3 \) of \( y_3 \) is 45 dB. Denote the denoised signal as \( \hat{\mathbf{y}} \), and the left noise is \( \mathbf{n}_0 = \hat{\mathbf{y}} - \mathbf{s} \). Then the new SNR is \( 10\log(P(s)/P(n_0)) \).

Larger new SNR means better noise tolerance for abnormality detection. The \( \mathbf{n}_0 \) waveforms of PM and wavelet method (Daubechies-4 wavelet, 3 level decomposition) at three different noise levels are shown in Table II. The noise variance of \( \mathbf{y} \) and the estimated ones, and the new SNRs of \( \hat{\mathbf{y}} \) by PM and wavelet are presented in Table III. All the results are the average of 100 times experiments.

This experiment shows that PM is more robust in noise environment than wavelet, and PM estimates the noise variance at a better accuracy. The reason is that the estimated noise variance of PM is attained by BCS iteration. Each step of the iteration corrects the estimation until the demanded signal recovered accuracy (the Threshold) is satisfied. While the wavelet does not have the iteration correction. After the UB decomposition which is fulfilled by BCS using Laplace prior, all representations of signals with different noise levels have
high SNR (larger than 60 dB), which nearly makes the abnormality detection of PM immune to noise interference in industrial environment.

**TABLE II**

<table>
<thead>
<tr>
<th>Left noise of</th>
<th>PM</th>
<th>Wavelet</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{y}_1$ (p.u)</td>
<td>![Graph]</td>
<td>![Graph]</td>
</tr>
<tr>
<td>$\hat{y}_2$ (p.u)</td>
<td>![Graph]</td>
<td>![Graph]</td>
</tr>
<tr>
<td>$\hat{y}_3$ (p.u)</td>
<td>![Graph]</td>
<td>![Graph]</td>
</tr>
</tbody>
</table>

**TABLE III**

<table>
<thead>
<tr>
<th></th>
<th>Mean SNR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PM</strong></td>
<td>66.61 43.19 50.07</td>
</tr>
<tr>
<td><strong>Wavelet</strong></td>
<td>69.78 48.23 70.21</td>
</tr>
</tbody>
</table>

**B. Analysis Accuracy of Electric Signature**

A general-purpose method is supposed to monitor multi-kinds of PEFs whose ESs are consisted of transient disturbances or steady disturbances or both without priori-knowledge. Therefore, a test ES is simulated as:

$$y = \sum_{i=1}^{9} \sin(2\pi \times 50t) \cdot \exp(-0.065t),$$

where $y$ contains 3rd to 9th odd harmonics and $y_2$ is a 0.0011s transient disturbances which starts at 0.0695s. A S-transform (ST) is used as the comparison.

The two methods performances are shown in Fig. 2, and the analysis results are given in Table IV.

In Fig. 2(a), both the transient impulse and harmonics are represented accurately by PM, while are represented ambiguously by S transform. The reason is that PM uses union of time and frequency bases, and both the transient impulse and harmonics can be represented with optimal resolutions in the corresponding domain. However, in Fig. 2(b), S transform uses single basis for the representation. In a single basis, according to Heisenberg uncertainty, time and frequency resolution cannot be optimal simultaneously. Increment of one resolution is with decrement of the other. If the analysis of both the transient impulse and harmonics are needed, both the results are inaccurate because of the lack of resolution. Other time-frequency analysis methods which employ single basis are complying with Heisenberg uncertainty, and PM is better than them in the aspect of ES analysis accuracy.

**IV. TESTS IN REAL APPLICATION**

In this section, PM is applied at a 220 kV smart power substation, Yangjiang, Guangdong province, China. The scheme of the application is shown in Fig. 3.

Voltage signals are captured by electronic voltage transformer with a capacitive divider. Current signals are captured by electronic current transformer with Rogowski coil. The accuracy of electronic transformers is 0.2 class. The merge unit captures the gapless waveform recorder in 220kV substation.
unit merges and synchronizes the signals, then transmits them to gapless waveform recorder complying with IEC 61850-9 by 100 Mbps fiber network. Normally, output voltage signals are 100/√3 V, and the one of current signals ranges from 0.3A to 1A. The $F_s$ is 6.4 kHz. The rated delay of electronic transformers is within 0.5ms and the frequency bandwidth ranges from 0 Hz to 3.2 kHz ($F_s/2$). A personal computer shares the electrical signals with the recorder and runs the PM. The computation platform is MATLAB 2012 under Window 10 system running on a personal computer with Inter i5-7200U CPU whose frequency is 2.5 GHz and 8 GB RAM.

A. Measurement System Failure Monitoring

In smart substation, the reliability of electronic measurement system is the premise of sensing. Many researches have explored the measurement system failure monitoring such as deviation of zero point and phase of electronic transformers [26] and physical fault of transformers [2]. However, failures caused by electromagnetic interference (EMI) are not easy to be detected because they seldom trigger alert. When EMI is gone, the measurement system works properly again. Hence, this kind of failure is also called as measurement soft failure. In this part, two typical EMI caused soft failures are detected.

Case 1: Electronic voltage transformer output failure by electromagnetic interference

The waveform recorder reports a false voltage sag as shown in Fig. 4(a). It should be a normal voltage signal. However, the merge unit outputs an incomplete voltage waveform with many missing points by EMI. The power source of voltage transformer is then verified to be vulnerable to high frequency impulse interference according to [27].

![Fig. 4. (a) The false voltage sag signal. (b) PM analysis performance. (c) RMS comparison.](image)

In Fig. 4(b), the missing points are deemed as transient disturbances and are represented in sub basis $I$ accurately. The $\hat{I}$ indicates the value and position of missing points but with opposite polarity. In Hartley spectrum, there is only fundamental component (1st harmonic) without distortion. Therefore, in Fig. 4(c), as the blue curve reveals, the RMS of the voltage signal is normal by PM. However, there is a voltage sag as the red curve indicates by calculating the RMS of the voltage with missing points directly. The false voltage sag may cause wrong voltage compensation.

Case 2: Electronic current transformer output failure by electromagnetic interference

Disconnector switch is one of main sources of EMI. When there is a switch operation, electronic transformer will receive high frequency impulses [28]. In this situation, the current transformer can output a false over current which is as hundreds of times as normal one.

![Fig. 5. (a) The false over current signal. (b) PM analysis performance.](image)

In Fig. 5(a), the missing points are deemed as transient disturbances and are represented in sub basis $I$ accurately. The $\hat{I}$ indicates the polarity, index and value of impulses accurately, and there is only fundamental component (1st harmonic) in Hartley spectrum. By Eq. (18), it can be found the over current is not from the fundamental component. Hence, the over current is impulsive current which is caused by EMI from disconnector switch with high possibility.

There are still kinds of measurement soft failures and many of them are caused by unqualified electromagnetic compatibility. PM can detect the measurement soft failures by faithful representation and accurate estimation of the electric disturbances, which can prevent false alarm as well as unexpected protection and compensation on the grid by measurement soft failures.

B. Other Kinds of Power Equipment Failure Monitoring

In each case of this part, the corresponding TSM is used as the reference to verify the effectiveness and accuracy of PM, and S transform is used as comparison because general-purpose method does not assume what kind of ES will be analyzed.
Case 1: Signature of incipient cable fault analysis

The incipient cable fault generates arc voltage which is usually self-cleared near zero point, because the phases of arc voltage and arc current are the same and the arc current extinguishes at zero point. The incipient cable fault causes a voltage signature which contains a voltage sag, and there is no transient disturbance when the sag recovered because of the self-clearance.

In this case, a sub cycle voltage sag is captured. TSM uses discrete wavelet transform which employs Daubechies-4 wavelet basis and 3 level decomposition for transient analysis and sliding 0.5 cycle length window RMS for the sag detection. The transient disturbances are shown by level 1 detail coefficient of wavelet. The voltage signature is shown in Fig. 6(a), the performances of PM, TSM and S transform are shown in Fig. 6(b), Fig. 6(c), and Fig. 6(d) respectively.

In Fig. 6(b), PM reveals a clear transient disturbance at the start of voltage sag and no transient disturbance at the end of sag in a clear way. However, in Fig. 6(c), the transient disturbance is still with some noise even the ES is already denoised by wavelet. In Fig. 6(b) and Fig. 6(c), both PM and TSM detect a sub cycle sag whose RMS is 11.55 V. The results of PM analysis make the voltage sag unique from other kinds of sub cycle sags such as the one caused by fusion blow and suggest that the sag is a self-cleared arc voltage, which gives a clue of incipient cable fault.

In Fig. 6(d), S transform also detects a transient disturbance and voltage sag but both the disturbances are represented ambiguously because of Heisenberg uncertainty. The duration and depth estimation of sag are 0.063s and 42.67 V which are obviously wrong, and the time index of transient impulse can hardly be identified, which conceal the incipient cable fault.

Case 2: Signature of saturated transformer analysis

When an idle transformer is going to be switched online, special control strategies are needed to avoid deep saturation of the transformer which results in large current [29]. The current contains intense harmonics which are harmful for the transformer and may even excite ferroresonance. Usually, because of the saturation, large odd harmonics can be found in the current and the percentage of 3rd harmonic may be larger than the half of fundamental component [30]. By the analysis of current signature, random phase angle switched transformer or mis operation of switch can be identified.

In this case, a heavy distorted current is captured. TSM employs Fourier transform. The current signature is shown in Fig. 7(a) and the performances of PM, TSM and S transform are shown in Fig. 7(b), Fig. 7(c), and Fig. 7(d) respectively. In Fig. 7(b), because there is no transient disturbance in the current, PM shows no transient disturbance in \( \hat{I}_x \).

Comparing Fig. 7(b) with Fig. 7(c), both PM and TSM yield clear harmonic spectrum which shows large 3rd, 5th, 7th, and 9th harmonics which are 0.428 A, 0.356 A, 0.191 A and 0.121 A respectively. And the 3rd harmonic is 97% of fundamental component, which reveal a deep saturation of the transformer.

In Fig. 7(d), the harmonics are represented ambiguously in the spectrum of S transform. Because of the lack of frequency...
resolution, the harmonics that should be intermittent in the spectrum become a continuous curve and the harmonic whose order is higher than 5th can hardly be detected.

In Case 1, PM can find an incipient cable fault based on optimal time resolution analysis of the sub cycle and self-cleared arc voltage. In Case 2, PM can identify a deep saturated transformer based on optimal frequency resolution analysis of the heavy distorted current. In these two experiments, no parameters and presetting of PM are changed, and the process of the abnormality detection and multi-kinds of ES analysis are done automatically and accurately, which meets the goal of general-purpose PEF monitoring.

Case 3: Signature of permanent cable fault analysis

Permanent cable fault results in a sustainable arc. When the arc current increases from zero to peak, the temperature of the arc becomes higher which increases the conductivity of the arc, and the arc voltage will decrease suddenly to be like a square wave because of the nonlinear arc resistance. If a sustainable arc voltage is detected, permanent cable fault can be known.

In this case, an arc voltage from permanent cable fault [30] is tested. TSM includes Fourier transform for harmonics analysis and wavelet transform for transient analysis. The voltage signature is shown in Fig. 8(a) and the performances of PM, TSM and S transform are shown in Fig. 8(b), Fig. 8(c), and Fig. 8(d) respectively.

Comparing Fig. 8(b) with Fig. 8(c), there are transients whose polarity changes at about each half cycle, which indicate the sudden drop of voltage at each half cycle because of the nonlinear arc resistance. The total harmonic distortion is 53.7% and the major harmonics are odd harmonics, which indicate that the voltage is nearly a square waveform. The RMS is keeping at 0.0103 p.u, which shows a sustainable low voltage. The transient and steady features can reflect the mechanism of permanent cable fault clearly, and translates the disturbed signal as the voltage signature of the equipment failure.

However, in Fig. 8(c), the transient disturbances are vague and the harmonics can hardly be detected accurately because of Heisenberg uncertainty. The features from S transform cannot identify the voltage signature of permanent cable fault clearly. If accurate harmonics analysis is needed, the representation of transient disturbances will be vague. While if accurate transient disturbance analysis is needed, the harmonics will be undetectable.

Case 4: Study of unknown signature

Electric signature of power equipment failure is a comparatively new study, and many of signatures are not well understood [2]. Therefore, representation of various power disturbances with optimal resolution and acquisition of accurate disturbance features are crucial for ES analysis.

In this case, the Phase B current of event 3326 of [32] is tested. The signal was captured in a lighting weather. What caused the disturbance and what the PEF was were unknown, but it can be inferred that the disturbance may not be from normal loads. To study the unknown signature, the premise is to represent each signal component of the signature faithfully. A finite impulse response (FIR) filter whose cut-off frequency is 55 Hz is used to filter the fundamental component from the transients, because the feature of fundamental component is one of the most important features to study ES. Fig. 9(a) shows the unknown current signature and its detail of fundamental waveform. Fig. 9(b) and Fig. 9(c) show the representation of fundamental waveform by PM and FIR filter respectively in time domain.

In Fig. 9(b), it can be seen clearly that PM gives a faithful representation of fundamental component of the current. The amplitude, frequency and phase are all matched with the ones in Fig. 9(a). However, the one of FIR filter is distorted and cannot be used for accurate fundamental component feature analysis. If PM is taken as a filter, the filtering principle is signal type oriented because both transient and steady signal components are represented in their corresponding bases or
domains. In this case, only $\hat{x}_H$ is responsible for the fundamental component, and the representation is without any interference of the transients. On the contrary, in Fig. 9(c), the filter of fundamental component is interfered seriously by the transients because the fundamental component and impulsive transients are represented in the same one basis and the transients are much larger than the fundamental component. This case also highlights the capability of weak ES analysis by PM. If the ES is much smaller than other disturbances in the waveform, PM will make the analysis much easier than traditional methods.

Fig. 9. (a) The current signature by unknown reason and its detail of fundamental component. (b) Representation of fundamental component by PM. (c) Representation of fundamental component by FIR lowpass filter.

Case 5: Signature of consistent maloperation of capacitor

Capacitors are common power equipment for reactive power compensation. A normal capacitor switch can be viewed by transient oscillation voltage. Fig. 10 shows a normal capacitor switch detected in the smart power substation by PM. The transient oscillation can be seen clearly in Fig. 10(b). The duration of the oscillation is 0.14s. The time-frequency features of the waveform show no faults of the capacitor.

Fig. 10. (a) Oscillation voltage caused by capacitor switch. (b) PM analysis performance.

VI. DISCUSSION OF THE PROPOSED METHOD IN GENERAL ELECTRICAL SIGNATURE ANALYSIS

Cases tested in Section III and Section IV have proved the PM can give faithful representation of ESs when the required $T_s$ and $F_s$ are satisfied. In fact, the PM gives better time-frequency representation of ESs than some TSMs. In Fig. 8, the PM gives more faithful representation of transient components than the TSM (wavelet transform). In Fig. 9, the PM gives more faithful representation of fundamental component than the TSM (lowpass filter). The reason is that the PM is without Eq. (3) restriction. Hence, the PEF which results in time-frequency disturbances of electrical waveforms can be monitored because of the optimal waveform representation with the smallest time-frequency uncertainty. Then, the PM can be used in the following applications:

1) works as a GPM in power substations, because multi-kinds of power equipment are connected here, and the time-frequency features of ESs yielded by the PEFs can be detected in similar ranges of $T_s$ and $F_s$.

2) works as a reference to develop TSMs for PEF monitoring, whose failure mechanism can be revealed by time-frequency features of electrical waveforms.

3) works as a method to study unknown or not clear PEFs by time-frequency analysis of electrical waveforms.

VI. CONCLUSION

For power equipment failure monitoring in smart grid, this paper proposes a general-purpose method to detect and analyze electric signature of power equipment failure. The method uses union of time and frequency bases to represent electric signatures with minimized time-frequency uncertainties. And
each time-frequency feature can be represented optimally and faithfully. By the connection of these features and equipment failure mechanism, the type of power equipment failure can be characterized accurately.

Multi-kinds of electric signatures of power equipment failure are tested, and the performance of our method is compared to different target shooting methods in each case. The results demonstrate the proposed method is as effective as target shooting methods and no presetting changes are needed. Not only can the new method detect and analyze multi-kinds of electric signatures for general-purpose power equipment failure monitoring in smart grid, but also is a powerful tool to study electric signatures which are not well understood in current stage because of its time-frequency interpretability.

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