Power Quality Detection and Classification in Active Distribution Networks Based on Improved Empirical Wavelet Transform and Dispersion Entropy

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Abstract—In this paper, a model including wind power generation, photovoltaic power generation and electric vehicle for high permeability active distribution network (ADN) is established. The power quality (PQ) disturbance signals in the high permeability are extracted, and the characteristics of disturbance signals are analyzed in the situation of grid connection, interruption and islanding. The multi-scale fluctuation dispersion entropy (MFDE) initialized by the improved empirical wavelet transform (IEWT) is utilized to detect and classify the disturbance signals in the high permeability ADN. First, the eigenvectors of the disturbance signals are obtained by using the multi-scale fluctuation dispersion entropy initiated by the IEWT, and then the reduced eigenvectors are put into the support vector machine to classify the PQ disturbances caused by the access of the different distributed generators accessed. The classification results are compared with that in the traditional methods and other similar ways; the effectiveness of the IEWT-MFDE system is verified.

Index Terms—Active distribution network, feature extraction, power quality.

I. INTRODUCTION

W ith the increasing integration of distributed generation in power systems [1], the electric signal has become more complex than ever. Due to the constraints of natural conditions such as environment and climate, the output of distributed generators (DGs) has the characteristics of randomness, volatility and intermittence, which may lead to oscillation or flicker. Moreover, the system is more vulnerable to various disturbances because of the characteristics of the low inertia of DGs. Greater attention should be paid in the detection and classification of the complex disturbance in higher permeability active distribution networks.

Due to the diversity and complexity of the power quality (PQ) disturbance signals in active distribution networks, some shortcomings still exist in power signal detection methods [2], [3]. For example, the local mean decomposition (LMD) is used to extract the features of non-stationary power signals in the micro-networks, and the signals are decomposed into a series of modal functions according to the decreasing frequency in the process of iterative screening [4]. However, the drawbacks of “endpoint effect” and “modal aliasing” greatly affect the accuracy of the results, and this method has no ability to decompose the signals adaptively. The additional decomposition quantities need to be considered for the different signals. In [5], [6], the variational mode decomposition (VMD) is adopted to extract power signal features in microgrids. Although the algorithm converts signal decomposition from recursive filtering mode to non-recursive filtering mode, which solves the problems of LMD at the cost of higher computational complexity, it still cannot be decomposed adaptively according to the different signal complexities. The parameters must be chosen carefully to achieve a proper result.

The empirical wavelet transform (EWT) has many advantages over the above algorithms [7]–[9], such as fast computation speed, no mode aliasing and adaptive decomposition. Empirical wavelet transform is an algorithm based on the framework of wavelet transform. It has the advantages of empirical mode decomposition (EMD) but differs from it in principle [10]. The difference lies primarily in the two aspects. First, EMD uses the cyclic methods to filter the signals repeatedly until the final residual is a monotonic function, so the computation speed is slower. However, EWT is better in computing speed. Secondly, EMD adopts the modal function screening of upper and lower envelopes. Therefore, the noise has a greater impact on it, while EWT focuses on the characteristics of the sparseness in the frequency domain and does not have sparseness in the time domain. The maximum or minimum in the frequency domain of the signals are found and the frequency band boundary is divided to ensure that the signal has the sparseness in the frequency domain. Since all modal components are decomposed at the same time, EWT has obvious advantages in anti-noise interference and avoids over-
enveloping, which is more suitable for the complex disturbance signals in the active distribution network.

The entropy method is used to measure the complexity of time series. The most common methods of single-scale entropy are approximate entropy (ApEn), sample entropy (SampEn), fuzzy entropy (FuzzyEn), permutation entropy (PE) and dispersion entropy (DispEn) [11]–[13] and so on. Dispersion entropy, which is faster in calculation, is less affected by the mutation signal, and takes into account the amplitudes relationship between the signals. The comparison among the DispEn method, the SampEn method and PE method [14]–[16] are used for analyzing and simulating nonlinear signals in the biological field. The results show that the DispEn method has better stability and faster in calculation. Based on this, the method of composite multiscale dispersion entropy (CMDE) is proposed and applied to the analysis of the biological signals. Compared with the other multiscale methods [17], the advantages of CMDE in calculation error and feature extraction effects have been shown. However, the original dispersion entropy cannot analyze the local or global trend of the signal. If the fluctuation of data is correlated or the local trend of time series is uncorrelated, there is no difference in its fluctuation mode. Therefore, multiscale fluctuation based DispEn [18] is introduced in this paper, which solves the above problems.

This study combines improved empirical wavelet transform (IEWT) with multi-scale fluctuation-based dispersion entropy (MFDE), and improves the EWT results of the amplitude disturbance signals. A new method of instantaneous feature extraction based on IEWT and MFDE is proposed. The disturbance signal is decomposed into the multiple intrinsic modal functions according to the characteristics of non-linear, non-stationary and multi-disturbance compounding of power signal disturbances in active distribution networks. The MFDE is calculated by the inherent mode decomposition, and the quantitative analysis of the disturbance signal is realized. An active distribution network based on IEEE 13 nodes is built as a test platform and the PQ disturbance signal is analyzed. The results show that the proposed method has the advantages in time-consumption and accuracy. Principal component analysis (PCA) is used to reduce the dimension of the feature matrix, and then the feature matrix is put into the support vector machines (SVM) classifier to complete the automatic recognition of the composite voltage disturbance signal, thus its effectiveness is proved.

II. SIGNAL EXTRACTION AND ALGORITHMS

A. Signal and Data Extraction

In this study, the voltage disturbance signals are extracted from the active distribution network (ADN) based on IEEE 13 node, as shown in Fig. 1.

The test feeder is connected to the grid with the rated power of 5 MVA and the operating voltage of 4.16 kV. The transformer parameters are shown in Table I, and the loads in the distribution network are shown in Table II, where the Y-PQ means the loads are connected in wye and its output power is constant. The two types of DGs, photovoltaic and wind turbine, are included in the model and an electric vehicle is connected as the non-linear load. The point of common coupling (PCC) in the system is the node 680 and the system frequency is 60 Hz. Moreover, the sampling frequency is 3.2 kHz, and the sampling time is 0.2 s.

In this study, the permeability in the active distribution network is calculated based on (1):

$$P_{\text{PERMEABILITY}} = \frac{\sum_{i=0}^{n} P_{L,DG,\text{non}}}{P_{L,\text{sum}}}$$

where $P_{L,DG,\text{non}}$ is the installed capacity of the first distributed power source; $n$ is the number of distributed power sources; $P_{L,\text{sum}}$ is the total load power [19]. In the system, the wind turbine adopts the doubly fed induction generator and is directly connected to the grid through the Tr3 transformer whose total capacity is 1.5 MW; the photovoltaic power generation is connected to the grid through the three-phase voltage pulse-width modulation (PWM) converter, with a total capacity of 1 MW; the electric vehicle adopts the three-phase bridge rectifier charger and is connected to the grid, with a total load of 0.5 MW. Moreover, there are three

![Fig. 1. The ADN constructed from IEEE 13 test feeder.](image-url)
types of charging methods for electric vehicles: fast charging, mechanical charging and conventional charging. The power of the fast charging charger is larger, which causes more serious disturbances for the PQ signals. This charging mode is primarily considered in this research. In the experimental system, the total installed capacity $P_{DG-non}$ is 2.5 MW, and the total load power $P_{Load}$ is 3.866 MW. According to (1), the permeability of the system is 64.66%, more than 60%, which is consistent with the description of high permeability. Disturbance signals in high-permeability ADN are affected by a variety of factors, including the capacity, locations, and methods of the DGs access. Any change of these factors will affect the characteristics of the final signal. For example, the electric vehicles using three-phase full bridge rectifier chargers usually generate more 5th and 7th harmonics than the ones using 12-pulse rectifier chargers.

The disturbance signal is generated by operating the circuit breakers CB1, CB2, CB3 and CB4, in which CB1 is closed by the default, CB2, CB3 and CB4 are open by the default. The C1–C11 event signals are derived from the open and close of different circuit breakers. The signals include:

1) The closing of CB2 generates the signal of grid connection C1 from the wind turbine;
2) The disconnection of CB2 generates the signal of the interruption C2 from the wind turbine;
3) The signal of the turbine island operation C3 will be caused while CB1 is disconnected and CB2 is closed;
4) The closing of CB3 generates the grid connection signal C4 from the photovoltaic grid;
5) The disconnection of CB3 generates the interruption signal C5 from the photovoltaic grid;
6) The opening of CB1 and the closing of CB3 cause the signal C6 of the photovoltaic island operation;
7) The closing of CB4 simulates the signal C7 for the large-scale electric vehicle connected to the grid;
8) The disconnection of CB5 tests the signal C8 for the large-scale electric vehicle off from the grid;
9) CB2 and CB3 are closed to simulate the connection of the wind turbine and the photovoltaic at the same time to the system, and the signal C9 is connected to the grid;
10) CB2 and CB3 simultaneously disconnect to simulate the wind turbine and the photovoltaic off from the grid and the signal is C10;
11) CB1 is off, while CB2 and CB3 are closed at the same time to simulate the simultaneous islanding signal C11 for the wind turbine and the photovoltaic.

**B. Empirical Wavelet Transform and its Improvements**

EWT is a method of time-frequency analysis to extract signal features. It decomposes the time-series signals into a series of single component amplitude modulation-frequency modulation (AM-FM) signals in the Fourier spectrum, and uses the single component Fourier spectrum to construct the empirical wavelet adaptively to complete the adaptive decomposition of the complex signals, which is suitable for analyzing the non-stationary time-varying signals. The procedure of extracting modal components is as follows:

1) The fast Fourier transform (FFT) transform is used to extract the main frequency of the signal $f = \{f_i\}_{i=1,2,...,N}$ [20]–[23].
2) The continuous Fourier spectrum is adaptively divided into several parts in order to determine the boundary value $\Omega = \{\Omega_i\}_{i=1,2,...,N}$. The initial boundary value $\Omega_0$ is set to 0, while the remaining $\Omega_i \forall i \in [1, N - 1]$ is set at the midpoint of the two adjacent local minimum frequencies $(f_i, f_{i+1})$ in the Fourier spectrum of the signal.
3) After the segmentation interval is determined, the empirical wavelet is defined as a band-pass filter on each segmentation interval, as shown in Fig. 2.

![Fig. 2. Spectrum with the empirical wavelet filters.](image)

In this paper, the Meyer wavelet is used to construct the empirical wavelet, and the sampling frequency is 3.2 kHz. Because this method can be an adaptive decomposition, it does not need to set the number of the decomposition and other parameters. The empirical wavelet function $\phi$ and $\Psi(\omega)$ empirical scaling function can be defined as follows:

$$\phi_1(\omega) = \begin{cases} 1, & \text{if } |\omega| \leq (1 - \gamma)\Omega_1 \\ \cos \left(\frac{\pi}{2} \beta(\gamma, \omega, \Omega_1)\right), & \text{if } (1 - \gamma)\Omega_1 \leq |\omega| \leq (1 + \gamma)\Omega_1 \\ 0, & \text{otherwise} \end{cases}$$

$$\Psi_1(\omega) = \begin{cases} 1, & \text{if } (1 + \gamma)\Omega_1 \leq |\omega| \leq (1 - \gamma)\Omega_{i+1} \\ \cos \left(\frac{\pi}{2} \beta(\gamma, \omega, \Omega_{i+1})\right), & \text{if } (1 - \gamma)\Omega_{i+1} \leq |\omega| \leq (1 + \gamma)\Omega_{i+1} \\ \sin \left(\frac{\pi}{2} \beta(\gamma, \omega, \Omega_i)\right), & \text{if } (1 - \gamma)\Omega_i \leq |\omega| \leq (1 + \gamma)\Omega_i \\ 0, & \text{otherwise} \end{cases}$$

where $\beta(\gamma, \omega, \Omega_i) = \beta(\frac{1}{2\gamma\Omega_i}(|\omega| - (1 - \gamma)\Omega_i))$ is a set of random functions with parameters given by [7]: $\gamma$ is an parameter to ensure the minimum overlapping area between two continuous state intervals, whose value is determined by the calculated boundary.

4) The EWT components after filtering can be obtained by (4) and (5), where $I$ represents inverse fast Fourier transform.

$$W_x(1, n) = I(X(\omega)\phi_1(\omega))$$

$$W_x(i, n) = I(X(\omega)\psi_1(\omega))$$
The segmentation of the Fourier spectrum directly affects the results of EWT. The different spectrum parts correspond to the different modes with the different specific support frequencies as the center. In the case of voltage sag, swell, interruption and other disturbance signals, inter-harmonics may be generated near the fundamental wave. The spectrum leakage of the fundamental component influences deviation of the EWT component. Generally speaking, the distance between two groups of continuous harmonics or between two groups of continuous inter-harmonics is longer than that between a group of harmonics and a group of inter-harmonics. In order to more accurately decompose the voltage and current signals, a more accurate spectral segmentation method is proposed in this study.

First, the frequency-domain sequence $\Lambda_1 = \{f_i\}_{i=1,2,...,M_1}$ of the fundamental and harmonics of the original disturbance signal is constructed, in which the amplitude of the minimum component is not less than 2% of the fundamental wave and the minimum frequency is not less than 45 Hz, and this group of frequencies is used as the central frequency to calculate in (2), where $\Omega_i = f_i - 5$, $\Omega_{i+1} = f_i + 5$ and $\gamma = 0.01$. The bandwidth of the band-pass filter is $BW_i = 10 + 2\gamma f_i$ Hz. The harmonic spectrum can be calculated from (6):

$$X_H(\omega) = \left( \sum_{i \in \Lambda_1} X(\omega)\Psi_i(\omega) \right)$$

(6)

The harmonic spectrum is subtracted from the original spectrum, and only the residual spectrum of inter-harmonics $X_R(\omega)$ is included. The amplitude of the minimum component shall not be less than 2% of the fundamental wave, and the minimum frequency $\Lambda_2 = \{f_i\}_{i=1,2,...,M_2}$ shall not be less than 5 Hz. The sequence of inter-harmonics $\Lambda_3 = \{f_i\}_{i=1,2,...,M_1+M_2}$ can be obtained by combining $\Lambda_1$ with $\Lambda_2$ and arranging in ascending order. However, there are still component residues in the fundamental and integral harmonic components of some extremely unstable signals due to the spectrum leakage. Therefore, for the sequence, the adjacent components not exceeding the difference $\pm 5$ Hz are divided into a group to ensure that the actual frequency is only considered for filter design, so as to extract the single frequency component. The processed frequency sequence, $A = \{f_i\}_{i=1,2,...,N}$, $(N \leq M_1 + M_2)$ is the final frequency sequence in the signal, and the frequency components with a spacing of more than 10 Hz can be accurately divided.

A signal of voltage sag is selected to explain the improvement. The unimproved EWT decomposition is utilized in Fig. 3(a) and the IEWT decomposition is adopted in Fig. 3(b). It can be seen that there is an over decomposition phenomenon in FFT. In Fig. 3(a), a simple voltage sag signal is partitioned into several modes due to the spectrum leakage phenomenon in FFT. The unimproved EWT will segment several times in the location of spectrum leakage, resulting in a large number of invalid or even erroneous modes, that is, the phenomenon of over segmentation.
this time, the adaptive recognition modes for the unimproved EWT becomes the source of the error. If these components are directly input into the subsequent classifiers, it is very likely that a simple signal of voltage sag will be identified as the voltage interruption, which greatly affects the accuracy of the results. The IEWT decomposition in Fig. 3(b) is not affected by spectrum leakage which decomposes a large number of error modes. The accuracy of subsequent classifications can be ensured by the improved EWT.

C. Multiscale Fluctuation-Based Dispersion Entropy

The FdispEn of a signal with the length \( n \): \( x = \{x_1, x_2, \ldots, x_N\} \) can be derived as follows:

1) \( x_j (j = 1, 2, \ldots, N) \) are mapped to the class \( c \) with the integer index, from 1 to \( c \). However, a problem that most of \( x_i \) may be assigned to a few classes occurs, especially when the maximum or minimum value is significantly greater than or less than the average or median value for the signal. The normal cumulative distribution function (NCDF) [24] can solve this problem and be used to map \( x \) to \( y \). From 0 to 1, as follows:

\[
y_j = \frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{x_j} e^{-\frac{(t - \mu)^2}{2\sigma^2}} dt
\]  

where \( \sigma \) and \( \mu \) are the standard deviation and the average value of time series \( x \) respectively. Each \( y_i \) is assigned linearly to integers from 1 to \( c \). \( z^c_j = \text{round} (c \cdot y_j + 0.5) \) was used to the each member of the mapped signal, where \( z^m_{i,c} \) represents the \( j \)-th member of the classified time series, and the rounding operator is adopted to increase or reduce the number to the next number.

2) The time series \( z^m_{i,c} \) is defined according to \( z^m_{i,c} = \{z^c_i, z^c_{i+d}, \ldots, z^c_{i+(m-1)d}\}, i = 1, 2, \ldots, N - (m - 1) d \). Where \( z^m_{i,c} \) is related to embedding the dimension \( m - 1 \) and the time delay \( d \). Each time series \( z^m_{i,c} \) is mapped to the fluctuation based on the dispersion mode \( \pi_{v_0,v_1,\ldots,v_{m-1}} \), where \( z^m_{i,c} = v_0, z^m_{i+d} = v_1, \ldots, z^m_{i+(m-1)d} = v_{m-1} \). The number of possible fluctuations based on the dispersion modes of each time series \( z^m_{i,c} \) is equal to \( (2c-1)^{(m-1)} \).

3) The following relative probability could be obtained from each \( (2c-1)^{m-1} \) potential dispersion mode \( \pi_{v_0,\ldots,v_{m-1}} \):

\[
p \left( \pi_{v_0,\ldots,v_{m-1}} \right) = \frac{Q \left[ \exists i \mid i \leq N - (m - 1) d, z^m_{i,c} \text{ has type } \pi_{v_0,\ldots,v_{m-1}} \right]}{N - (m - 1) d}
\]  

where \( Q \) is the cardinality. In fact, \( p \left( \pi_{v_0,\ldots,v_{m-1}} \right) \) means the
number of the dispersion modes for $\pi_{V_0...V_{m-1}}$, which is assigned to $z^m_{i,m,c}$ is divided by the total number of embedded signals. Its embedding dimension is $m$.

4) $F\text{dispEn}$ value is calculated as follows according to Shannon’s definition of entropy.

$$F\text{dispEn}(x, m, c, d) = - \sum_{\pi=1}^{(2c-1)m-1} p(\pi_{V_0...V_{m-1}}) \cdot \ln (p(\pi_{V_0...V_{m-1}}))$$ (9)

Combined with the methods described above, the technical roadmap diagram of this work can be shown in Fig. 4.

![Fig. 4](image)

Fig. 4. The overall technical roadmap.

III. DISTURBANCE SIGNALS DETECTION

A. Wind Turbine Operation

The wind turbine connected to the grid, interrupted from grid and island are simulated by C1–C3 events respectively. In this case, the wind turbine is directly connected to the transformer which makes the main disturbance feature as the voltage fluctuation. The instantaneous IEWT components of the wind power system connected to the system are shown in Fig. 5(a). The main feature which the wind turbine is connected to the grid is voltage sag because the demand for reactive power becomes larger. The voltage signal appears voltage sag from 0.06 s to 0.14 s, and the disturbance type and the disturbance duration can also be distinguished from the IEWT time-frequency spectrum of the C1 signal, as shown in Fig. 5(b). The signal shows a significant amplitude decrease, while the frequency does not change.

![Fig. 5](image)

Fig. 5. The characteristics of the C1 signal. (a) The IEWT decomposition of C1. (b) IEWT time-frequency spectrum of C1 signal.

While the wind power system is interrupted (C2), the reactive power demand becomes smaller, and its main feature is amplitude disturbance. It can be seen from Fig. 6(a) that the IEWT component has an obvious temporary rise of the voltage amplitude, and its temporary rise duration is 0.05 s to 0.13 s. The color change in the IEWT time-frequency spectrum in Fig. 6(b) also reflects the feature that the amplitude suddenly rises between 0.05 s and 0.13 s while the frequency is not affected. It shows that the disturbance caused by the off-grid event of the wind turbine connected with the power grid through the transformer is primarily the amplitude disturbance.

The main characteristic of the wind energy system island (C3) reflecting on the IEWT components is the voltage amplitude fluctuation as shown in Fig. 7(a). It can be seen that it drops within 0.05 s to 0.1 s and rises within 0.1 s to 0.15 s, which is also reflected in the IEWT time-frequency spectrum in Fig. 7(b). The amplitude change in the above corresponding time can be directly reflected in color, and it can be observed that it drops first and then obviously rises.
B. Photovoltaic Operation

The C4–C6 events simulate the power disturbance of the photovoltaic connected to the grid, interrupted and island operation respectively. In the process of the photovoltaic connected to the grid (C4), due to the randomness of the photovoltaic power generation and the use of the three-phase voltage source PWM converter, harmonic interference is the main feature. The IEWT components of the PV grid connected to the grid are shown in Fig. 8(a). It can be observed that the third, fifth and seventh harmonic components are the main parts. Meanwhile, the harmonic component amplitudes are 0.22, 0.36 and 0.40 in the fourth, fifth and sixth IEWT components respectively. The harmonic frequency can be observed better in the IEWT time-frequency spectrum, so the disturbance signal generated by the event includes four types of frequencies, as shown in Fig. 8(b).

Due to the sudden disconnection of the photovoltaic interruption (C5) from the distribution network, the voltage amplitude fluctuates smaller, however the frequency fluctuates greatly. The IEWT components are shown in Fig. 9(a), the third component is the signal fundamental frequency, and the main disturbance features are concentrated in the fourth and fifth components, characterized by a high-frequency flicker. Moreover, the disturbance frequency is higher in the IEWT spectrum while the amplitude fluctuation is not obvious, as shown in Fig. 9(b).
The operation of the Photovoltaic island (C6) means that the photovoltaic power generation system operates independently after losing the support of the public grid. Due to the randomness of the solar light intensity and duration, the power disturbance is primarily characterized by the flicker component and the harmonic component, as shown in Fig. 10(a). It can be seen that the power quality disturbance is primarily harmonic from 0.6 seconds to 1 second, which is reflected in the components 4, 5 and 6, and the high-frequency flicker after 1 second is reflected in several of the minutes. In the IEWT spectrum, not only can the frequency change be observed, but also the duration of each disturbance can be reflected. It shows that the flicker frequency after 1 second is about 900 Hz, and the amplitude fluctuation is smaller, as shown in Fig. 10(b). The duration and amplitude components for the two disturbances can be identified accurately by EWT.

C. Large-scale Grid Connection and Off-grid of Electric Vehicles

The event C7 simulates the large-scale electric vehicles connection to the grid, i.e. the centralized charging. The event C8 simulates the large-scale off grid for the electric vehicles. Due to the three-phase bridge rectifier charger, the overall power disturbance features are reflected in the voltage amplitude sag and harmonics while the motor vehicle is connected to the grid in large scale (C7). The IEWT components are shown in Fig. 11(a), where the voltage sag feature is in the third component and the harmonics are in the fourth, fifth, sixth and seventh components. The amplitudes of the 5th and

Fig. 9. The characteristics of the C5 signal. (a) The IEWT decomposition of C5. (b) IEWT time-frequency spectrum of C5 signal.

Fig. 10. The characteristics of the C6 signal. (a) The IEWT decomposition of C6. (b) IEWT time-frequency spectrum of C6 signal.

Fig. 11. The characteristics of the C7 signal. (a) The IEWT decomposition of C7. (b) The IEWT time-frequency spectrum of C7 signal.
7th harmonic components are higher, while the amplitude of the 11th and 13th harmonic components are smaller, and the amplitude of the harmonic components are 0.26, 0.16, 0.08 and 0.05 respectively. The duration and frequency characteristics of each disturbance can be observed from the IEWT time-frequency spectrum in Fig. 11(b). The sag disturbance is similar to the previous one, which is obviously reflected in the color change of the basic frequency signal, while the harmonic component is higher than the previous photovoltaic events (C4–C6), which is caused by the different switching frequency of the different grid connection modes.

The large-scale off grid (C8) for the electric vehicles is similar to the grid connection, and the disturbance characteristics are primarily reflected in the temporary rise of the voltage amplitude and the harmonics, as shown in Fig. 12(a). The characteristics of the voltage temporary swell are in the third component, while the harmonic characteristics are in the fourth, fifth, sixth and seventh components. Similarly, these disturbance characteristics can also be observed in the IEWT time-frequency spectrum, and the voltage sag disturbance time lasts from 0.05 to 0.1 while the harmonic characteristics run from 0.05 s to the end, which is consistent with the information reflected in the IEWT time-frequency diagram in Fig. 12(b). The disturbance related to the amplitude can still be directly observed through the color change, and the frequency is consistent with the event C7 in terms of the harmonic frequency, but the amplitude differs.

D. Simultaneous Operation of the Wind Power System and Photovoltaic System

The events C9–C11 simulate the simultaneous operations of the photovoltaic system and wind energy system which include connection, interruption, and island. Due to the high permeability of the distribution network, the simultaneous wind and solar grid connection (C9) is primarily reflected in the oscillation at the moment of grid connection, and the frequency and amplitude of the signal have changed, as shown in Fig. 13(a). The oscillation time is located between 0.08 s and 0.14 s. It can be seen in Fig. 13(b) that the frequency is about 600 Hz;

The event C10 simulates the interruption of the wind energy system and photovoltaic system at the same time. The power flow is bidirectional in the normal condition, while the power flow routes from the public grid to the distribution network as the event C10 takes place. The IEWT components are shown in Fig. 14(a). The main disturbance feature is pulse, which is located at 0.86 s. Similarly, the same result can be obtained in the IEWT time-frequency spectrum in Fig. 14(b). The signal is almost unaffected in the frequency domain.

The systems of wind and photovoltaic power generation operate in isolated islands with constant wind speed and illumination intensity (C11). The main characteristics of the electric energy disturbance are spikes and notches. The periodic frequency depressions and protrusions correspond to
notch and spike characteristics, as shown in Fig. 15(a). The spikes and notches change corresponding to the original signal. As shown in Fig. 15(b), its frequency is seriously affected.

IV. POWER QUALITY DISTURBANCE SIGNALS CLASSIFICATION

The algorithm MFDE is used for the extracted IEWT component to form the eigenvector $s = \{M_{u1}, M_{u2}, \cdots, M_{uk}\}$ of the signal with the scale factor $\tau = [1, 2, \cdots, \tau_{\text{max}}]$ as follows. Where $M_{uk}$ is the entropy value of the IEWT component at the different scales; $k$ is the number of the modes decomposed by EWT, and the length($M_{uk}$) = $\tau_{\text{max}}$ is the dimension of multi-scale fluctuation dispersion entropy which is calculated from each IEWT component. The diagram of the MFDE characteristic for the signals C1–C11 is shown in Fig. 16.

![Fig. 14. The characteristics of the signal C10. (a) The IEWT decomposition of C10. (b) The IEWT time-frequency spectrum of C10.](image)

![Fig. 15. The characteristics of the signal C11. (a) The IEWT decomposition of C11. (b) The IEWT time-frequency spectrum of C11.](image)

![Fig. 16. FdispEn for each signal. (a) C1 FdispEn signal value. (b) C2 FdispEn signal value. (c) C3 FdispEn signal value. (d) C4 FdispEn signal value. (e) C5 FdispEn signal value. (f) C6 FdispEn signal value. (g) C7 FdispEn signal value. (h) C8 FdispEn signal value. (i) C9 FdispEn signal value. (j) C10 FdispEn signal value. (k) C11 FdispEn signal value.](image)
At present, there are many novel and advanced classifiers [25]–[33]. However, in order to prove the effectiveness of the proposed IEWT-CFDE system, SVM is still selected as the classifier in this study. SVM can be regarded as a binary classifier. It abstracts a decision boundary from the data and classifies two groups of similar patterns according to it. The edge value is the distance between the optimal separating hyperplane and its two side instances. The vector of the edge values is the support vector. In the case of linear separability, the solution of SVM is a linear combination of support vectors. Therefore, the complexity of the SVM model is not affected by the number of selected features. In essence, SVM projects the input data which cannot be separated linearly into high-dimensional space, and finds the optimal hyperplane in the feature space with the maximum possible margin. In this study, a set of binary support vector machines are adopted to solve the problem of multi-class signal classification of the PQ voltage. One-against-all (OAA) and One-against-one (OAO) are the most commonly used methods of multi-class classification. OAO performs pairwise classification by constructing the $K(k-1)/2$ binary model of the $k$-class problems. In this method, each model is trained with two different types of data, so that the $k$-class problems can be transformed into the $K(k-1)/2$ different tasks. The other method, OAA solves the multiclassification problem by solving the number of $K$ two-classification problems, so it needs to build $K$ binary models, each model is specially used to detect specific types. Both of these methods are considered to be suitable for multi-class classification of the PQ disturbances.

SVM needs a lot of data for training, but it is very difficult to get a large amount of data from the simulation system. In this study, the simulation data given in the IEEE standard is selected for training [34]. The training classification object of SVM for disturbance is the eigenvectors obtained from the decomposition of IEWT in the earlier stage, and the disturbance characteristics of the simulation signals extracted from the distribution network are consistent with the above training signal characteristics, so the mathematical model can be used for training. The standard frequency of the signal is 60 Hz and varies within the range of 0.5 Hz. All signals are set as 200 ms as the value duration according to IEC standard 61000-4-7 [35], [36]. In order to improve the recognition accuracy of the noise interference, the noise with signal-to-noise ratio of 20–50 dB is randomly added. A set of single disturbance signals which are randomly generated according to the mathematical model from the IEEE standard are put into the classifier to test the performance. The classification results of simple signals are shown in Fig. 17. It can be seen from its confusion matrix that the method in this study is competent.

The algorithm PCA is employed to reduce the dimension of 11 types of disturbance signals obtained from the above

![Confusion Matrix](image-url)

**Fig. 17.** The confusion matrix of the simple signals classification.
simulation, and the feature matrix after dimension reduction is as the input of SVM, and the classification results are shown in Table III. It can be seen that the accuracy is 99.73% in the case of no noise and 99.36% in the case of 20 dB noise, which shows that the classification algorithm SVM based on EWT-MFDE is more effective.

Table III: SVM Classification Results for Different Signals

<table>
<thead>
<tr>
<th>Event</th>
<th>Noises</th>
<th>Error case</th>
<th>Noises</th>
<th>Error case</th>
<th>Accuracy rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>100</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>C2</td>
<td>100</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>C3</td>
<td>100</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>C4</td>
<td>100</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>C5</td>
<td>100</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>C6</td>
<td>98</td>
<td>96</td>
<td>2</td>
<td>96</td>
<td>98</td>
</tr>
<tr>
<td>C7</td>
<td>99</td>
<td>99</td>
<td>1</td>
<td>100</td>
<td>99</td>
</tr>
<tr>
<td>C8</td>
<td>100</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>C9</td>
<td>100</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>C10</td>
<td>100</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>C11</td>
<td>100</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Compared with the traditional method in the PQ disturbance detection and classification, the proposed method has more advantages in accuracy, which are shown in Table IV. Moreover, some comparisons with similar methods are also proposed in this study, such as EWT-SVM, EWT-composite multiscale permutation entry (CMPE)-SVM, IEWT-CMPE-SVM and IEWT-MFDE-SVM. The results show that the decomposition results of IEWT greatly improve its accuracy, and MFDE is more suitable for feature extraction of amplitude disturbance than CMPE and other traditional entropy methods. The effectiveness of the proposed method can be proved.

Table IV: Performance Comparison of PQ Algorithm for Disturbance Classification

<table>
<thead>
<tr>
<th>Literature</th>
<th>Method</th>
<th>Accuracy (%)</th>
<th>Overall accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>[37]</td>
<td>S-transform + T2FK-SVM</td>
<td>99.44</td>
<td>96.44</td>
</tr>
<tr>
<td>[38]</td>
<td>SSA-CT-DCNNs</td>
<td>99.52</td>
<td>99.20</td>
</tr>
<tr>
<td>Similar methods</td>
<td>EWT-SVM</td>
<td>95.87</td>
<td>95.66</td>
</tr>
<tr>
<td>EWT-CMPE-SVM</td>
<td>97.22</td>
<td>95.73</td>
<td>96.48</td>
</tr>
<tr>
<td>IEWT-CMPE-SVM</td>
<td>99.64</td>
<td>99.27</td>
<td>99.46</td>
</tr>
<tr>
<td>Proposed method</td>
<td>IEWT-MFDE-SVM</td>
<td>99.73</td>
<td>99.36</td>
</tr>
</tbody>
</table>

V. CONCLUSION

In this paper, a feature extraction algorithm EWT-MFDE for a power quality signal is proposed, and the corresponding simulations are done and verified based on the IEEE13 node test feeder. The proposed method is universal, not only limited to the IEEE 13 node experimental system, but can also obtain correct results in the larger and more complex networks with the help of partition, and the parameter settings are not specific. The improvement of the IEWT spectrum segmentation avoids the error decomposition or over-decomposition of the IEWT algorithm in the face of the problem of spectrum leakage, such as voltage amplitude fluctuation, etc., and makes use of FFT computing advantages and the design of adaptive spectrum segmentation. It also makes the decomposition of the disturbance signal faster and more accurate. The modified EWT-MFDE is adopted to extract the power quality features, and PCA is employed to reduce the dimensions. Finally, the SVM classifier is used to complete the classification work. The accuracy is 99.73% in a noiseless environment and 99.36% in a Signal-to-noise ratio (SNR) up to 20 dB environment, which proves the effectiveness of the proposed method.

REFERENCES


