IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 11 December 2022, accepted 29 December 2022, date of publication 2 January 2023, date of current version 5 January 2023.

Digital Object Identifier 10.1109/ACCESS.2022.3233767

RESEARCH ARTICLE

Classification of Power Quality Disturbance Using Segmented and Modified S-Transform and DCNN-MSVM Hybrid Model

MINGPING LIU[1], YUE CHEN[2], ZHEN ZHANG[1], AND SUHUI DENG[1,3]

[1]School of Information Engineering, Nanchang University, Nanchang 330031, China
[2]School of Qianhu, Nanchang University, Nanchang 330031, China
[3]Jiangxi Provincial Key Laboratory of Interdisciplinary Science, Nanchang University, Nanchang 330031, China

Corresponding author: Suhui Deng (shdeng@ncu.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 61865011 and Grant 62065012; in part by the Natural Science Foundation of Jiangxi Province of China under Grant 20212BAB202031; in part by the Interdisciplinary Innovation Fund of Natural Science, Nanchang University under Grant 9167-28220007-YB2111; and in part by the National College Students' Innovation and Entrepreneurship Training Program under Grant 202110403063.

ABSTRACT In this paper, a novel approach to classify the signals of power quality (PQ) disturbance is proposed based on segmented and modified S-transform (SMST), deep convolutional neural network (DCNN), and multiclass support vector machine (MSVM). The idea of frequency segmentation with different adjustable parameters was used in the Gaussian window function. The accurate time-frequency localization and efficient feature extraction of different PQ disturbances then could be achieved. Firstly, the SMST was used to analyze the PQ disturbance signals and obtained two-dimensional (2D) contour maps with high time-frequency resolution. Then, the DCNN was employed to automatically extract features from the 2D contour maps. Finally, the MSVM classifier was developed for the classification of single and complex signals of PQ disturbance. In order to demonstrate the effectiveness and robustness of the proposed model, eight single and thirteen complex waveforms of PQ disturbances were considered without noise and with different noise level, respectively. Extensive simulations were performed and compared to other existing methods. The simulation results show that the proposed method has better performance than several state-of-the-art algorithms in classifying PQ disturbances under different noise level.

INDEX TERMS Power quality disturbance, classification, segmented and modified S-transform, deep convolutional neural network, multiclass support vector machine.

I. INTRODUCTION

In recent years, with the development of the smart grid, power systems have more and more nonlinear loads, such as electronic converters, transfer switches, adjustable speed drives, etc. In addition, the distributed generation power using renewable energy like wind and photovoltaic has also great influence on the signals of power grids. Thus, power quality (PQ) has been recognized as one of most crucial issue in modern power systems. The extensive use of various types of aforementioned devices creates unprecedented challenges in the functioning of the reliable and stable operation of the power system, resulting many PQ disturbance events [1], [2].

The associate editor coordinating the review of this manuscript and approving it for publication was Nagesh Prabhu.

These PQ disturbances have negative impact on the power systems and may lead to maloperation or even failure of sophisticated electronic devices. Therefore, it is necessary to accurately detect and classify to avoid disturbance pollution and improve power supply quality [3].

Particularly, under the noisy environment, it struggles to accurately classify the signals of PQ disturbances, especially for the complex signals. In the past few decades, many researchers have explored the problem of classification of PQ disturbances. Generally, these methods mainly include two steps: feature extraction and classification [4]. In the first step, the features of PQ disturbances can be extracted by using the signal processing techniques. It is very important for this stage to enhance the recognition among these disturbances and then be beneficial to the implementation of classification.

In the next step, the classifiers are fed with the features of PQ disturbance signals that can be effectively identified.

For feature extraction from the signals of PQ disturbance, multiple approaches have been used to analyze the disturbances and obtain good results. The main techniques for feature extraction include short time Fourier transform (STFT) [5], [6], wavelet transform (WT) [7], [8], S-transform (ST) [9], [10] and Hilbert-Huang Transform (HHT) [11], all of which have been widely reported in the literatures for time-frequency analysis of PQ disturbance signals. However, the STFT is insufficient for the analysis of the non-stationary signal due to its fixed window size. The WT has addressed the limitations of STFT by adjusting the size and shape of Gaussian window (GW). Although the WT is superior in performance compared to the STFT, it is still challenge to select the appropriate fundamental signal and its performance degrades in noisy environment [12]. To overcome the drawbacks of STFT and WT, the ST was proposed by Stockwell [9]. Moreover, the ST is a combination of STFT and WT, which can be considered as the STFT with a variable window width or the WT with a corrected phase. Hence, the ST has become one of the most widely used method for detecting the signals of PQ disturbance. However, the ST is constrained by Heisenberg's uncertainty principle [13] which states that the optimal resolutions for time and frequency cannot be obtained simultaneously [14].

It has been observed that different versions of modified ST (MST) [15], [16], [17] were proposed to improve the adaptability of GW and maintain the optimal time-frequency resolutions. In [15] and [17], two and four adjustable parameters were introduced to control the modified GW and achieved promising results for the detection of single PQ disturbances. But the aforementioned versions of MST only used an improved GW in the entire frequency band, which means it is hard to accurately detect and analyze the complex PQ disturbances, and simultaneously obtain the time-frequency resolution. In [16], the frequency spectra of PQ disturbance signals were divided into two parts and used different parameters in each frequency band to achieve double resolutions. However, it is challenging to enhance the adaptability of the GW by using only one parameter and the selection of frequency separator is insufficient to consider all kinds of PQ disturbances, which may lead to poor performance for the detection of PQ disturbances. Therefore, it is urgent to find effective methods to enhance the accuracy of the time-frequency resolution of PQ disturbance signals.

Therefore, a new algorithm called segmented and modified S-transform (SMST) [18] is proposed and improved to overcome the disadvantages of the models mentioned above. The SMST divides the frequency spectrum of PQ disturbance signals into three bands i.e., low-, medium-, and high- frequency bands. Then three adjustable parameters are introduced to optimize the GW functions in each frequency band, respectively. In this way, the GWs can be adaptively adjusted through the frequency of PQ disturbance signals in each frequency band, which achieve higher time-frequency resolution and deliver a good performance for the detection of PQ disturbances

In the PQ classification stage, choosing an appropriate classifier is the most important part of the disturbance classification. In recent decades, many advanced classifiers have been designed to process the extracted features. The most widely used classifiers mainly include: artificial neural network (ANN) [19], [20], support vector machine (SVM) [16], [21] and decision tree (DT) [22]. The ANN is a significant classification method and has been widely used because of its simple structure and automatic learning capability. However, the ANN suffers from slow performance and local minima convergence problems. In this case, the SVM is further proposed to improve the ANN performance. However, the SVM is constrained by choosing proper kernel function and regularization parameter that limits data mapping capabilities. The DT-based classifiers are also broadly used in power systems, which are easy to implement and rely on specific rules. However, the performance of DT can be affected by uncorrelated feature set because it works by seeking the correlations among date samples. In recent research, most features extracted from PQ disturbances are handcrafted with different numbers and types [23], [24], [25], and the accuracy of the classifier is heavily relied on the selection of features. However, the selection of features lacks of uniform criteria and may lead to information loss due to manual factors, which may reduce the accuracy of classification of PQ disturbances.

Recently, deep learning methods such as probabilistic neural network and convolutional neural network were proposed to automatically extract features of PQ disturbances and used to classify the PQ disturbances [26], [27]. It has proven that the deep learning methods had excellent performance for feature extraction in the face of noisy environment. However, the performance of their classifiers usually needs a lot of training samples and is easy to appear convergence stagnation. In addition, the classical classifier such as the SVM or its improved version, has stronger generalization ability and fast computation speed, performing better than the classifiers of deep learning methods for multi-classification problems. In terms of this, the combination of deep learning methods and traditional classifiers has drawn more and more attention all over the world.

In this study, deep learning and classical machine learning methods will be combined to automatically extract in-depth features and obtain a higher classification accuracy of PQ disturbance signals under different noisy levels. Therefore, a novel approach based on the segmented and modified S-transform (SMST), deep convolutional neural network (DCNN), and multiclass support vector machine (MSVM) for the recognition of PQ disturbances is proposed. The SMST is employed to preprocess and analyze the PQ disturbance signals and transfer 1D signals into 2D time-frequency image data set. Then, these 2D time-frequency images are considered as the input of the DCNN, which can automatically extract and learn the features of PQ disturbances. Finally, the MSVM can be used to classify the PQ disturbance signals to obtain high classification accuracy due to its better ability of classifying multi-classification events.

The main contributions of this paper are listed as follows:

1) To improve time-frequency resolution of signal processing, the SMST method was proposed to analyze the signals of PQ disturbance. Integrating the idea of frequency segmentation with different adjustable parameters of GW width, the GWs can be adaptively adjusted through the frequency of signals in each frequency band. Then, the SMST can improve time-frequency resolution and achieve a higher accuracy of detection.

2) To enhance the capability of classification, the improved DCNN combined with MSVM was used to classify the single and complex signals of PQ disturbances. The DCNN has been established for automatically learning the features from 2D time-frequency images and avoided the manual feature selection. Furthermore, the MSVM has been used to replace the softmax of DCNN to achieve a higher classification accuracy.

3) Extensively comparative experiments were conducted to verify the proposed framework. The experimental results show that the proposed model is efficient in classifying PQ disturbances with better accuracy, even under noisy conditions.

The remaining part of this article is organized as follows. Section II introduces the proposed SMST. Section III discusses the classification method based on the DCNN and MSVM. In Section IV, the framework of the PQ disturbances classification is presented. The simulation and classification results are discussed in Section V. Finally, Section VI concludes the paper.

II. SEGMENTED AND MODIFIED S-TRANSFORM

In this section, a novel technique based on the segmented idea of frequency band is introduced to detect the signals of PQ disturbance. The basic theory of the traditional ST is presented firstly and the structure of SMST is further elaborated. Finally, the SMST is used to analyze the complex signal of PQ disturbance to verify its superior performance.

A. S-TRANSFORM

In recent years, although the variants of the traditional ST have been widely used in detecting the signals of PQ disturbance, it is still necessary to introduce the principle of the traditional ST. The original ST of a signal $x(t)$ could be denoted as [9]

$$S(t,f) = \int_{-\infty}^{\infty} x(t)g(t-\tau,f)e^{-i2\pi ft}dt \tag{1}$$

$$g(t,f) = \frac{|f|}{\sqrt{2\pi}}e^{\frac{-t^2f^2}{2}} \tag{2}$$

where f is the signal frequency, τ gives the position of wavelet and $g(t-\tau,f)$ is the Gaussian window function with a width of $1/|f|$.

It is quite apparent that the Gaussian window width is only determined by frequency in the traditional ST, which means the resolution of ST varies with the frequency. Therefore, it is difficult for the traditional ST to satisfy the requirements of high resolution in both high- and low-frequency bands.

B. PROPOSED SMST

In order to overcome the drawbacks of the ST, the SMST has been proposed to improve time-frequency resolution of signal processing. Three adjustable parameters, i.e., m, n, p in Eq. (3), are introduced to the window function. According to the time-frequency characteristics of PQ disturbances, the parameters m, n, and p can be adaptively selected to adjust the window width. Then, the width of window function can be expressed as

$$\sigma(f) = \frac{1}{|mf^n + p|} \tag{3}$$

where m, n, and p are three adjustable parameters.

However, the signals of PQ disturbance are usually mixed in the power systems. That is to say, it is hard to achieve high resolution in both high- and low-frequency bands. In terms of this case, the frequency component is divided into three parts and different parameters (m, n, p) are introduced in these three bands. According to the frequency characteristics of PQ disturbance [28], the separator lines ($f = 100$ Hz for low-frequency band and $f = 700$ Hz for high-frequency band) are used in the middle to divide the entire frequency range. Therefore, the frequency spectrum can be divided into low-frequency band ($1\text{ Hz} \le f < 100\text{ Hz}$), medium-frequency band ($100\text{ Hz} \le f < 700\text{ Hz}$) and high-frequency band ($f \ge 700$ Hz), respectively. In this way, the Gaussian windows at three different frequency bands can be used to analyze PQ disturbances separately to obtain higher time-frequency resolution and detection accuracy, laying a solid foundation for the subsequent classification work.

According to the theories mentioned above, the SMST of a signal $x(t)$ can be defined as [18]

$$S_{SMST}(\tau,f) = \begin{cases} \int_{-\infty}^{\infty} x(t)\frac{|m_1f^{n_1}+p_1|}{\sqrt{2\pi}}e^{\frac{-(\tau-t)^2|m_1f^{n_1}+p_1|^2}{2}}e^{-j2\pi ft}\mathrm{dt} \\ \quad \text{if } 1 \le f < 100\text{Hz} \\ \int_{-\infty}^{\infty} x(t)\frac{|m_2f^{n_2}+p_2|}{\sqrt{2\pi}}e^{\frac{-(\tau-t)^2|m_2f^{n_2}+p_2|^2}{2}}e^{-j2\pi ft}\mathrm{dt} \\ \text{if } 100\text{ Hz} \le f < 700\text{Hz} \\ \int_{-\infty}^{\infty} x(t)\frac{|m_3f^{n_3}+p_3|}{\sqrt{2\pi}}e^{\frac{-(\tau-t)^2|m_3f^{n_3}+p_3|^2}{2}}e^{-j2\pi ft}\mathrm{dt} \\ \quad \text{if } f \ge 700\text{Hz} \end{cases} \tag{4}$$

where (m_1, n_1, p_1), (m_2, n_2, p_2) and (m_3, n_3, p_3) correspond to the adjustable parameters of the window width in the low-, medium-, and high-frequency bands, respectively.

C. SIGNAL ANALYSIS USING SMST

To evaluate the efficiency of the SMST to detect PQ disturbances, the comparisons between the SMST and the variants of ST have been carried out as shown in Figure 1. A complex

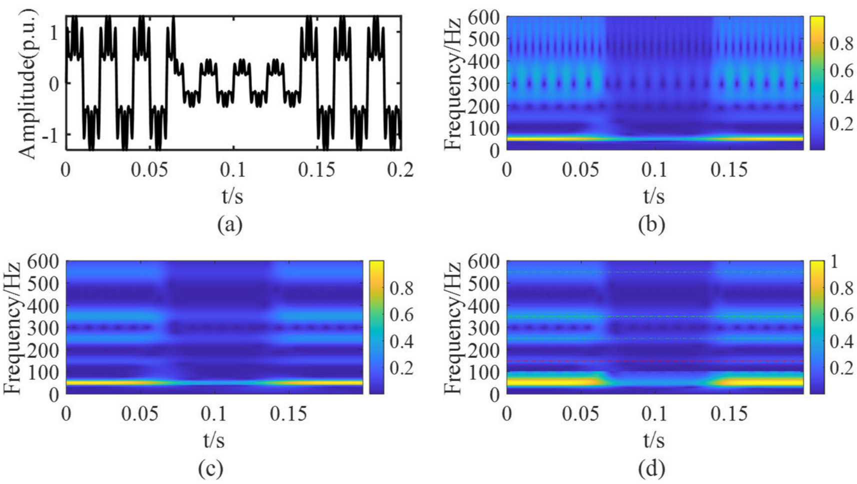

FIGURE 1. Time-frequency analyzing results for complex disturbance. (a) Original signal. (b) Standard ST. (c) MST. (d) Proposed SMST.

signal of PQ disturbance, which has a voltage sag with harmonics, is used as the test signal. The signal can be defined as

$$x(t) = \sum_{3}^{11} \alpha_k \sin(k2\pi ft) \cdot \{1 - \alpha[u(t-t_1) - u(t-t_2)]\} + \sin(2\pi ft) \quad (5)$$

The waveform of original signal is displayed in Fig. 1(a). One can see that the voltage sag starts at 0.065 s and ends at 0.14 s. Moreover, the input signal contains the third, fifth, seventh, and 11th harmonics, with corresponding magnitude 0.15, 0.3, 0.35, and 0.25 p.u., respectively. Figs. 1(b)-(d) show the results of detection of the complex signal based on the ST, MST [17] and SMST, respectively. As shown in Fig. 1(b), the ST are unable to accurately localize each frequency component of the harmonics and its time resolution at the fundamental frequency was relatively low under voltage sag condition, which gives poor performance for the complex PQ disturbance. The MST provides better frequency localization compared to the results of Figs. 1(c) and 1(b). However, it gives poor time resolution and then is unable to accurately detect the start and end times of voltage sag. In Fig. 1(d), it is clear that the signal of voltage sag with harmonics can be accurately detected by using the proposed SMST. In other words, the proposed SMST gives better time-frequency localization and provides great time-frequency resolutions.

Hence, by selecting optimal parameters in each frequency band, the SMST can provide a higher accuracy for analysis of PQ disturbance signals, especially for the complex signals, which demonstrates a solid foundation for the subsequent classification of the signals of PQ disturbance.

III. PROPOSED CLASSIFIERS

Deep convolutional neural network (DCNN), as a deep learning method, has been a strong candidate for pattern recognition and image classification [29], [30]. In recent years, the DCNN has been used to process various types of data, such as three-dimensional (3D) data, pictures, and 1D signals [31]. In this paper, the DCNN is proposed for automatic feature extraction and the MSVM is used to classify of PQ disturbance signals.

A. ALEXNET

The AlexNet [32] is a novel learning method and achieves high classification accuracy, which is trained on 1000 classes of images and 1.2 million images from the ImageNet. The AlexNet is a large network structure that has 60 million parameters and 650,000 neurons. In general, the network contains 8 layers including five convolutional layers and three fully connected layers. The output of the last fully-connected layers is connected with a 1000-way softmax classifier. To prevent the neural network over-fitting in the fully connected layers, the dropout method is used. The rectified linear units (ReLUs) are applied to every convolutional and fully-connected layers for activation and faster learning. The size of first convolutional layer is 11×11 and the size of the second convolution layer is decreased to 5×5, after which the size of rest layers is 3×3. Figure 2 shows the structure of the AlexNet.

B. MULTICLASS SUPPORT VECTOR MACHINES

Support vector machine, put forward by Cortes and Vapnik [33], has been widely used for classification of PQ disturbances [16]. It was originally developed for binary classification, which is not suitable for classification for twenty-one types of PQ disturbances. Therefore, it is necessary to use multiclass SVMs for the classification of PQ disturbances. Various methods have been proposed to extend SVM for multiclass classification. In [34], a comparative experiment has been conducted and showed that one-against-one and directed acyclic graph SVM (DAGSVM) methods are more appropriate for classifying multiple PQ disturbance signals.

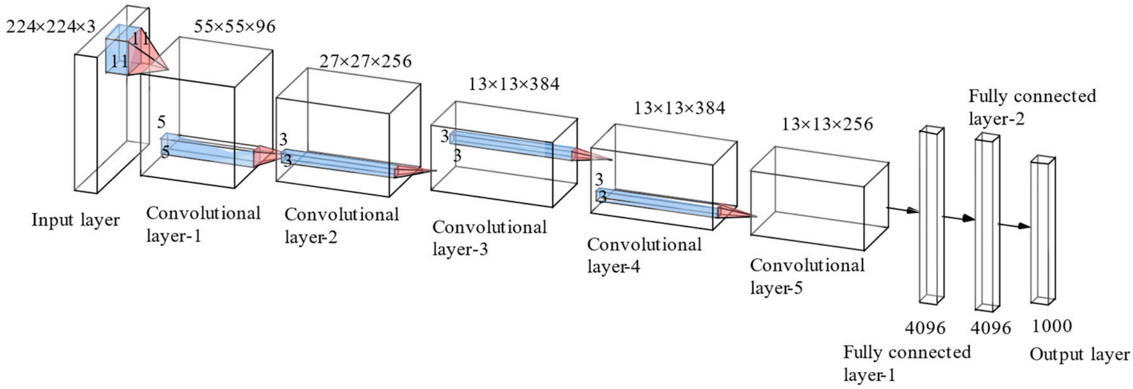

FIGURE 2. An illustration of the architecture of AlexNet.

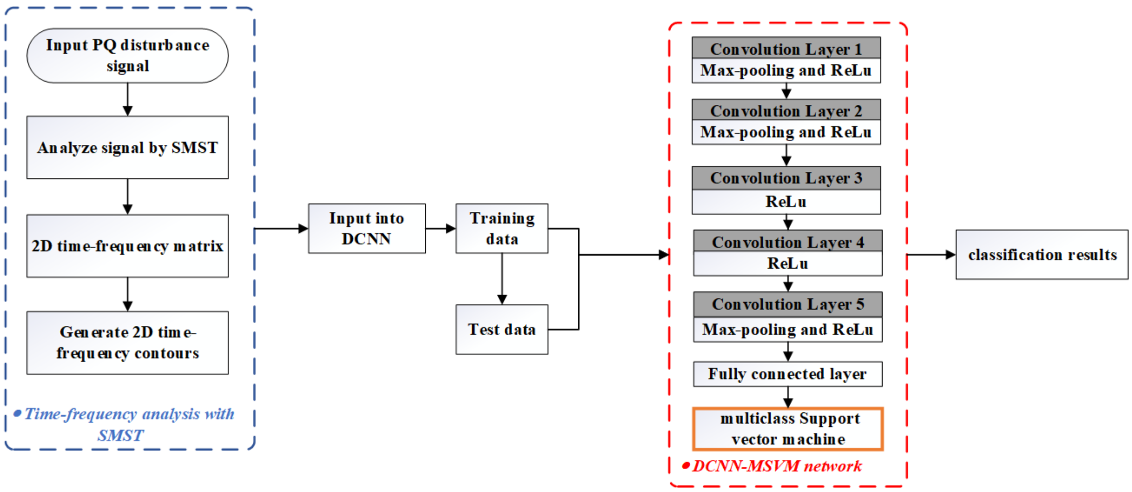

FIGURE 3. Flow-chart for PQ disturbances classification.

In this paper, the features extracted from the training samples as predictor variables are used and one-again-one support vector machines are fitted to replace the softmax classifier. Then, the MSVM can be used to classify the test samples to improve the training efficiency and high classification accuracy.

IV. PROPOSED METHODLOGY

Based on the SMST and DCNN-MSVM models mentioned above, this section proposes a framework for PQ disturbance classification. Its schematic diagram is depicted in Fig. 3. The framework can be divided into two parts, which can be described in detail as follows.

1) Time-frequency analysis: The PQ disturbance signals are processed by the SMST. Then, 2D time-frequency matrix can be obtained from signals, the row information of which represents the frequency information and the column information for the time information. Finally, twenty-one kinds of 2D contour of PQ disturbance signals according to the formulae of Table 1 can be achieved by using the SMST. These time-frequency contour maps are in the size of 224×224 as input to the improved AlexNet. In addition, all samples are divided into 8400 cases for the training model and 2100 for the test set.

2) Automatic classification of PQ disturbance: The 2D contour maps of PQ disturbance achieved from the SMST can be considered as the input of the DCNN. Then, the DCNN is used to extract features from 2D contour maps and these features are fed into the MSVM to train the classifier. The output of MSVM determines which class of the PQ disturbances belongs to. Finally, the PQ disturbance signals can be classified by the hybrid DCNN-MSVM model.

V. EXPERIMENTS AND EVALUTIONS

A. DATASET

In order to verify the effectiveness of the proposed algorithm, twenty-one different PQ disturbance signals are synthetically generated using MATLAB 2020 according to the

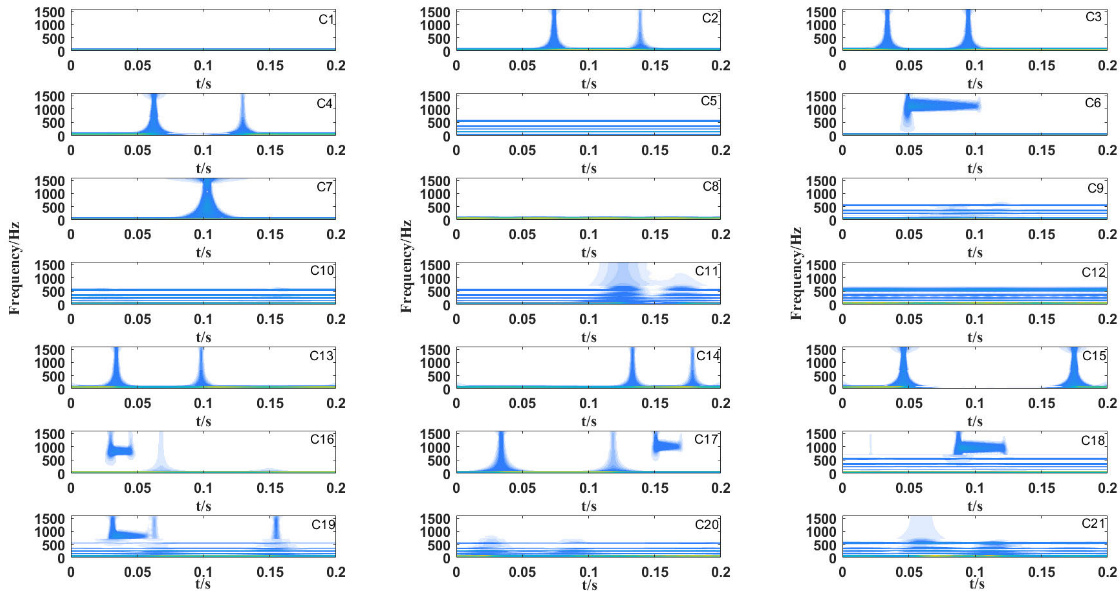

FIGURE 4. 2D contour maps of twenty-one kinds of PQ disturbances according to the formulae of Table 1.

IEEE standard 159-2019 and the disturbance models of [35]. PQ disturbances usually include harmonics, voltage swell, voltage sag, flicker, interruption, impulsive transient and oscillatory transient. These seven typical PQ disturbances are summarized as shown in Table 1 (C2-C8). More specifically, multiple PQ disturbances can be generated when two or more PQ disturbances occur at the same time. To better simulate the disturbance signals and make all disturbances closer to the real dataset in actual power grid, nine double disturbances (C9-C17) and four triple disturbances (C18-C21) are generated in this study. Table 1 shows these PQ disturbance categories, labels and equations. 500 cases of each class with unique parameters such as starting time, magnitude, ending time and frequency are allowed to change randomly, which make the testing of SMST more reliable since none of these parameters is fixed in practical power systems. Furthermore, all samples are divided into 8400 cases for the training model and 2100 for the test set randomly. The fundamental frequency of the signals is 50 Hz and the sampling frequency of 3.2 kHz is considered in this paper.

B. PERFORMANCE UNDER DIFFERENT NOISY LEVEL

To validate the effect of the proposed algorithm under different noisy level, different noisy conditions are also included and verified, as shown in Tables 2 and 3. From Table 2, it can be observed that the classification accuracy of the DCNN-MSVM classifier is higher than DCNN based classifier in each noisy condition when using the same time-frequency analysis method. For example, 88.62% and 93.1% classification rates have been achieved using the ST-DCNN and the ST-DCNN-MSVM in 20 dB, respectively, which demonstrates that the proposed DCNN-MSVM based classifier enhances the capability of classification and improves the classification accuracy compared to the DCNN based model. In addition, the SMST is able to capture and display the features more effectively than the ST, which contributes to the higher classification accuracy compared with the ST. Obviously, the classification accuracy based on the SMST significantly increases compared to ST with the same classifier even under a low noisy condition.

Table 3 shows the detailed performance of each PQ disturbances under different noisy level. One can find that the overall classification accuracy of PQ disturbances is all above 98.5% under different noisy conditions. As is clear from Table 3, the classification accuracy significantly increases even at a low noisy level. For instance, the accuracy of single disturbances (C1-C8) is higher than that of complex disturbances (C9-C21), which demonstrates that the single PQ disturbance signals are easy to be classified. Meanwhile, the average percentage of classification of the complex events increases to 98.85% even with the noisy level of 20 dB. The high accuracy of the classification for PQ disturbances obviously indicates that the proposed SMST-DCNN-MSVM has higher capabilities to classify PQ disturbances, especially for complex disturbances. The results also show that the proposed model is more suitable for detecting and classifying the PQ disturbance signals under the noisy environment, even with high noisy level.

C. PERFORMANCE COMPARISON

To further evaluate the performance of the proposed method, it is compared with these recently proposed state-of-the-art methods and the comparative results are shown in Table 4 under the high noisy interferences. One can see that these methods have achieved great accuracy, but the

TABLE 1. List of PQ disturbances.

PQ disturbance class	Label	Modeling Equations
Normal	C1	$x(t) = A\sin(\omega t)$
Swell	C2	$x(t) = A\{1+\alpha(u(t-t_1)-u(t-t_2))\}\sin(\omega t)$
Sag	C3	$x(t) = A\{1-\alpha(u(t-t_1)-u(t-t_2))\}\sin(\omega t)$
Interruption	C4	$x(t) = A\{1-\alpha(u(t-t_1)-u(t-t_2))\}\sin(\omega t)$
Harmonic	C5	$x(t) = A\{a_1\sin(\omega t)+a_3\sin(3\omega t)+a_5\sin(5\omega t)+a_7\sin(7\omega t)+a_{11}\sin(11\omega t)\}$
Oscillatory transient	C6	$x(t) = A\{\sin(\omega t)+\alpha e^{-\beta(t-t_1)}[u(t-t_1)-u(t-t_2)]\sin(\omega_n t)\}$
Impulsive transient	C7	$x(t) = A\{\sin(\omega t)+\alpha[u(t-t_1)-u(t-t_2)]\}$
Flicker	C8	$x(t) = A[1+\alpha\sin(\beta\omega t)]\sin(\omega t)$
Harmonic with swell	C9	$x(t) = A\left\{\sin(\omega t)+\sum_3^{11}\alpha_k\sin(k\omega t)\right\}\{1+\alpha(u(t-t_1)-u(t-t_2))\}$
Harmonic with sag	C10	$x(t) = A\left\{\sin(\omega t)+\sum_3^{11}\alpha_k\sin(k\omega t)\right\}\{1-\alpha(u(t-t_1)-u(t-t_2))\}$
Harmonic with interruption	C11	$x(t) = A\left\{\sin(\omega t)+\sum_3^{11}\alpha_k\sin(k\omega t)\right\}\{1-\alpha(u(t-t_1)-u(t-t_2))\}$
Flicker with harmonic	C12	$x(t) = A\left\{\sin(\omega t)+\sum_3^{11}\alpha_k\sin(k\omega t)\right\}[1+\alpha\sin(\beta\omega t)]$
Flicker with sag	C13	$x(t) = A[1+\alpha_1\sin(\beta\omega t)]\{1-\alpha_2(u(t-t_1)-u(t-t_2))\}$
Flicker with swell	C14	$x(t) = A[1+\alpha_1\sin(\beta\omega t)]\{1+\alpha_2(u(t-t_1)-u(t-t_2))\}$
Flicker with interruption	C15	$x(t) = A[1+\alpha_1\sin(\beta\omega t)]\{1-\alpha_2(u(t-t_1)-u(t-t_2))\}$
Oscillatory transient with sag	C16	$x(t) = \alpha_1 e^{-\beta(t-t_1)}[u(t-t_1)-u(t-t_2)]\sin(\omega_n t)+A\{1-\alpha_2(u(t-t_3)-u(t-t_4))\}\sin(\omega t)$
Oscillatory transient with swell	C17	$x(t) = \alpha_1 e^{-\beta(t-t_1)}[u(t-t_1)-u(t-t_2)]\sin(\omega_n t)+A\{1+\alpha_2(u(t-t_3)-u(t-t_4))\}\sin(\omega t)$
Harmonics with oscillatory transient with sag	C18	$x(t) = \sum_3^{11}\alpha_k\sin(k\omega t)+A\{1-\alpha_1(u(t-t_1)-u(t-t_2))\}\sin(\omega t)+\alpha_2 e^{-\beta(t-t_3)}[u(t-t_3)-u(t-t_4)]\sin(\omega_n t)$
Harmonics with oscillatory transient with swell	C19	$x(t) = \sum_3^{11}\alpha_k\sin(k\omega t)+A\{1+\alpha_1(u(t-t_1)-u(t-t_2))\}\sin(\omega t)+\alpha_2 e^{-\beta(t-t_3)}[u(t-t_3)-u(t-t_4)]\sin(\omega_n t)$
Harmonics with flicker with sag	C20	$x(t) = \sum_3^{11}\alpha_k\sin(k\omega t)+A\{1-\alpha_1(u(t-t_1)-u(t-t_2))\}\sin(\omega t)+[1+\alpha_2\sin(\beta\omega t)]$
Harmonics with flicker with swell	C21	$x(t) = \sum_3^{11}\alpha_k\sin(k\omega t)+A\{1+\alpha_1(u(t-t_1)-u(t-t_2))\}\sin(\omega t)+[1+\alpha_2\sin(\beta\omega t)]$

TABLE 2. Performance under different noise level.

Method	Classification accuracy, %			
	0 dB	20 dB	30 dB	40 dB
ST+DCNN	97.1	88.62	94.3	97.2
SMST+DCNN	99.1	98.43	98.95	99
ST+DCNN-MSVM	98.76	93.1	97.38	98.1
SMST+DCNN-MSVM	**99.7**	**98.86**	**99.52**	**99.6**

TABLE 3. Detailed performance of the proposed method.

Label	Classification accuracy, %			
	0 dB	20 dB	30 dB	40 dB
C1	100	100	100	100
C2	100	99	100	100
C3	100	99	100	100
C4	100	100	100	100
C5	100	100	100	100
C6	100	100	100	100
C7	100	100	100	100
C8	100	93	99	100
Average accuracy	**100**	**98.5**	**99.88**	**100**
C9	100	99	100	99
C10	100	100	100	100
C11	99	100	99	97
C12	100	100	100	100
C13	99	95	98	98
C14	98	98	98	100
C15	100	100	100	100
C16	100	100	100	100
C17	100	99	99	99
C18	100	100	100	100
C19	100	100	100	100
C20	99	98	99	100
C21	99	96	98	98
Average accuracy	**99.54**	**98.85**	**99.3**	**99.3**
Overall accuracy	**99.7**	**98.86**	**99.52**	**99.6**

categories of these PQ disturbance signals are relatively fewer than our proposed model.

For example, in [16] and [38], both the DRST and DAG-SVMS method and HT and slip-SVDNSA method obtained the classification accuracy of 97.77% and 98.45% respectively. Although these classification accuracies were appreciable, only nine and eleven types of PQ disturbance signals were designed for verification. In [37], a new method based on adaptive wavelet threshold denoising and deep

TABLE 4. Comparison of different classification methods.

Method	Num. of PQD	Noise (dB)	Accuracy (%)
SAE [36]	16	20	92.3
DBN+ELM[37]	21	20	95.8
DRST+DAG-SVM [16]	9	20	97.77
MGST+DT[23]	14	30	95.25
VMD+DT [25]	14	30	96.73
TQWT+MSVM [8]	14	20	96.42
HT+ slip-SVDNSA[38]	11	20	98.45
SMST+DCNN-MSVM	**21**	**20**	**98.86**

belief network fused with extreme learning machine was proposed to classify twenty-one types of PQ disturbance signals including eleven complex PQ disturbances. However, the classification accuracy is not relatively high compared to other methods. Moreover, the algorithms in [8], [23], and [25] failed to consider more types of complex PQ disturbances, especially for complex PQ disturbances containing three or more single disturbances. Therefore, the comparative results show that the proposed method performs better and achieves higher classification accuracy than these benchmarking methods.

VI. CONCLUSION

In this paper, a hybrid approach based on the combination of SMST and DCNN-MSVM for classification of single and combined PQ disturbances was proposed. In the SMST, a new window function is proposed with the idea of frequency segmentation and adjustable parameters, which achieves better time-frequency resolution and provides a higher extracting accuracy for PQ disturbances. This lays a solid foundation for the subsequent classification of PQ disturbance signals. Thereafter, a 2D feature matrix is extracted from the PQ disturbance signals and the corresponding 2D contour maps can be obtained by using the SMST. Then, the DCNN is proposed for automatically extracting and learning the features through the image data that contains time-frequency features of PQ disturbances. Finally, the MSVM classifier is developed for the classification of PQ disturbances. Simulation results showed that the proposed method effectively classified eight single and thirteen complex PQ disturbance signals under different noisy environment. Meanwhile, the proposed method has been compared with other state-of-the-art algorithms, and the classification results demonstrated that the proposed algorithm had higher classification accuracy and stronger anti-noise.

Considering that the selection of three parameters in the SMST is manually determined, our future work will focus on the adaptive optimization of three parameters in the SMST to achieve better time-frequency resolution and improve classification accuracy.

REFERENCES

[1] U. Subudhi and S. Dash, "Detection and classification of power quality disturbances using GWO ELM," *J. Ind. Inf. Integr.*, vol. 22, Jun. 2021, Art. no. 100204, doi: 10.1016/J.JII.2021.100204.

[2] I. S. Samanta, P. K. Rout, K. Swain, M. Cherukuri, and S. Mishra, "Power quality events recognition using enhanced empirical mode decomposition and optimized extreme learning machine," *Comput. Electr. Eng.*, vol. 100, May 2022, Art. no. 107926, doi: 10.1016/J.COMPELECENG.2022.107926.

[3] Y. Xi, Z. Li, X. Tang, and X. Zeng, "Classification of power quality disturbances based on KF-ML-aided S-transform and multilayers feedforward neural networks," *IET Gener., Transmiss. Distrib.*, vol. 14, no. 19, pp. 4010–4020, Oct. 2020, doi: 10.1049/IET-GTD.2019.1678.

[4] S. Jamali, A. R. Farsa, and N. Ghaffarzadeh, "Identification of optimal features for fast and accurate classification of power quality disturbances," *Measurement*, vol. 116, pp. 565–574, Feb. 2018, doi: 10.1016/J.MEASUREMENT.2017.10.034.

[5] J. B. Allen, "Short term spectral analysis, synthesis, and modification by discrete Fourier transform," *IEEE Trans. Acoust., Speech Signal Process.*, vol. ASSP-25, no. 3, pp. 235–238, Jun. 1977, doi: 10.1109/TASSP.1977.1162950.

[6] K. Satpathi, Y. M. Yeap, A. Ukil, and N. Geddada, "Short-time Fourier transform based transient analysis of VSC interfaced point-to-point DC system," *IEEE Trans. Ind. Electron.*, vol. 65, no. 5, pp. 4080–4091, Mar. 2018, doi: 10.1109/TIE.2017.2758745.

[7] A. G. Ramakrishnan and S. Saha, "ECG coding by wavelet-based linear prediction," *IEEE Trans. Biomed. Eng.*, vol. 44, no. 12, pp. 1253–1261, Dec. 1997, doi: 10.1109/10.649997.

[8] K. Thirumala, M. S. Prasad, T. Jain, and A. C. Umarikar, "Tunable-Q wavelet transform and dual multiclass SVM for online automatic detection of power quality disturbances," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 3018–3028, Jul. 2018, doi: 10.1109/TSG.2016.2624313.

[9] R. G. Stockwell, L. Mansinha, and R. P. Lowe, "Localization of the complex spectrum: The S transform," *IEEE Trans. Signal Process.*, vol. 44, no. 4, pp. 998–1001, Apr. 1996, doi: 10.1109/78.492555.

[10] M. V. Reddy and R. Sodhi, "A modified S-transform and random forests-based power quality assessment framework," *IEEE Trans. Instrum. Meas.*, vol. 67, no. 1, pp. 78–89, Jan. 2018, doi: 10.1109/TIM.2017.2761239.

[11] M. Sahani and P. K. Dash, "Automatic power quality events recognition based on Hilbert Huang transform and weighted bidirectional extreme learning machine," *IEEE Trans. Ind. Informat.*, vol. 14, no. 9, pp. 3849–3858, Feb. 2018, doi: 10.1109/TII.2018.2803042.

[12] B. Choudhary, "An advanced genetic algorithm with improved support vector machine for multi-class classification of real power quality events," *Electr. Power Syst. Res.*, vol. 191, Feb. 2021, Art. no. 106879, doi: 10.1016/J.EPSR.2020.106879.

[13] D. Gabor, "Theory of communication," *J. Inst. Elec. Eng.*, vol. 93, no. 26, pp. 429–441, Nov. 1946, doi: 10.1049/JI-1.1947.0015.

[14] Q. Tang, W. Qiu, and Y. Zhou, "Classification of complex power quality disturbances using optimized S-transform and kernel SVM," *IEEE Trans. Ind. Electron.*, vol. 67, no. 11, pp. 9715–9723, Nov. 2020, doi: 10.1109/TIE.2019.2952823.

[15] S. Assous and B. Boashash, "Evaluation of the modified S-transform for time-frequency synchrony analysis and source localisation," *EURASIP J. Adv. Signal Process.*, vol. 2012, no. 1, p. 49, Dec. 2012, doi: 10.1186/1687-6180-2012-49.

[16] J. Li, Z. Teng, Q. Tang, and J. Song, "Detection and classification of power quality disturbances using double resolution S-transform and DAG-SVMs," *IEEE Trans. Instrum. Meas.*, vol. 65, no. 10, pp. 2302–2312, Oct. 2016, doi: 10.1109/TIM.2016.2578518.

[17] D. Su, K. Li, and N. Shi, "Power quality disturbances recognition using modified S-transform based on optimally concentrated window with integration of renewable energy," *Sustainability*, vol. 13, no. 17, p. 9868, Sep. 2021, doi: 10.3390/SU13179868.

[18] M. Liu, Y. Chen, Z. Zhang, S. Deng, and Q. Wang, "Highly accurate detection of power quality disturbance using segmented and modified S-transform," *Electr. Power Syst. Res.*, vol. 212, Nov. 2022, Art. no. 108664, doi: 10.1016/J.EPSR.2022.108664.

[19] R. J. Haddad, B. Guha, Y. Kalaani, and A. El-Shahat, "Smart distributed generation systems using artificial neural network-based event classification," *IEEE Power Energy Technol. Syst. J.*, vol. 5, no. 2, pp. 18–26, Jun. 2018, doi: 10.1109/JPETS.2018.2805894.

[20] R. Kumar, B. Singh, D. T. Shahani, A. Chandra, and K. Al-Haddad, "Recognition of power-quality disturbances using S-transform-based ANN classifier and rule-based decision tree," *IEEE Trans. Ind. Appl.*, vol. 51, no. 2, pp. 1249–1258, Mar. 2015, doi: 10.1109/TIA.2014.2356639.

[21] M. D. Borras, J. C. Bravo, and J. C. Montano, "Disturbance ratio for optimal multi-event classification in power distribution networks," *IEEE Trans. Ind. Electron.*, vol. 63, no. 5, pp. 3117–3124, May 2016, doi: 10.1109/TIE.2016.2521615.

[22] T. Zhong, S. Zhang, G. Cai, and N. Huang, "Power-quality disturbance recognition based on time-frequency analysis and decision tree," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 18, pp. 4153–4162, Oct. 2018, doi: 10.1049/IET-GTD.2018.5780.

[23] N. Huang, S. Zhang, G. Cai, and D. Xu, "Power quality disturbances recognition based on a multiresolution generalized S-transform and a PSO-improved decision tree," *Energies*, vol. 8, no. 1, pp. 549–572, Jan. 2015, doi: 10.3390/EN8010549.

[24] K. Manimala, K. Selvi, and R. Ahila, "Optimization techniques for improving power quality data mining using wavelet packet based support vector machine," *Neurocomputing*, vol. 77, pp. 36–47, Feb. 2012, doi: 10.1016/J.NEUCOM.2011.08.010.

[25] P. D. Achlerkar, S. R. Samantaray, and M. S. Manikandan, "Variational mode decomposition and decision tree based detection and classification of power quality disturbances in grid-connected distributed generation system," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 3122–3132, Jul. 2018, doi: 10.1109/TSG.2016.2626469.

[26] S. Khokhar, A. A. M. Zin, A. P. Memon, and A. S. Mokhtar, "A new optimal feature selection algorithm for classification of power quality disturbances using discrete wavelet transform and probabilistic neural network," *Measurement*, vol. 95, pp. 246–259, Jan. 2017, doi: 10.1016/J.MEASUREMENT.2016.10.013.

[27] W. Qiu, Q. Tang, J. Liu, and W. Yao, "An automatic identification framework for complex power quality disturbances based on multifusion convolutional neural network," *IEEE Trans. Ind. Informat.*, vol. 16, no. 5, pp. 3233–3241, May 2020, doi: 10.1109/TII.2019.2920689.

[28] R. Machlev, A. Chachkes, J. Belikov, Y. Beck, and Y. Levron, "Open source dataset generator for power quality disturbances with deep-learning reference classifiers," *Electr. Power Syst. Res.*, vol. 195, Jun. 2021, Art. no. 107152, doi: 10.1016/J.EPSR.2021.107152.

[29] M. Mishra, "Power quality disturbance detection and classification using signal processing and soft computing techniques: A comprehensive review," *Int. Trans. Electr. Energy Syst.*, vol. 29, no. 8, Aug. 2019, doi: 10.1002/2050-7038.12008.

[30] K. Cai, W. Cao, L. Aarniovuori, H. Pang, Y. Lin, and G. Li, "Classification of power quality disturbances using Wigner–Ville distribution and deep convolutional neural networks," *IEEE Access*, vol. 7, pp. 119099–119109, 2019.

[31] J. Li, H. Liu, D. Wang, and T. Bi, "Classification of power quality disturbance based on S-transform and convolution neural network," *Frontiers Energy Res.*, vol. 9, p. 325, Jun. 2021, doi: 10.3389/FENRG.2021.708131.

[32] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in *Proc. Adv. Neural Inf. Process. Syst.*, Jun. 2017, vol. 60, no. 6, pp. 84–90, doi: 10.1145/3065386.

[33] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, pp. 273–297, Oct. 1995, doi: 10.1007/BF00994018.

[34] C.-W. Hsu and C.-J. Lin, "A comparison of methods for multiclass support vector machines," *IEEE Trans. Neural Netw.*, vol. 13, no. 2, pp. 415–425, Mar. 2002, doi: 10.1109/72.991427.

[35] Y. Han, Y. Feng, P. Yang, L. Xu, and A. S. Zalhaf, "An efficient algorithm for atomic decomposition of power quality disturbance signals using convolutional neural network," *Electr. Power Syst. Res.*, vol. 206, May 2022, Art. no. 107790, doi: 10.1016/J.EPSR.2022.107790.

[36] S. Wang and H. Chen, "A novel deep learning method for the classification of power quality disturbances using deep convolutional neural network," *Appl. Energy*, vol. 235, pp. 1126–1140, Feb. 2019, doi: 10.1016/J.APENERGY.2018.09.160.

[37] Y. Gao, Y. Li, Y. Zhu, C. Wu, and D. Gu, "Power quality disturbance classification under noisy conditions using adaptive wavelet threshold and DBN-ELM hybrid model," *Electr. Power Syst. Res.*, vol. 204, Mar. 2022, Art. no. 107682, doi: 10.1016/J.EPSR.2021.107682.
[38] Y. Wang, Q. Li, F. Zhou, Y. Zhou, and X. Mu, "A new method with Hilbert transform and slip-SVD-based noise-suppression algorithm for noisy power quality monitoring," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 4, pp. 987–1001, Apr. 2019, doi: 10.1109/TIM.2018.2864446.

MINGPING LIU received the B.Sc. and M.Sc. degrees from Jiangxi Normal University, Nanchang, China, and the Ph.D. degree from Beijing Normal University, Beijing, China. He is currently an Associate Professor with the School of Information Engineering, Nanchang University. His research interests include power quality, power system analysis, and deep learning.

YUE CHEN is currently pursuing the B.Sc. degree with the School of Qianhu, Nanchang University, Nanchang, China. Her research interests include power quality, machine learning, and deep learning.

ZHEN ZHANG is currently pursuing the M.Sc. degree with the School of Information Engineering, Nanchang University, Nanchang, China. His research interests include power system analysis, power quality, and deep learning.

SUHUI DENG received the B.Sc. and M.Sc. degrees from Jiangxi Normal University, Nanchang, China, and the Ph.D. degree from the Shanghai Institute of Optics and Fine Mechanics, Chinese Academy of Sciences, Shanghai, China. She is currently a Professor with the School of Information Engineering, Nanchang University. Her research interests include image processing, machine learning, and deep learning.