Fast-Fourier-Transform Enhanced Progressive Singular-Value-Decomposition Algorithm in Double Diagnostic Window Frame for Weak Arc Fault Detection

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\textbf{ABSTRACT} In this study, a novel method that progressively applies the fastest form of singular-value decomposition (SVD) to extract nonperiodic arc-fault features is proposed in order to pursue a competent solution for AC weak arc fault detection. First, bus-current signals of the normal state and the arc-fault state are collected and normalized before being processed by progressive SVD (PSVD) to detect the discrepancy brought by comparatively stronger arc-fault nonperiodic components expressed in singular values. To provide a more comprehensive feature extraction for an enhanced accuracy, the fast Fourier transform (FFT) is incorporated for accumulating periodic variations caused by arc faults. Because weak arc faults are difficult to distinguish from normal signals when they start, a double diagnostic window frame (DDWF) is designed to reduce false negative errors. The effectiveness of each partial design of the method is verified by experiments with numerous load types and current amplitudes conducted on an industrial experimental platform. The proposed PSVD-FFT algorithm has achieved a satisfactory and consistent performance measured by both the detection accuracy and diagnosis time in all of the experiments. The proposed method is on average at least 10\% more accurate than the selected methods for a parallel comparison (in total more than a thousand experimental cases), with a satisfactory range of execution time.

\textbf{INDEX TERMS} Arc fault, singular value decomposition (SVD), fast Fourier transform (FFT), support vector machine (SVM).

I. INTRODUCTION

As shown in the “Home Electrical Fires” report published by the National Fire Protection Association (NFPA) in March 2019 [1], arc faults are a contributing factor to 39\% of the approximately 224,000 home fires involving electrical distribution or lighting equipment, which accounted for 44\% of civilian home fire deaths in 2012-2016. Due to the severity of arc fault-induced damage, the longing for timely and precise arc fault detection has attracted increasing attention from researchers in the field of electrical safety. In recent years, with the growing calculative power of circuit protective devices, the focus of arc fault detection has shifted from threshold diagnoses based on empirical and deterministic features, such as zero crossing distortion [2], to machine learning (ML) diagnoses based on more comprehensive and heuristic feature extraction [3] in an attempt to answer the flawed performance of the former. The arc fault is still a phenomenon that is not fully understood and impossible to replicate perfectly using any current mathematical model [2]. Due to the dynamic nature of arc faults, the inducements can be random and varied [4], and the fault current level can be higher or lower than the normal current [5]. Therefore, relying on a too deterministic or empirical feature extraction procedure may lead to failures in dissimilar environments or situations.

This study focuses on detecting arc faults from bus current signals such that it can avoid the extra costs of monitoring...
the voltage-current (VI) data of any specific load in the circuit. A relatively cheap sampling chip for bus-current measurements is sufficient for industrial products based on the proposed method. It is a continuation of a previous study of the same subject [6]. The detection method presented in [6] was accurate with a slow speed, and the process was complicated, which made it difficult to apply practically. The aim of this study is therefore to provide a much faster and simpler detection method while preserving the detection accuracy. For the sake of a comprehensive and fair comparison, all of the experiments in [6] are incorporated for the evaluations of the proposed method in this study.

From the perspective of this study, the key to accurate arc fault detection is successful feature extraction; without effective feature extraction, even a sophisticated and well-refined ML algorithm can only lead to a low detection accuracy or overfitting. The voltage-current (VI) characteristics of arc faults are not decisive or constant, while the occurrences of arc faults are always accompanied by certain non-VI physical phenomena, including arc flash, magnetic flux, and radiation [7]. Therefore, many researchers have also attempted to detect arc faults through non-VI characteristics. Zhao et al. [8] proposed a method of arc fault detection based on the influence of arc light on the light spectrum. There are other methods to detect arc faults by arc light, for instance, a diagnosing method based on the intensity and duration of arc flashes [9]. Another method explores the synthetic relationship between strong arc flashes and abnormal voltage signals [10]. Arc light is not the only non-VI arc feature suitable for this task; detection methods based on magnetic flux [11] and radio frequency [12] were also investigated by previous researchers. In general, non-VI arc characteristics are more distinctive than VI characteristics. However, extra equipment is required to capture non-VI features for this category, and equipment up to the standard can be quite expensive when precision is strictly demanded. In addition, the detection accuracy is inversely proportional to the distance to the arc-fault occurrence location for most non-VI detection methods; the further from the arc-fault occurrence, the more likely the detection is to be jeopardized by interferences. Due to the explained limitations, arc fault detection based on non-VI feature extraction is only applicable in certain situations. Thus, most studies in this field are still concerned with VI feature extraction.

Earlier works on detection via VI characteristics attempted to discover an empirical set of arc fault features so that certain patterns of such features indicate the occurrences of arc faults. Artale et al. [13] suggested nonstationary activities of low-frequency harmonic components as arc-fault signature features. A feature extraction method based on performing the wavelet transform (WT) on the 7.8–62.5 kHz frequency band for the 1 MHz sampling rate of the load voltage was presented in [14], along with WT-based feature extractions for the ML diagnosing algorithms proposed in [15]–[17]. These algorithms in the time-frequency domain are already more advanced than the most basic methods that extract only the deterministic features, such as the derivative of the current signals in the time domain. Nevertheless, this category of feature extraction is insensitive to weak arc faults, and the accuracy is not ideal due to the randomness of the arc faults.

The next stage of development in arc-fault feature extraction is not to rely on the existence of arc-fault signature features; instead, the focus is shifted to the variations in the VI aspects. Liu et al. [18] introduced a method that detected arc faults via variational mode decomposition (VMD) in selected frequency bands. Comparably, Park and Chae [19] illustrated another method based on the deviation of the current in the time domain coupled with high frequency spectra extracted by the FFT. Other feature extraction methods in this category include parameters calculated by the standard deviation of the current and voltage [20], as well as changes in the voltage and current amplitudes combined with differences in the WT coefficients [21]. One branch in this category is actually quite popular in earlier studies and industrial applications due to the simplicity and low calculative demands, which is to detect arc faults by current variations in the time domain alone [22]–[25]. This category of feature extraction is still insensitive to weak arc faults, and the targeted features are not as decisive as non-VI characteristics because some normal operations also produce arc fault-like variations.

Arc-fault detection by discovering variations brought by arc faults is more adaptable than searching for predetermined empirical arc-fault features, but distinguishing arc-fault signals and normal signals by the deviation obtained in basic manners may not suffice. In general, feature engineering has been adopted to tackle this problem. Researchers further process the primary features to acquire refined secondary features, such that the arc-fault features can be magnified. Zeng et al. [26] proposed a method that extracted indices from FFT coefficients of harmonic components between 360 Hz and 800 Hz. Similarly, Ilman and Dzulkiflih [27] presented a method of detection by variations in peak values of discrete wavelet transform (DWT) coefficients, and Gao et al. [7] introduced another method that extracted arc fault features by performing the singular value decomposition (SVD) on fractional Fourier transform (FRFT) coefficients of the first-order differential waveforms of the signals. Other extracted features, including the deviation of PCA eigenvectors between consecutive current signals [28] and SVD singular values obtained from Hankel matrices constructed from WA coefficients [6], were verified to be useful in their own scenarios. This category has more strength in weak arc fault detection because after secondary processing and magnification of heuristic arc-fault VI characteristics, the algorithms are capable of learning to recognize arc faults from the given data and training models. Since the features are no longer empirical or deterministic, the final diagnosis is always conducted by an ML algorithm with the downside of higher calculative power demands; thus, in order to apply it in industrial applications, chip embedding is often necessary.

Pinching a single aspect of VI signals is not sufficient in many cases; thus, recent studies have turned to another...
The proposed algorithm is completed by the double diagnostic feature extraction to enhance the accuracy. Moreover, the FFT is combined for periodic arc-fault features. The fast Fourier transform (PSVD-FFT) method utilizes the nonperiodic and periodic variations. To increase the sensitivity of arc-fault features regardless of the detection range, the bus current is the only source of data sampling. The aim is to overcome the drawbacks of previous studies in feature extraction for an accurate, fast, and reliable AC weak arc-fault detection method.

The major contributions of this study are briefly summarized as follows. (1) The invention of a PSVD approach to extract heuristic features of comparatively strong nonperiodic distortions caused by arc faults; (2) The incorporation of the original double diagnostic window frame (DDWF) to address the dilemma of false negative errors in weak arc fault detection; (3) The property of simple structure, fast execution, accurate detection, and easy implementation.

After the Introduction, the remainder of this study is arranged as follows. In Section II, the literature review of feature extraction methods is discussed to show the research motivation of this study. Moreover, the experimental platform and design of the proposed method are provided in Section III. In Section IV, experimental results and analyses are expressed in detail. Finally, some conclusions and future research directions are given in Section V.

II. LITERATURE REVIEW

Normally, detection devices for trivial and local arc faults rely on simple features and threshold detection for lower costs, but extensive devices designed to function well in different situations (especially when the detection of weak arc faults is required), a more thorough feature extraction is necessary for an improved adaptation and appropriate sensitivity. The review of feature extraction methods is summarized in Table 1, which briefly describes the development in feature extraction as a key element of arc fault detection over the years. The motivation of this study is to overcome the drawbacks of previous studies in feature extraction for an accurate, fast, and reliable AC weak arc-fault detection method.

To avoid extra detection equipment and a limited detection range, the bus current is the only source of data sampling. To increase the sensitivity of arc-fault features regardless of the interferences, the focus of the feature extraction is the variations brought by arc faults among the signals. To make the proposed method more adaptive and robust, appropriate feature engineering is adopted such that the arc-fault bus current features are magnified. VI features of the arc-fault bus current are extracted in multiple aspects, including both nonperiodic and periodic variations.

The proposed progressive singular-value decomposition fast Fourier transform (PSVD-FFT) method utilizes the potential of the SVD in component extraction to recursively analyze signals and capture nonperiodic variations brought by arc faults. The FFT is combined for periodic arc-fault feature extraction to enhance the accuracy. Moreover, the proposed algorithm is completed by the double diagnostic window frame (DDWF) to reduce false negative errors, and the SVM is used to conduct the final diagnosis to avoid rigid threshold detection. Satisfactory experimental results and comparisons with established methods will be provided to justify the effectiveness and efficiency of the proposed method. With the progressive incorporation of the folding-in-half form of the SVD, which is the fastest form of the SVD, the proposed method exerts the strength of the SVD without paying a heavy toll on the executional time.

This study applies the original idea of progressive SVD (PSVD) to extract nonperiodic arc-fault features, where the FFT is used to extract periodic arc-fault features such that the bus-current signals collected with a sampling frequency of 100 kHz can be diagnosed more thoroughly. The simple structure, fast execution, accurate detection, and easy implementation of the proposed algorithm enable practical designs for industrial products.

III. EXPERIMENTAL PLATFORM AND DESIGN OF THE PROPOSED METHOD

A. EXPERIMENTAL PLATFORM

A schematic diagram of the experimental platform is depicted in Fig. 1. Two arc generators are provided: a rods-pulling arc generator to simulate series arc faults caused by a loose terminal or bad connections, and a carbonized-path arc generator to simulate parallel arc faults caused by carbonized paths between wires with damaged insulation layers. The experimental platform is the same one incorporated by a previous study [6], and Fig. 1 is identical to Fig. 1 in [6].

This platform is composed of electromagnetic switches, arc generators, a voltage sensor, a current sensor, and a variety of loads. S1, S2, S3, and S4 are contactors controlled by the host computer to conduct various arc fault tests. The voltage of the power source is 50 Hz AC 220 V, where a Hall sensor is used to record the bus current signals in the circuit, and a voltage sensor is adopted to measure the voltage of the arc generator. In parallel load experiments, the current and voltage of each branch are collected separately. The bus current is the only source for feature extraction, and the weak arc faults that do not cause obvious distortions on the bus current are the main research subject. Experimental data are collected from the bus current using a model PCIe1816H high-speed sampling card purchased from Advantech Co.,
TABLE 1. Comparison of the feature extraction methods for arc fault detection.

| Targeted Areas                  | Features Category | Feature Extraction Examples                                                                 | Drawbacks                                                   |
|--------------------------------|-------------------|---------------------------------------------------------------------------------------------|-------------------------------------------------------------|
| Non-VI arc-fault characteristics | Existence         | 1. Light intensity [8], [9], [10]  
2. Magnetic flux [11]  
3. Radio frequency [12]   | 1. Extra detection equipment  
2. Limited to close range detection                                                   |
| VI characteristics: Arc-fault signature patterns | Existence         | 1. Non-stationary activity by low frequency harmonic current analysis [13]  
2. WT feature extraction on certain frequency band of voltage [14]  
3. WT based feature extractions for ML diagnosing algorithms [15], [16], [17] | 1. Insensitive to weak arc faults  
2. Vulnerable to interferences from normal operations                                     |
| VI characteristics: overall analysis of current or voltage | Variation in primary parameters (amplitudes and frequency components) | 1. Variational Mode Decomposition of VI characteristics in specific frequency bands [18]  
2. Deviation of current and high frequency spectra extracted by FFT [19]  
3. Variations of standard deviation of current and voltage [20]  
4. Changes in both VI amplitudes and DWT coefficients [21]  
5. Different indices calculated from current signals in time domain [22], [23], [24], [25] | 1. Higher demand on calculative power                                                     |
| Two or more of above areas     | Flexible          | 1. FFT transforms and correspondent feature vectors produced by different algorithms [29]  
2. Electromagnetic transients combined with energy indices of certain frequency band [30]  
3. PSVD values combined with calculated indices from FFT coefficients (proposed method) | 1. Higher demand on calculative power                                                     |

Ltd., a Taiwanese company, with the sampling frequency of 100 kHz. The PCIe1816H high-speed sampling card is capable of a maximum sampling frequency of 1 MHz; the reason for limiting the sampling frequency to 100 kHz in this study is to prepare for potential industrial applications in the future. Equipping a PCIe1816H high-speed sampling card in each local sampling device is too costly; however, a 100 kHz sampling frequency can easily be achieved by an AD7606 sampling chip, which is commonly used for commercial arc-fault detection devices (AFDDs). A generic AD7606 sampling chip has a maximum sampling frequency of 200 kHz and costs less than one tenth of most detective devices that are capable of capturing non-VI arc-fault characteristics in an open environment precisely and in a timely manner, e.g., a high-speed camera.

The two terminals (rods) of the rods-pulling arc generator move away from one another at a fixed speed of 0.015 mm/s to 0.03 mm/s for experiments with a current level below 10 A in order to prolong the stable periods of the weak arc faults. For experiments with a current level above 10 A, the speed can be adjusted up to 0.5 mm/s to avoid over-energizing the arc so that the excessively dispersed heat may cause the rods to melt. When two rods are just separated, the newly generated arc is in an unstable state. As the ionization of the air gap progresses and approaches completion, the arc becomes relatively stable until it breaks when the consistently growing distance between the two rods is too large for this arc to maintain itself with the energy stored. The random nature of the arc makes it difficult to generalize the maximum distance between two rods for arc sustainment of any experiment, but from the experiments of this research, arcs with a current level below 10 A could not be sustained when the distance was larger than 5 mm.

Two standards for arc-fault circuit interrupters (AFCIs) or arc-fault detection devices (AFDDs) are considered for the experimental conduction and method design. UL 1699-2008 [31] is an American standard for AFCIs with a maximum rating of 20 A$_{ac}$ intended for use in 120 V$_{ac}$ and 60 Hz circuits, and cord AFCIs are rated up to 30 A$_{ac}$. GB/T 31146-2014 [32] is a Chinese standard for AFDDs with a maximum rated current smaller than 63 A$_{ac}$ and a maximum rated voltage smaller than 240 V$_{ac}$ for use in 50 Hz or 60 Hz AC circuits.

Twelve experiments are conducted to verify each partial design of the proposed method, evaluate its performance under various conditions, and compare it with selected methods from previous studies. The set of loads contains an electronic dimming light, a squirrel-cage induction motor, resistors, a fluorescent light, a hand drill, a halogen lamp, a switching power supply, and a vacuum cleaner. There are a total of 1160 datasets are generated from the experiments, including 580 weak arc-fault datasets and 580 normal datasets of a variety of load-settings and bus current amplitudes.

The details of the experimental conditions and data formation for the proposed method in this study will be introduced in Section IV. This section gives a brief summary of the common conditions and settings of the experimental platform. The experiments can be divided into three categories of (a), (b) and (c), as shown in Fig. 2, to present a clear design of the experiments. The bus current is the only data source, and only one arc generator is adopted for each experiment. During an experiment, the arc generator is mounted in the indicated position, or each one of the indicated positions (P1
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G(\cdot) for type (c) experiments. In Fig. 2, Category (a) mounts a rods-pulling arc generator in series with a single load for the series arc-fault experiments. Category (b) incorporates a carbonized-path generator to generate arc faults that connect two parallel branches with resistor loads in order to simulate the parallel arc faults. Category (c) simulates series arc faults in one of the parallel single-load branches of the circuit by alternatively connecting the rods-pulling arc generator with the load in each parallel branch while multiple parallel branches are operating.

Experiments 1-9 simulate series arc faults by connecting the single load of each experiment in series with the rods-pulling arc generator, which belong to type (a) of Fig. 2, except for Experiment 2 with the resistive loads and the carbonized-path arc generator simulating parallel arc faults, which corresponds to type (b) of Fig. 2. Experiments 10 and 11 simulate multiple loads connected in parallel while operating, but the arc faults of these parallel loads experiments are series ones generated by the rods-pulling arc generator, and they are the type (c) of Fig. 2. For Experiment 10, an electronic dimming light, a fluorescent light, and a halogen lamp are connected in three parallel branches, and arc faults are alternatively generated in series with each load. The current amplitude of the halogen lamp is 9 A, the current amplitude of the electronic dimming light is 5 A, and the current amplitude of the fluorescent light is 8 A. Regarding Experiment 11, a switching power supply and a vacuum cleaner are connected in two parallel branches, while arc faults are generated in series with each load. The current amplitudes of the switching power supply and the vacuum cleaner are 14 A and 20 A respectively. Experiment 12 combines all 1160 datasets from Experiments 1-11, including 580 normal datasets and 580 arc-fault datasets, in order to simulate realistic situations, where the occurrences of arc faults are accompanied by unpredicted arc-fault types, fluctuating current amplitudes, and varying load characteristics. All the remaining information of the experiments is given in Section IV.

B. CURRENT AMPLITUDE NORMALIZATION

Varying current amplitudes inflict negative effects on the detection accuracy when input data are composed of signals obtained from operations with different experimental settings, e.g., Experiment 12. Thus, the following current amplitude normalization (CAN) approach is applied in this study, which cancels out such negative effects while preserving all the remaining VI characteristics.

\[
G'(g_l) = \frac{G(g_l)}{\max[G(g_l)] - \min[G(g_l)]}, \quad l = 1, 2 \ldots, L
\]

(1)

where \( L \) is the length of the data window, \( G(g_l) \) is the collected signal, and \( G'(g_l) \) is the produced signal from the CAN. The current amplitude normalization in (1) was also incorporated in a previous study [6].

C. PROGRESSIVE SINGULAR VALUE DECOMPOSITION (PSVD)

SVD is a popular tool in arc-fault data handling, especially for noise deduction. However, in this study applying it progressively to extract arc-fault features for machine learning (ML) analyses is an innovative idea. The designed PSVD progressively performs singular value decomposition (SVD) on a signal sequence until the feature extraction is complete. SVD is a popular matrix orthogonal decomposition tool that is usually used for noise reduction. With the capability of extracting components in descending order of energy levels (the correspondent proportions of the original signal in the time-frequency domain), the SVD makes the selection of the targeted components (or the components to be filtered) possible [33], [34]. The traditional approach is to construct a Hankel matrix from the coefficients of the original signal sequence in the following form [19]:

\[
A = \begin{bmatrix}
x(1) & x(2) & \cdots & x(n) \\
x(2) & x(3) & \cdots & x(n+1) \\
\vdots & \vdots & \ddots & \vdots \\
x(N-n+1) & x(N-n+2) & \cdots & x(N)
\end{bmatrix}
\]

(2)
where \( N \) is the length of the collected signal and \( x(1)\ldots x(N) \) are the signal sequences. Then, matrix orthogonalization \( A = U D V^T \) is performed on \( A \) to obtain \( D \), which is a diagonal matrix with eigenvalues of matrix \( A \) as its diagonal values. The eigenvalues are the singular values of the SVD, and the correspondent components extracted can be reconstructed from the eigenvalues, the matrix \( U \), and the matrix \( V \). The downside is that the computational space and time costs are highly dependent on the size of matrix \( A \). When thousands of data points are processed all together by the traditional SVD, the execution time of the SVD can be the bottleneck of the diagnosis speed.

To resolve this problem, the method proposed in this study intends to replace traditional SVD with a progressive SVD (PSVD) approach. The PSVD constructs matrix \( A \) not by the traditional Hankel matrix construction, but by the folding-in-half of the signal. Each signal sequence of length \( N \) is folded in half and turned into the following matrix with dimensions of 2 by \( (N/2) \):

\[
A_1 = \begin{bmatrix}
p_0(1) & p_0(2) & \cdots & p_0(N/2) \\
p_0(N/2 + 1) & p_0(N/2 + 2) & \cdots & p_0(N) 
\end{bmatrix}
\]

\[
A_2 = \begin{bmatrix}
p_1(1) & p_1(2) & \cdots & p_1(N/4) \\
p_1(N/4 + 1) & p_0(N/4 + 2) & \cdots & p_0(N/2) 
\end{bmatrix}
\]

(3a)

(3b)

where \( A_1 \) and \( A_2 \) are the matrices constructed from the original signal sequence and the sequence of the component extracted in the first iteration, respectively. In each iteration, the corresponding sequence is folded in half to construct the matrix to be analyzed by the PSVD. The sequences \( p_0 \) and \( p_1 \) represent the original signal sequence and the sequence of the component extracted in the first iteration. In the first iteration, the secondary component is the targeted component for a further recursive analysis because the primary component extracted by the PSVD in the first iteration is the component with the highest energy level of the entire signal, which is always the dominant AC/DC component, regardless of the arc-fault features, as verified by a previous study [6]. After the unwanted AC/DC components are filtered, the primary component is always the target for extraction in the remaining iterations to capture the distortions brought on the nonperiodic component by arc faults and to neglect other unrelated noises. The environmental and impulsive noises only exist in the secondary component of each iteration due to their negligible energy levels in the signal sequence. Because each coefficient of the component sequence is contained by the matrix in this form, the calculation is legitimate. It is the fastest SVD because the running time of the SVD is exponentially proportional to the size of the matrix \( A \). The limitation is that only two components are extracted in each iteration; hence, the feature extraction is not sufficient in the first iteration. To tackle this weakness, folding-in-half SVD is recursively performed in a progressive manner until enough features (singular values from iterations) have been extracted.

The recursive form of the PSVD can be represented as:

\[
A_j = \begin{bmatrix}
p_{j-1}(1) & p_{j-1}(2) & \cdots & p_{j-1}(N/2^j) \\
p_{j-1}(N/2^j + 1) & p_{j-1}(N/2^j + 2) & \cdots & p_{j-1}(N/2^{j-1}) 
\end{bmatrix}
\]

(4)

where \( j \) is the serial number of the current iteration, \( p_{j-1} \) indicates the sequence of the component extracted in the \( j \)-th iteration, and \( A_j \) is the matrix to be analyzed in the \( j \)-th iteration, constructed by the folding-in-half of the sequence \( p_{j-1} \).

The entire process of the proposed PSVD is to perform the explained folding-in-half SVD recursively on the given signal sequence. The first iteration extracts the secondary component to eliminate the unwanted dominant AC/DC components. After that, the primary component is extracted in each of the remaining iterations to filter the irrelevant random noises and to analyze the comparatively strong nonperiodic variations as arc-fault features. From the perspective of this study, the arc-fault features can be generalized as strong nonperiodic noise (compared to random noise) and distortions on the periodic components. The PSVD primarily extracts the arc fault features from the strong nonperiodic noise aspect. Enhancing the ability to extract the distortions on the periodic components will be introduced later.

The corresponding results support the aforementioned logic chain by showing a reliable performance in terms of detection accuracy and diagnosis time. Details of the experiments will be explained in Section IV. Because the designed PSVD has a recursive structure, each iteration of the PSVD can be taken as a layer, where the number of iterations is the layer number. The process of the PSVD requires at least two iterations, where the upper limit of the layer number is the base 2 Logarithm of length \( N \) of the given signal sequence, in theory. However, blindly increasing the layer number does not necessarily produce a higher detection accuracy, since once the extraction of the arc-fault nonperiodic features is complete, further analysis of the component would decrease the detection accuracy. To discover the optimal layer number of the PSVD approach, a comparison of layer numbers from 2 to 6 is conducted on every experimental dataset, and the results are displayed in Fig. 3. The detection time and the accuracy on display is the average time and accuracy of the diagnosis results for the PSVD method with the corresponding layer number on all of the experimental data, with the assistance of the support vector machine (SVM) and double diagnostic window frame (DDWF) to be introduced in the following sections. The features extracted are the training features for the SVM to label each sampling window, and the DDWF is incorporated to reduce false negative errors.

As seen from Fig. 3, the diagnosis time does not show an obvious growth with an increasing layer number. Fig. 3 is the demonstration of correlations between the execution time, the detection accuracy, and the layer number, as shown by all of the experimental results. Although the accuracy is stable, due to the computational randomness, the execution time is not as consistent. The time records shown in Fig. 3 give an intuitive...
expression of the ignorable differences in the diagnosis speed brought by different layer numbers. When the experiments with the exact same settings are repeated, the execution time of a higher layer number is sometimes less than the execution time of a lower layer number. This fact suggests that the definite but exponentially small increase in execution time due to a higher layer number in theory is insignificant in reality regarding the computational randomness.

The range of execution time is decided by the actual diagnosis time of every experimental case shown in Section IV. Referring to (4), since the execution time of the SVD is exponentially proportional to the size of matrix \( A \) and the number of coefficients is reduced by half every time the PSVD is performed, then the execution time of the \( j \)th iteration is exponentially less than that of the \( j-1 \)th iteration. Judging from the results of the comparison experiment, the layer numbers larger than 3 end up bringing down the detection accuracy, so the layer number of the PSVD is set to 3. Thus, the feature number for the SVM from the PSVD is 3, which are the three eigenvalues of the corresponding components extracted in the 1st to 3rd iterations.

D. ENHANCEMENT WITH A FAST FOURIER TRANSFORM (FFT)

Although the average detection accuracy of the PSVD algorithm reaches 92.97%, the effort to achieve a higher accuracy has been made. Since the PSVD tackles the arc-fault feature extraction from the angle of nonperiodic features and a higher layer number does not necessarily lead to a higher accuracy, a reasonable conclusion has been made that the proposed method could be enhanced with the aid of periodic feature extraction. The fast Fourier transform (FFT) was proven effective in arc-fault feature extraction by the standard deviation and the summation of harmonic components within frequency bands between 360 Hz and 800 Hz by an earlier study in [26]. The idea from [26] is incorporated in this study; two extra features, including the standard deviation and the summation of harmonic components between 360 Hz and 800 Hz, are added to the feature set prepared for the SVM. The proposed method of combining the PSVD and the FFT is named PSVD-FFT. In the proposed PSVD-FFT method, the features for the SVM training are three eigenvalues from three layers of the PSVD combined with the standard deviation and the summation of harmonic components between 360 Hz and 800 Hz, adding up to five SVM features.

E. DOUBLE DIAGNOSTIC WINDOW FRAME

A double diagnostic window frame (DDWF) is designed to reduce the common false negative errors in weak arc fault detection. When a weak arc fault has just occurred, its VI characteristics can be almost identical to the normal operational ones. To avoid incorrect judgments of no arc fault occurring in this situation, the proposed method diagnoses arc faults by not only the VI features extracted from the sampling window under examination, but also the VI features of the consecutive windows afterward. A brilliant idea of a double-layer model for industrial process monitoring was proposed by Huang et al. [35]. The first layer processes sequential information for the state characteristics and assignment of the variables to the static or dynamic blocks in the second layer based on correlations. The second layer analyzes the static and dynamic blocks separately, and then the results are integrated. The DDWF in this study is similar but not as sophisticated because the nature of the problem is different. Each diagnosis result is whether an arc fault has occurred. However, the DDWF can be expanded if in potential future studies the target is to detect not only arc faults but also the faulted location or deterioration of the system, such that the correlations of sampling windows can be analyzed to integrate information.

A small diagnostic window is a sampling window that slides through the given signal until all data are processed. When a sampling window is passed to the algorithm, the feature extraction and the SVM diagnosis are conducted on the small window. Each large diagnostic window is decomposed into a number of consecutive small diagnostic windows. The diagnosis for a large diagnostic window is made by the detection results of its corresponding small diagnostic windows. Once an arc fault is detected in a small window, the large windows that contain this small window are labeled, as in the arc-fault state. The size of each sampling window can be relatively more flexible for methods that primarily rely on feature extraction in the frequency domain, e.g., the fractional Fourier transform (FRFT) [36]. On the other hand, methods extracting features in the time-frequency domain for AC arc-fault detection often require each sampling window to capture at least a complete period of the signal. In this study, the sampling frequency is 100 kHz, and the feature extraction is operated in the time-frequency domain. Thus, the size of the sampling window is set to be 4000 in order to capture two periods of the signals. A demonstration of the DDWF is depicted in Fig. 4.

The part of the waveform marked in red in Fig. 4 indicates that an arc fault is detected, such that large diagnostic windows 1 and 2 receive consequent arc-fault diagnoses. The detection time is not influenced by the size of each large diagnostic window because feature extraction and SVM labeling are performed on each sampling window, and the diagnosis of each large window is performed by the labels of its small windows. To determine the optimal size of each large diagnostic window, a comparison test with different sizes on data of different load settings by PSVD feature extraction is conducted. The size of each large diagnostic window is determined to be 12000 by the test results, as shown in Fig. 5.

The load settings labeled on the horizontal axis will be introduced in the experiment section. A value of 4000 is the minimum size of each large window, which is the same as the size of each sampling window, which indicates the abandonment of the DDWF. A value of 12000 is the maximum size because, according to the GB/T 31146-2014 standard for arc-fault detection devices (AFDDs), an arc fault with a current amplitude under 75 A should be addressed in at
most 12 half cycles after its occurrence, and 12 half cycles are 12000 data points in this study. As seen from Fig. 5, a size of 4000, which is the absence of the DDWF, has the worst performance. Moreover, a size of 8000, which indicates that each large window includes two small windows, shows a stable improvement on every dataset. The best performance belongs to the big window size of 12000, meaning each big window is formed by three consecutive sampling windows. Thus, a value of 12000 is selected to be the size of each large window. The application of the frame does not slow down the sampling of data for each single case detection. For signals collected by sampling windows with a size of 4000, after the feature extraction and the SVM diagnosis on each of the three small windows belonging to the same large window are complete, the diagnosis of this large window is conducted by the labels of the small windows. However, if an arc fault is detected in any of the small windows, the process is terminated in order to reduce the diagnosis time since the big window has already received an arc-fault diagnosis.

The average accuracies of the PSVD and the proposed PSVD-FFT schemes without and with the DDWF on every experimental setting are displayed in Fig. 6. As shown in Fig. 6, the DDWF shows a consistent improvement across all experiments for both the PSVD and the proposed PSVD-FFT schemes. The designed frame produces a steady improvement for both the PSVD and the PSVD-FFT algorithms in each experiment. In weak arc fault detection, the greatest difficulties are to capture arc-fault features precisely and to avoid false negative errors. The comparative test demonstrates that the proposed frame effectively alleviates the problem of false negative errors.

F. SUPPORT VECTOR MACHINE (SVM) FOR SMALL DIAGNOSTIC WINDOW LABELING
The labeling of each small diagnostic window is performed by the SVM. The SVM is a useful tool for nonlinear classification by heuristic characteristics; thus, it is suitable for arc fault detection, or fault detection in general [37]–[39].
The SVM classifier in this study is the C-support vector classification (C-SVC) type from the libsvm library with the radial basis kernel function (RBF), where the cost and gamma parameters are 2 and 1, respectively, according to the default settings. The combinations of integer cost values from 2 to 10 and gamma values from 1 to 5 are explored. It is discovered that the SVM converges quickly, and that the detection accuracies for Experiment 12 are the same for different testing combinations. This is due to the scaling of parameters to adjust to different value ranges of the features, the limited number of features (in the case of this study, five in total), and an apparent gap between the arc-fault features and features of normal signals. Hence, the detection accuracies are crucially determined by the features extracted rather than other factors. After the labeling of each small diagnostic window, the final diagnosis is made for large diagnostic windows based on the labels of each small window.

G. DESIGN AND IMPLEMENTATION PROCEDURE

The experiments of this study are conducted on the same platform with similar experimental settings from the previous research in [6]. However, the algorithm design is quite different (referring to Fig. 10 in [6]). The wavelet-transform singular-value-decomposition (WA-SVD) method proposed in [6] relied on the feature extraction strength of both the wavelet analysis (WA) and SVD. With the help of the entropy calculation, the WA-SVD method detected the peak values in variational models obtained from the coefficients by consecutively performing WA and SVD on signals to locate and filter all the components unrelated to arc faults for the optimal detection accuracy. Then, the coefficients were reconstructed to have features extracted the second time for the SVM to make the final diagnosis. The accuracy of the method in [6] is commendable, but the diagnosis time on the same laptop used in this study is approximately 4 s, which is approximately 100 times more than the data collection for each sampling window with a size of 4000 incorporated with the sampling frequency of 100 kHz in this study. Although the speed can be improved with better microprocessors, the excessive execution time is still a burden.

Seeking to achieve timely detection, the method proposed in this study utilizes the advantages of the SVD to extract heuristic features directly with the fastest folding-in-half construction of the SVD matrices. Without the burden of the slow traditional SVD process and signal reconstruction, the diagnosis speed of the proposed PSVD-FFT algorithm is much faster than that of the WA-SVD algorithm, judging by the results of this study and the results previously presented in [6].

The algorithmic design of the proposed PSVD-FFT detection method is shown in Fig. 7, and the training of the proposed method is implemented offline. The algorithm does not need to go through training to make a diagnosis for each single case, and the execution of the method is fast. The execution time can be significantly shortened on a hardware platform built to execute the proposed PSVD-FFT algorithm. After the completion of the training process, the proposed PSVD-FFT method conducts the diagnosis for each sampling window in real time following the process for single-case detection, which is displayed in Fig. 8.

Ideally, the speed of detection can eventually be improved by future research to be faster than data sampling (0.04 s) with a sampling window size of 4000 points and a frequency of 100 kHz. Then, the bottleneck of the responding speed will shift from the execution of the algorithm to the data sampling.

The PSVD-FFT method processes normalize bus current signals and extract nonperiodic arc-fault features by the PSVD algorithm and periodic arc-fault features by the FFT algorithm. Then, each sampling window is labeled by the SVM. The big diagnostic window receives an arc-faulted diagnosis if any of the sampling windows are labeled as arc faulted. Each partial design of the proposed method has been introduced above followed immediately by the corresponding verification. The complete implementation flowchart of the proposed method is demonstrated in Fig. 9.

IV. EXPERIMENTS AND ANALYSES

A. EXPERIMENTAL SETUP

The performance of the proposed method is evaluated on 1160 datasets from twelve previously introduced experiments. Each experiment has a different operational current amplitude and load setting. The experiments include ten series arc-fault experiments conducted with a rods-pulling arc generator, one parallel arc-fault experiment conducted with a carbonized-path (CP) arc generator, and one data experiment that contains the signals from all other experiments. A conclusive experiment on all of the experimental data is performed to simulate a realistic working environment.
FIGURE 9. Implementation flowchart of the proposed PSVD-FFT algorithm.
TABLE 2. Summary of the experimental conditions.

| Experimental Settings | Load Type                                      | Arc-fault Type | Current Amplitude | Data Formation                       |
|------------------------|------------------------------------------------|----------------|------------------|--------------------------------------|
| Experiment 1           | electronic dimming light                       | series         | 5A               | 60 normal data, 60 arc-fault data    |
| Experiment 2           | resistors                                      | parallel       | 15A              | 60 normal data, 60 arc-fault data    |
| Experiment 3           | squirrel-cage induction motor                  | series         | 14A              | 60 normal data, 60 arc-fault data    |
| Experiment 4           | fluorescent light                              | series         | 8A               | 60 normal data, 60 arc-fault data    |
| Experiment 5           | hand drill                                     | series         | 6A               | 50 normal data, 50 arc-fault data    |
| Experiment 6           | halogen lamp                                   | series         | 9A               | 50 normal data, 50 arc-fault data    |
| Experiment 7           | resistors                                      | series         | 5A               | 50 normal data, 50 arc-fault data    |
| Experiment 8           | switching power supply                         | series         | 14A              | 50 normal data, 50 arc-fault data    |
| Experiment 9           | vacuum cleaner                                 | series         | 20A              | 30 normal data, 30 arc-fault data    |
| Experiment 10          | electronic dimming light, fluorescent light,   | series         | 5A of electronic | 50 normal data, 50 arc-fault data    |
|                        | and halogen lamp in parallel                   |                | dimming light, 9A of |                                     |
|                        |                                                 |                | halogen lamp, and 8A of |                                     |
|                        |                                                 |                | fluorescent light |                                     |
| Experiment 11          | switching power supply and vacuum cleaner in   | series         | 14A of switching  | 60 normal data, 60 arc-fault data    |
|                        | parallel                                      |                | power supply and 20A of |                                     |
|                        |                                                 |                | vacuum cleaner      |                                     |
| Experiment 12          | all load types from experiments 1-11           | series and     | current amplitudes | all data from experiments 1-11       |
|                        |                                                 | parallel       | from experiments 1-11|                                     |

The detailed experimental conditions, including load types, arc-fault types, current amplitudes, and the data formation for all 12 experiments, are summarized in Table 2, and the 6 diagram of each experiment is depicted in Fig. 10.

The data collection regarding the voltage of the arc generator and the bus current for each experiment are demonstrated in Fig. 10. Fig. 10 (a)-(k) partially displays the voltage-current (VI) waveforms of the related experiment. The boxes in each VI graph demonstrate the VI information of two consecutive sampling windows. The voltage of the arc generator seems to be a far better indicator of the arc occurrences, but in reality, the arc-fault locations cannot be predetermined; hence, voltage signals of specific circuit sections, such as the arc generator, should not be used to detect arc faults. The voltage signals of the arc generators are just indicators of the experimental states, including whether the arcs are generated properly and when the arcs break during rods-pulling experiments.
FIGURE 10. Voltage/current waveforms and data collection demonstration.
B. DESCRIPTION OF THE ALGORITHMS SELECTED FOR PERFORMANCE COMPARISONS

Five arc-fault detection methods, including the principal-component-analysis support-vector-machine (PCA-SVM) [28], the empirical-mode-decomposition probabilistic-neural-network (EMD-PNN) [25], the support vector machine (SVM), the progressive singular-value decomposition (PSVD), and the proposed progressive singular-value decomposition enhanced with the fast Fourier transform (PSVD-FFT), are selected for performance comparisons in terms of detection accuracy and diagnosis time. The major differences in the results are mainly caused by disparities between the extracted features since all of the algorithms are in the same structure of extracting heuristic features for machine learning (ML) algorithms to label each sampling window. In addition, for the sake of fair comparisons, all algorithms are programmed to have the final diagnosis conducted in the same double diagnostic window frame (DDWF). The feature extraction approaches and key points of the algorithms are described as follows.

The PCA-SVM algorithm extracts each pair of two adjacent sampling windows to form vectors that capture the timely variations [28]. The vectors then go through the PCA component extraction, and the selected PCA eigenvector is used to label each sampling window. This method actually incorporates the double sampling window design for the data collection. The original study in [28] applied the threshold diagnosis. In this study, the threshold diagnosis is replaced by the SVM to focus on a comparison of the feature extraction approaches. The variance, standard deviation, sum of squares, square roots of sum of squares, sum, mean, skewness, and kurtosis are selected as the SVM features, as decided by exhaustive trial-and-error experiments. Although all the features are highly correlated according to the results of the Pearson correlation studies, adding more correlated features helps make the SVM converge faster, which was verified by the experimental results in [6].

The EMD-PNN algorithm extracts the layer-by-layer intrinsic mode function (IMF) numbers obtained from the differences between the local maxima sequence and the local minima sequence of the curve-fitting functions constructed from the waveforms of the signals [25]. The features are passed to a probabilistic neural network (PNN) to label the sampling windows. The number of IMF number extraction iterations is taken as the layer number. In the original research [25], the IMF number for each load setting was determined empirically by the test runs. However, in this study because Experiment 12 contains datasets from various load settings, the optimal layer number is determined by an exhaustive search during the training of the PNN to emphasize (with the best possible choice of the IMF layer number) how the feature extraction approach performs compared to the proposed PSVD-FFT algorithm.

The SVM algorithm extracts the skewness and the kurtosis of the collected signals according to a method for the performance comparison presented in [7]. This feature extraction is complete in the time domain. Moreover, the PSVD and the proposed PSVD-FFT are two original algorithms presented in this study. Their only difference is that the PSVD extracts three recursive singular values as SVM features, but the proposed PSVD-FFT also extracts the summation and the standard deviation of the selected harmonic components by the FFT, adding up to five SVM features.

The analysis of periodic and nonperiodic features of the proposed method is conducted with the data from Experiment 12. The detection accuracies relying on only the periodic features in [26], the nonperiodic PSVD features, and the combination of both periodic and nonperiodic features of the proposed PSVD-FFT are presented in Fig. 11. The proposed PSVD-FFT algorithm has achieved a detection accuracy of 92.56%, which is superior to the ones of the fast FFT in [26] and the PSVD. This result clearly shows that although periodic and nonperiodic feature extraction are both applicable for the weak AC arc-fault detection, by incorporating them both, the proposed PSVD-FFT method can obtain a more satisfactory performance in the detection accuracy.

C. SVM KERNEL VERIFICATION

A radial kernel is the best choice for multidimensional arc-fault nonlinear feature vectors with limited dimensions, and it is always chosen for arc fault detection. This research verifies this by a thorough accuracy comparison test of different SVM kernels by the proposed PSVD-FFT algorithm without the DDWF on every experiment with gamma = 1 and cost = 2. The detection time does not show any notable differences, and the accuracies are summarized in Table 3. The accuracy of the radial kernel here is also the detection accuracy of the PSVD-FFT method on each experiment without the DDWF, such that the improvement in the PSVD-FFT method brought by the designed frame on each experiment is contained in Table 3 as well.

Shown clearly by the results in Table 3, the radial kernel is indeed the best option for the SVM in the arc fault detection for the proposed PSVD-FFT method. The radial kernel demonstrates the highest accuracy in every experiment, especially in Experiment 12, where the dominant position of the radial kernel is established by at least 6% leading margins. Experiment 12 is the most challenging experiment with the greatest diversity and largest quantities of both normal and arc-fault data from all other experiments, and it best distinguishes the accuracy performances of the different SVM kernels.

D. ANALYSIS OF THE RESULTS

The detection accuracies of the five methods from all comparison experiments are summarized in Table 4. As seen in Table 4, the proposed PSVD-FFT algorithm shows an indisputable supremacy in terms of the detection accuracy. Most algorithms achieve accuracies from 96% to 99% in Experiment 1, except for the 82.76% of the EMD-PNN, where it could be caused by the mixed data of the relatively strong faulted data and the arc-fault signals being almost
TABLE 3. Accuracy comparison of the SVM kernels.

| SVM Kernel | Experiment 1 | Experiment 2 | Experiment 3 | Experiment 4 | Experiment 5 | Experiment 6 | Experiment 7 | Experiment 8 | Experiment 9 | Experiment 10 | Experiment 11 | Experiment 12 |
|------------|-------------|--------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Linear     | 95%         | 100%         | 95%         | 100%         | 98%         | 100%         | 100%         | 100%         | 96%         | 100%         | 96%         | 81.03%      |
| Polynomial | 96.67%      | 86.67%       | 76.67%      | 100%         | 94%         | 90%          | 84%          | 100%         | 96%         | 96.67%       | 96.67%       | 74.83%      |
| Sigmoid    | 88.33%      | 100%         | 93.33%      | 100%         | 96%         | 100%         | 100%         | 100%         | 96%         | 100%         | 96%         | 80.69%      |
| Radial     | 98.28%      | 100%         | 95%         | 100%         | 100%        | 100%         | 100%         | 100%         | 96%         | 100%         | 96%         | 87.07%      |

TABLE 4. Comparisons of the Detection Accuracies of Different Methods for Various Load Combinations.

| Method      | Experiment 1 | Experiment 2 | Experiment 3 | Experiment 4 | Experiment 5 | Experiment 6 | Experiment 7 | Experiment 8 | Experiment 9 | Experiment 10 | Experiment 11 | Experiment 12 |
|-------------|-------------|--------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| SVM         | 98.21%      | 93.10%       | 86.21%      | 93.10%      | 95.83%      | 72.92%      | 93.75%      | 91.67%      | 92.86%      | 100.0%       | 98.21%       | 53.98%      |
| PCA-SVM [28]| 98.21%      | 98.21%       | 75.86%      | 91.38%      | 81.25%      | 95.83%      | 95.83%      | 91.67%      | 92.86%      | 100.0%       | 94.83%       | 82.50%      |
| EMD-PNN [25]| 82.76%      | 84.48%       | 94.83%      | 94.83%      | 93.75%      | 89.58%      | 89.58%      | 95.83%      | 89.29%      | 91.67%       | 91.38%       | 80.10%      |
| PSVD        | 96.55%      | 98.28%       | 96.55%      | 100.0%      | 100.0%      | 91.67%      | 95.83%      | 100.0%      | 100.0%      | 100.0%       | 100.0%       | 87.54%      |
| PSVD-FFT    | 98.28%      | 100.0%       | 96.55%      | 100.0%      | 100.0%      | 100.0%      | 100.0%      | 100.0%      | 100.0%      | 100.0%       | 100.0%       | 92.56%      |

Identical to the operational ones. In Experiment 12, the SVM stops functioning since variations in the current amplitudes and VI characteristics of load settings severely distort the uniformity of the operational and arc-fault patterns in the time domain, where the excellence of the proposed algorithm becomes most apparent, with a detection accuracy of 92.56% on 1160 datasets from all experiments. The proposed PSVD-FFT algorithm consistently achieves the highest accuracies in every experiment, as shown by the results of Experiment 12, which is the most challenging experiment in this study. The improvement in the detection accuracy by choosing the proposed PSVD-FFT algorithm consistently achieves the highest accuracies in every experiment, especially in Experiment 12, where the lead in accuracy ranged from 10.6% to 38.58% compared with the selected methods from previous studies.

From the comparative results, the PSVD-FFT algorithm demonstrates a leading performance in every experiment, which establishes the superiority over other methods brought into comparison. The valued consistency of the proposed method is also supported by all of the experimental results on the detection accuracy, and the diagnostic ability is not jeopardized by any experimental condition in this study. Thus, the proposed method can be robust in realistic environments. Experiment 12 combines all datasets from Experiments 1-11, including 580 normal datasets and 580 arc-fault datasets, in order to simulate realistic situations, where the occurrences of arc faults are accompanied by unpredicted arc-fault types, fluctuating current amplitudes, and varying load characteristics. Thus, the performance of the proposed PSVD-FFT on Experiment 12 is not as good as it obtains on the other Experiments in Tables 3 and 4. To emphasize the differences in the performances are solely due to the choices of SVM kernels and to magnify the gaps between kernels, the DDWF is not adopted in Table 3. Therefore, the performance of the proposed PSVD-FFT method in Table 3 are different from the final experimental results in Table 4.

The experimental results of the proposed method and the methods used for the comparison in terms of detection time and average accuracy are presented in Table 5. The average accuracy of 96.18% supports the practicality of the proposed method. Accurate detection is not the only advantage of the proposed PSVD-FFT algorithm. Since folding-in-half SVD
TABLE 5. Comparisons of the detection times for different methods.

| Method     | Detection Time | Average Accuracy |
|------------|----------------|------------------|
| SVM        | 0.009s - 0.025s | 72.97%           |
| PCA-SVM [28] | 7.425s - 24.619s | 85.03%           |
| EMD-PNN [25]    | 0.222s - 0.342s | 86.10%           |
| PSVD       | 0.066s - 0.195s | 92.97%           |
| PSVD-FFT   | 0.068s - 0.198s | 96.18%           |

is the fastest form of SVD and FFT is one of the fastest feature extraction approaches in the frequency domain, the proposed algorithm achieves an adequate diagnosis speed. The time consumed to perform a diagnosis on an outdated laptop ranges from 0.068 s to 0.198 s, which has shortened the detection time by at least 94.89% from the previous research in [6]. With this significant speed-up, the execution of the method can be faster than the data sampling, which paves the way for realistic applications. An i7-7700 HQ processor has a maximum frequency of 3.8 GHz, which is the CPU model of the computer used in this study. To demonstrate how the execution speed can be improved with a more advanced CPU, all of the experimental data were processed with the proposed PSVD-FFT method on another computer with an i7-1165 G7 processor. This more advanced CPU has a maximum frequency of 4.7 GHz, and the resulting time range of more than a thousand data processing tasks is 0.057 s – 0.176 s, which shows an over 10% improvement of the execution time.

Although the SVM algorithm, which only extracts two basic features in the time domain, shows the dominant speed, an average accuracy of 72.97% is not acceptable. The average accuracies of 85.03% and 86.10% of the PCA-SVM and the EMD-PNN, respectively, are not satisfactory either. Because the execution time of the PCA grows exponentially with the size of the sampling window, the PCA-SVM shows the dominant speed, which shows an over 10% improvement of the execution time.

V. CONCLUSION

The major contributions of this study are expressed as follows. First is the invention of the progressive singular-value-decomposition (PSVD) approach, which conducts a repetitive SVD analysis on each matrix constructed by the folding-in-half of the component passed down from the previous layer in a recursive manner in order to extract heuristic features of comparatively strong nonperiodic distortions caused by arc faults. Second, the incorporation of the original double diagnostic window frame (DDWF) is used to address the dilemma of false negative errors in weak arc fault detection, with a generic applicability to improve other detection methods as well. The efficiency and accuracy of the proposed method are supported by all of the experiments and comparative tests, along with clear logic behind every step of the algorithm design. Finally, with the practical concept of industrial design, the outbreaks in executional time, and the independence from relying only on the arc-fault features in AC systems, this method has promising potential in different fields for realistic applications.

Despite a satisfactory experimental performance, the proposed method still has the following improvement directions for future research. (1) Since the key to an accurate arc fault detection is successful feature extraction, the feature extraction approach still has room for improvement. (2) The execution speed can be further enhanced with more advanced hardware or multithreading programming on a multiprocessor platform. (3) Industrialization can be realized through digital signal processor (DSP) programming for the development of independent detection devices or a detection network that combines local sampling devices and a computer as the data processing center, with the help of such designs as integrating...
parallel data blocks by the principal component analysis (PCA) presented in a previous study [40]. (4) Because the bottleneck of the detection time may be shifted to data collection time, which associated with the sampling window size directly, an exploration of smaller sampling windows while preserving or improving the accuracies can lead to another breakthrough in the diagnosis speed.

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Y.-L. Shen, R.-J. Wai: Fast-Fourier-Transform Enhanced Progressive Singular-Value-Decomposition Algorithm

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