Voltage Transient Disturbance Detection Based on the RMS Values of Segmented Differential Waveforms

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ABSTRACT Voltage transient disturbance is one of the key voltage quality disturbances, which can be classified into oscillatory transient and impulsive transient. Currently, there is no simple, accurate and general method to detect, extract, and characterize the voltage transient disturbance. This paper proposes a time-domain voltage transient disturbance detection method based on the RMS (root mean square) values of segmented differential waveforms. Firstly, the abnormal voltage waveforms are detected and extracted, which will be used for further analysis. Secondly, the extracted abnormal voltage waveform data are pre-processed, and then each power frequency cycle are processed in segment. Thirdly, by considering the influence of the system frequency variation, the differential waveform can be obtained by calculating the difference between two consecutive cycles. Finally, the voltage transient disturbance is detected by calculating and comparing the segmented RMS values of differential waveforms and steady-state waveforms. The transient component is extracted as well. Four indicators, i.e., dominant frequency, polarity, magnitude and duration, are used to characterize the voltage transient disturbance. In order to verify the accuracy and feasibility of the proposed method, both simulated data from an improved IEEE-13 node test system and actual voltage transient signal from a laboratory experiment are used.

INDEX TERMS Voltage transient disturbance, differential waveform, segmented RMS value, frequency variation, transient component.

I. INTRODUCTION

With the high penetration of non-linear loads and power electronic based equipment into power systems, voltage quality problems are becoming more and more prominent. A single equipment failure or an abnormal operation may bring huge economic losses to power companies or customers [1]. Therefore, it is necessary to take corresponding mitigation measures for voltage quality disturbances, in which the precondition is to accurately detect and extract these disturbances [2], [3].

Voltage quality disturbance refers to any disturbance that deviates from the perfect sinusoidal voltage waveform,

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including voltage transient, long or short duration voltage variations, voltage unbalance, harmonics, etc. [4]. In this line, researches on long and short duration voltage variations, voltage unbalance, and harmonics have been extensively conducted [5], [6]. However, there is still a lack of simple and general methods for detecting, extracting, and characterizing voltage transient disturbances.

In power systems, voltage transient disturbances are generally caused by lightning, capacitor or end-user equipment switching [7]. According to the definitions given in IEC 61000-4-30 [8] and IEEE Std. 1159 [9], voltage transient disturbance includes both oscillatory transient and impulsive transient disturbance. Oscillatory transient refers to the phenomenon of non-power frequency and sudden changes of voltage with positive and negative polarities, while impulsive

transient refers to the phenomenon of non-power frequency and sudden changes of voltage with unipolar. The typical duration of the former one ranges from $5\mu s$ to 50ms, while the latter ranges from 1ns to 1ms. Oscillatory transient disturbances are generally caused by capacitive load or large end-user equipment switching, and impulsive transient disturbances are generally caused by lightning or inductive load switching [7].

To our best knowledge, efforts have been made to identify the transient disturbances, which can be classified into four categories, i.e., methods based on signal processing [10]–[20], methods based on machine learning [21]–[28], methods based on IEC standard [8], [29]–[32], and other methods [4], [33]–[36]. For signal processing-based transient detection method, Fourier transform (FT) [14], [15], wavelet transform (WT) [16], [17], Hilbert Huang transform (HHT) [18], Stockwell transform (ST) [19], [20] are mostly utilized to generate information and extract features in time-frequency domain, which are used to extract features and judge whether there is transient or not. For example, references [10]–[13] utilized Fourier or/and wavelet transform to identify capacitor switching transients. The transient disturbance is identified if the energy of each frequency band exceeds the set detection threshold. However, the FT is developed for stationary signals. Short-term FT (STFT) is an improvement of FT, which can be used to study the non-stationary signals [14]. Reference [15] proposed a method based on Kalman filter and STFT to detect the transient disturbance. But STFT cannot track transient signals whose amplitude changes with time because of the lack of variable windows in STFT's structure. On the other hand, WT can only provide the frequency range, rather than the dominant frequency due to spectral leakage [16]. What's more, WT's performance highly depends on the decomposition layers and the choice of mother wavelets [17]. ST is a modified WT. One-cycle windowing technique based on the continuous ST for efficient detection of voltage transient was proposed in [19]. However, the ST is not able to mark the required transient component's high frequency because of the window width's dependence on the middle frequency. HHT is an advancement of FT and WT. A method based on HHT was proposed in [18] to analyze transient disturbance, which provides a good performance. However, HHT is sensitive to the singular points of the signal and has a long-time consuming problem of high-order spline interpolation.

Besides the signal processing-based methods, machine learning-based methods are another category of method to detect the voltage transient events. Neural network (NN) [21], [22], support vector machine (SVM) [23], [24], expert system (ES) [25]–[27], and genetic algorithm (GA) [28] are the most common voltage transient detection methods. For example, based on NN and WT, some patterns have been developed for identification and classification of high-frequency and low-frequency disturbances [21]. A new dual NN-based methodology is presented in [22] to detect single and combined power quality disturbances. Although

the accuracy of the NN-based transient detection methods are high, the performance is degraded in noisy conditions. SVM is a supervised learning method that goes well in PQ disturbance detection. For example, a technique based on N-1 SVM was proposed in [23] to identify the voltage transient disturbances, while the SVM is very effective in the automatic classification of voltage disturbances [24]. Although the SVM is capable of extracting complex features with high learning rate, the transient detection accuracy is poor when the training samples are limited. ES is usually combined with fuzzy logic (FL) which is helpful to get a result with high accuracy and less convergence time [25]. A hybrid method based on linear Kalman filter and the fuzzy ES has been explored to characterize the transient disturbances [26]. And to detect the transient issues, a fuzzy ES utilized the time series voltage data which were pre-processed through ST [27]. FL can simulate and analyze transient problems at high accuracy, but is not capable of handling any change in the transient disturbance as the number of training samples is constant. What's more, the ES is very expensive and has a high convergence time. As for GA, it is developed based on human genetic and works with generation, mutation, and cross-over. By using enhanced GA and WT, reference [28] proposed a technique for the placement of PQ monitors to identify transient disturbances. The accuracy of the results is high at the sacrifice of the convergence time.

As seen from the above analysis, the signal processing methods are always combined with the machine learning methods to detect transient disturbances in the time-frequency domain. In addition, the third category of transient detection methods are performed in time domain, which are based on IEC standard [8]. In the standard, methods based on the comparison of the difference between two consecutive cycles, which have high detection accuracy, have been adopted by the CEA power quality detection project and some power quality detection instrument companies [29], [30], [32]. For example, the transient disturbance is detected if two consecutive cycles' magnitude difference and the duration are larger than the set threshold [29]. This method is flexible. However, unreasonable threshold setting may capture many insignificant disturbances or miss some important disturbances. Reference [30] proposed a transient detection method by calculating the average of the absolute value of the squared difference between two consecutive cycles. But the reason why squared difference is used is not clear. Differential waveform of thirty-cycle (i.e., the 30th cycle minus the 1st cycle, the 31st cycle minus the 2nd cycle, *et al.*) was used by [31] to detect the transients, ignoring the power system frequency variation. And the transient duration was obtained by detecting the peaks, which cannot ensure the accuracy as the starting time of the transient may not appear at the peak. Reference [32] detects the transient disturbance by comparing the RMS values of two consecutive cycles' differential waveform and the healthy cycle. Moreover, test results in an actual 120V-500kV grid showed that by using the difference between two consecutive waveform

cycles to detect power quality disturbances would effectively reduce the impact of noise on the detection results. However, the comparison between the whole cycle cannot determine the accurate starting time and duration of the voltage transient if the duration of the disturbance is less than a cycle. Thus, an improved differential-waveform-based detection method should be provided.

Moreover, besides detecting the transient disturbances, extracting the transient components are also important. Reference [33] obtained the time-domain transient component through the subtraction between the original waveform with transient component and the fitted 50Hz voltage waveform obtained by a numerical approximation, which ignored that the actual steady-state waveform may also include harmonic components. Moreover, the system frequency is not always constant at 50Hz or 60Hz, and the direct subtraction between two waveforms will bring great error to the extraction result of the transient component [34]. In reference [4], a voltage transient detection and characterization method based on spatial vector model and Gaussian model was proposed. This method only extracts sampled voltage waveform with transient disturbance, without extracting the transient component. References [35] and [36] proposed a real-time transient disturbance detection method based on DSP (digital signal processing) equipment that could not extract the transient disturbance signal without fundamental frequency component.

In addition, in real practice, voltage transient disturbance detection is usually applied to develop the fault protection scheme. For example, reference [37], [38] proposed a DC line fault protection scheme based on high frequency components of transient voltages to identify the faulted lines and poles, in which, WT is used to deal with the transient voltage. The difference in the ratio of the transient voltage were used for DC lines' fault detection, and then a protection scheme was proposed in [39]. On the other hand, as repetitive impulsive transient voltage can lead to partial discharge, causing insulation failure and equipment malfunction, the earlier the voltage transient disturbance is detected, the easier to avoid the disaster. Thus, voltage transient detection can also be applied to detect and analysis the partial discharge in electrical insulation [40].

In total, based on the above analysis, the signal processing-based transient detection methods extract the features in the frequency domain, which cannot mark the high-frequency transient component whose amplitude changes with time, and has a long-time consuming problem. The machine learning-based methods can extract complex features and detect transient disturbance with a high accuracy, but highly depends on the training samples, and at the sacrifice of the convergence time. IEC standard-based methods analyze the transient signals in the time-domain by the subtraction between two consecutive whole cycles which cannot determine the accurate starting time and duration of the voltage transient if the duration of the disturbance is less than a cycle. In addition, there are methods discussing extracting the transient component, which do not consider the power system frequency variation

correction. Though the existing methods provide some ideas for the voltage transient disturbance detection, the performance cannot be ensured, which are difficult to be applied in practical cases. Therefore, proposing a simple, intuitive and practical method to detect, extract and characterize the voltage transient disturbance is of great theoretical value and practical significance.

This paper will propose an RMS values of segmented differential waveforms-based voltage transient disturbance detection method. The basic idea is to compare the RMS values of the segmented differential waveforms with that of the segmented steady-state waveforms. With respect to previous work, the main contributions of this manuscript are 1) the proposed method is time-domain-based, thus is applicable to the voltage transient disturbance detection, 2) the proposed time-domain method is simple and straightforward for the field technicians to use, which does not depend on the training samples, 3) the proposed voltage transient disturbance detection method is based on the RMS values of the segmented differential waveforms considering the power system frequency variation, which can provide more accurate results of the starting time and duration of the voltage transient disturbances, 4) the duration determination methods of impulsive transient and oscillatory transient, based on the principle of energy equivalence, are proposed respectively, which provide a good guidance for setting the protection schemes.

The remainder of the paper is organized as follows. Section II explains the voltage transient disturbance detection method considering the influence of the power system frequency variation. Section III presents the voltage transient component extraction method. Section IV calculates the characteristic parameters describing the transient component, i.e., dominant frequency, polarity, magnitude, and duration. Simulation and experimental analysis are shown in Section V. Finally, conclusions are drawn in Section VI.

II. VOLTAGE TRANSIENT DISTURBANCE DETECTION
The proposed voltage transient disturbance detection method consists of two steps. First, the abnormal voltage waveforms are detected and extracted. Then, based on the extracted abnormal voltage waveforms, the segment-differential-waveform-based voltage transient disturbances detection method is applied to judge if the disturbance is the voltage transient disturbance.

A. ABNORMAL VOLTAGE WAVEFORMS DETECTION AND EXTRACTION
For the proposed voltage transient disturbance detection method, at each sampling point, the number of samples used for analysis depends on the extracted abnormal voltage waveforms. In this paper, the generic method proposed in [41] is adopted for waveform abnormality detection, where the normal voltage waveform contains steady-state component and random fluctuation component, and an abnormality exists

when a fault component is superimposed on the normal voltage waveform. The steps are briefly summarized as follows.

1) Estimate the steady-state components, as shown in equation (1).

$$\hat{v}(t) = \sum_{q=0}^{Q} \hat{A}_q \cos\left(2\pi q f_n t + \hat{\varphi}_q\right) \tag{1}$$

where $\hat{A}_q$ and $\hat{\varphi}_q$ are magnitudes and phase angles of the steady-state component obtained by applying fast FT to the reference cycles of the voltage waveform. f_n is the operating frequency.

2) Characterize the random fluctuation components by using the probability density function (PDF) of the Gaussian distribution.

3) Get the residual voltage waveform by the subtraction between the measured voltage waveform and the estimated steady-state components.

4) Estimate the PDF of the residual voltage waveform by the Kernel density estimation method. The standard Gaussian distribution function is taken as the kernel function.

5) Calculate the Kullback-Leibler divergence (KLD) values to quantify the distance between the estimated PDF of the residual voltage waveform and the PDF of the random fluctuation components.

6) If the KLD is larger than a threshold, the abnormality is detected.

7) At least five cycles before the disturbance and five cycles after the disturbance, as well as the disturbance are recorded.

As this paper mainly focuses on the detection of the voltage transient disturbance, detailed steps and explanations can be found in [41].

Based on the above analysis, the total number of the samples of the recorded waveforms are the number of samples taken at each sampling point, i.e., "at least three cycles before the disturbance + disturbance + at least three cycles after the disturbance".

It should be noted that the recorded waveforms will be used further to detect the voltage transient disturbance. If the voltage transient disturbance is detected, three consecutive cycles before the disturbance and three consecutive cycles after the disturbance need to be recorded for further analysis. Thus, in order to ensure the accuracy of the analysis results, at least three cycles of pre-disturbance and three cycles of post-disturbance should be recorded when detecting the abnormality. In this paper, three cycles are selected. Other number of cycles can also be chosen, which can be set by the technicians.

Moreover, subtraction between two waveforms in step 3) is needed to obtain the residual waveforms. However, the power system frequency is not always constant at 50Hz or 60Hz [36]. In this sense, even if two identical waveforms are directly subtracted, the result cannot be zero. Therefore, in order to accurately detect the abnormal voltage waveforms, it is necessary to resample the waveform according to the

actual power system frequency obtained by correcting the frequency variation.

To correct the power system frequency variation, the actual frequency is calculated and the waveform is resampled. Assume that $v'(k)$ is the resampling point of $v(k)$, where $k = 1, 2, 3, \ldots, N$. N is the waveform sampling rate, i.e., the number of samples per cycle. Based on Figure 1, the detailed steps to determine $v'(k)$ are as follows:
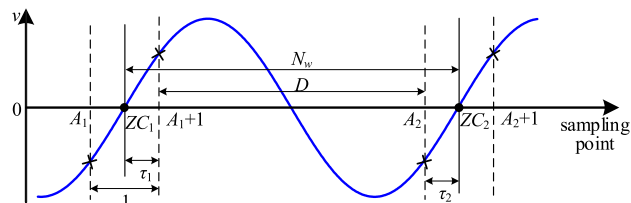
FIGURE 1. Parameters for frequency variation correction.

1) Choose a steady-state cycle as a reference cycle. Suppose that the first cycle is regarded as the reference cycle.

2) Determine the parameters shown in Figure 1. ZC_1 is the positive zero-crossing point of the first cycle, which is between the two adjacent samples, i.e., $A_1(<0)$ and $A_1 + 1(>0)$. $\tau_1(<1)$ is the difference between $A_1 + 1$ and ZC_1. ZC_2 is the positive zero-crossing point of the second cycle, which is between the two adjacent samples, i.e., $A_2(<0)$ and $A_2 + 1(>0)$. $\tau_2(<1)$ is the difference between ZC_2 and A_2. N_w is the actual number of sampling points in a cycle, as follows in (2).

$$N_w = A_2 - (A_1 + 1) + \tau_1 + \tau_2 = D + \tau_1 + \tau_2 \tag{2}$$

3) Determine the real period of the disturbance waveform, T_w, as shown in (3).

$$T_w = N_w \times \Delta t \tag{3}$$

4) Calculate the time difference, T_{diff}, between $v(k)$ and the first positive zero-crossing point ZC_1 of the reference cycle, see (4).

$$T_{diff} = (k - ZC_1) \times \Delta t \tag{4}$$

The number of cycles between $v(k)$ and ZC_1, N_{diff}, is shown in (5).

$$N_{diff} = T_{diff}/T_w = (k - ZC_1)/N_w \tag{5}$$

In equation (5), N_{diff} is not an integer, whose remainder is denoted as $N_R \in [0, 1]$, representing the actual location of the resampling point $v'(k)$. For example, $N_R = 0.5$ means that $v'(k)$ is just in the middle of the reference cycle.

5) Determine the two adjacent sampling points of $v'(k)$ in the reference cycle by using N_R. First, calculate the intermediate value N'_r according to equation (6):

$$N'_r = N_R \times N_w - \tau_1 + 1 \tag{6}$$

N'_r in equation (6) will be between two integers, denoted as K_1 and K_2. And the remainder of N'_r is expressed as τ.

For example, if $N'_r = 5.34$, then $K_1 = 5$, $K_2 = 6$, and $\tau = 0.34$. $v'(k)$ can be obtained by the linear interpolation of $v(K_1)$ and $v(K_2)$, as shown in Figure 2 and equation (7).

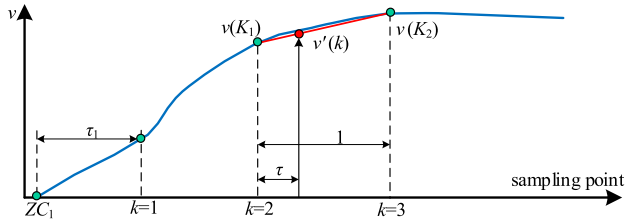$$v'(k) = v(K_1) + \tau[v(K_2) - v(K_1)] \qquad (7)$$

FIGURE 2. Determining the value of $v'(k)$.

When $K_1 = 0$, ZC_1 is the first point, then $v(K_1) = 0$. If K_1 is the last sampling point of the reference cycle, $v'(k)$ can be obtained by the linear interpolation of $v(K_1)$ and $v(ZC_2)$.

In addition, as the voltage waveforms are monitored at the substation and the power quality disturbances can occur everywhere in the power system, the voltage waveforms monitored at the substation contain noise. In order to improve the reliability and accuracy of the data, pre-processing the monitored voltage waveform data is necessary before detecting the voltage transient disturbance. Low-pass and high-pass filters [42], [43], empirical mode decomposition [44], wavelet transform [45], and wavelet packet decomposition [46] are common methods for noise reduction. As the frequency band of the noise and the monitored voltage waveform always overlaps, the low-pass filter and high-pass filter will filter out the useful information in the voltage waveform. What's more, the empirical mode decomposition method exists boundary effect, and wavelet transform method is usually developed for low frequency signals. Considering that the wavelet packet decomposition can deal with both low frequency signals and high frequency signals, wavelet packet energy denoising method is utilized in this paper to reduce the noise. The detailed steps are summarized as follows.

1) Choose db8 as the wavelet basis, and set the number of decomposition layers, denoted as j ($j = 8$ in the revised manuscript).

2) Wavelet packet decomposition is applied to the monitored voltage waveform data $v(t)$ until the decomposition layer number reaches j. The number of wavelet packet is 2^j.

3) Calculate each wavelet packet's energy. The energy of the i-th wavelet packet in the j-th layer is $E_j^i = \sum \left(C_j^i\right)^2$, where C_j^i is the coefficient of the wavelet packet.

4) Rank E_j^i from large to small.

5) Reconstruct the voltage waveform by using the first P wavelet packet. The reconstructed voltage waveform is denoted as $v'(t)$.

6) Calculate the mean square error (MSE) between $v(t)$ and $v'(t)$, i.e.,

$$MSE = \frac{1}{L}\sum_{t=1}^{L}\left[v'(t) - v(t)\right]^2 \qquad (8)$$

in which L is the total number of sampling points for $v(t)$.

7) If MSE is smaller than ε (ε is set as 0.01 in this paper), $v'(t)$ is the voltage waveform after noise reduction. Otherwise, $P = P + 1$, and return to step 5).

By taking the above steps, the noise component can be filtered. In order to simplify, the filtered signal is still denoted as $v(t)$. Based on the filtered voltage waveform, further analysis will be conducted to detect the voltage transient disturbance in the next subsection.

B. VOLTAGE TRANSIENT DISTURBANCE DETECTION

Based on the extracted abnormal voltage waveforms, a method based on the RMS value of segmented differential waveform is proposed in this paper to detect the voltage transient disturbance, shown in Figure 3. Suppose that the voltage waveform of each cycle is divided into K segments. Generally, N can be 128, 256, or 512, and K is decided by the customers. In Figure 3, $N = 128$, and $K = 8$, then, each segmented waveform contains 16 samples.
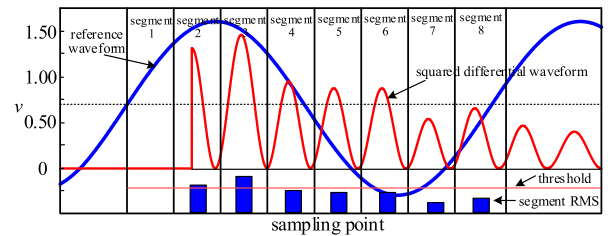

FIGURE 3. Scheme to detect transients using segmented differential waveforms.

The detailed steps of detecting voltage transient disturbances based on the RMS values of segmented differential waveforms are shown as follows.

1) Suppose that the first cycle of the detected waveform does not contain any disturbance, which is called the steady-state cycle or reference cycle. First, detect the first positive zero-crossing point, and the data points of the first cycle starting from the first positive zero-crossing point are recorded as $v(1), v(2)\ldots v(N)$.

2) Split the reference waveform in 1) into K segments and calculate the voltage RMS value $V_{RMS}(i)$ of each segment according to equation (9).

$$
\begin{aligned}
V_{RMS}&(i) \\
&= \sqrt{\frac{1}{N/K}\left[v^2((i-1)N/K+1) + \cdots + v^2(iN/K)\right]} \\
&= \sqrt{\frac{1}{N/K}\sum_{k=(i-1)N/K+1}^{iN/K} v^2(k)}
\end{aligned}
$$

$$= \sqrt{\frac{\sum\limits_{k \in i} v^2(k)}{\frac{N}{K}}} \qquad (9)$$

In equation (9), $V_{RMS}(i)$ refers to the voltage RMS value of the i-th segment in the reference cycle, where $i = 1, 2, \ldots, K$ represents the segment number. $k \in i$ represents all samples belonging to the i-th segmented waveform. As stated in step 1), the samples in the reference cycle are denoted as $v(1), v(2), \ldots, v(N)$. If the reference cycle is divided into K segments, the number of the samples in the i-th segment is N/K, i.e., $v((i-1)N/K+1), v((i-1)N/K+2), \ldots, v(iN/K)$. That is, $k = (i-1)N/K + 1, (i-1)N/K + 2, \ldots, iN/K$.

Voltage RMS value of each segmented waveform obtained by equation (9) is called the reference value, which will be used as the standard to judge whether there is difference between two consecutive cycles.

3) The sampling points of the second cycle are $v(N+1), \ldots, v(N+N)$, and the second cycle is called the current cycle, which should be judged whether there exists disturbance.

4) Calculate the segmented RMS value of the differential waveform between the current cycle and the reference cycle, as shown in equation (10). It should be noted that the system frequency variation correction should be considered when obtaining the differential waveforms.

$$\Delta V_{RMS}(i) = \sqrt{\frac{\sum\limits_{k \in i} [v(N+k) - v(k)]^2}{\frac{N}{K}}} \qquad (10)$$

5) Compare the segmented RMS value of the differential waveform and the reference waveform. If the results satisfy (11), voltage transient disturbance is detected, and the sampling data points of the current cycle are recorded, which will be analyzed further.

$$\Delta V_{RMS}(i) > \alpha V_{RMS}(i) \quad i = 1, 2, \cdots, K \qquad (11)$$

In equation (11), α (%) is the threshold set by the customers. Considering the minimal magnitude of various voltage transient disturbances and the noise level of differential waveforms, the values of K and α are shown in Table 1. The segmented RMS value V_{RMS} calculated by reference waveform is called the rated RMS value.

TABLE 1. Typical input parameters for voltage transient detection.

Level	K	α
1	8 or 16	7%~20%
2	16 or 32	7%~20%
3	3000 to 4000	7%~20%
4	Specific equipment has its own disturbance detection method	

If the segmented RMS value of the differential waveform exceeds the threshold, the instant corresponding to the first sampling point of the corresponding segment is recorded as the starting time of the voltage disturbance.

6) Update the previous cycle's sampling points with $v(N+1), v(N+2), \ldots v(N+N)$, and return to step 3). If a disturbance is not detected in three consecutive cycles, the current cycle is regarded as a healthy cycle, and the segment RMS value is calculated to update $V_{RMS}(i)$ in step 2). Calculate the positive zero-crossing point of the healthy cycle, and replace $v(1), v(2) \ldots v(N)$ in step 1) with the data of one cycle starting from the positive zero-crossing point.

7) If the voltage of each phase does not satisfy equation (11) for three consecutive cycles, the transient disturbance is considered to come to an end. It should be noted that three consecutive cycles and three-phase voltage should be satisfied, in which the third cycle is called the last cycle of the disturbance and the instant corresponding to the last sampling point is called the ending time of the disturbance.

8) The three-phase voltage waveform containing the disturbance is recorded for further analysis, including three cycles before the disturbance occurs and at least three cycles after the disturbance, which is convenient for engineers to identify the root cause of the disturbance.

The above steps 1)-8) detail the voltage transient disturbance detection method based on segmented differential waveforms, which is shown in Figure 4. It should be noted that if each cycle is divided into K segments, the shortest disturbance duration that can be detected is $1/K$ of a cycle, i.e., if a disturbance with a duration of $1/X$ cycle wants to be detected, the minimum value of K should be X.

In addition, the proposed detection method requires that the comparison of waveforms starts from the positive zero-crossing point, which ensures the consistency of the method. However, when a disturbance occurs, the zero-crossing point obtained from the waveform containing disturbances may not be accurate. At this time, the stored $V_{RMS}(i)$ and steady-state waveform data should not be updated. Details are in step 6).
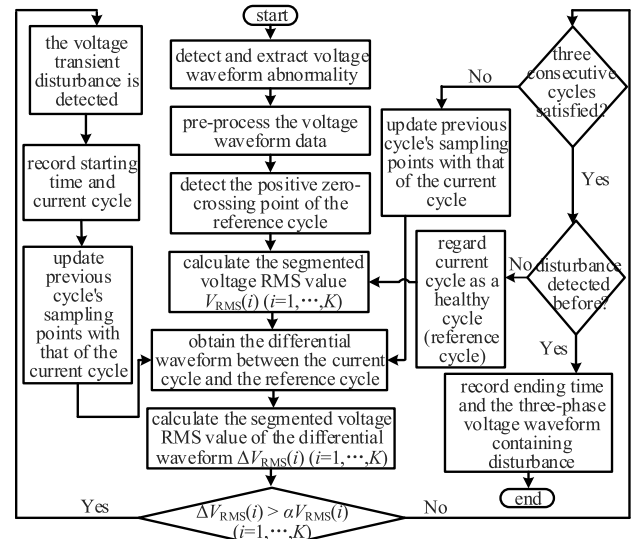

FIGURE 4. Flowchart to detect the voltage transient disturbances.

From Figure 4, the complexity of the proposed voltage transient disturbances detection method can be determined, which depends on the complexity of power system frequency variation correction, the abnormality of voltage waveforms detection, the monitored voltage waveform data pre-processing, and voltage transient disturbance detection.

1) POWER SYSTEM FREQUENCY VARIATION CORRECTION

The steps to correct the power system frequency include the actual number of sampling points per cycle determination, time difference calculation, adjacent sampling points of $v'(k)$ in the reference cycles determination, and $v(k)$ calculation. Suppose that the total number of the sampling points is L, and the number of sampling points per cycle is N, the complexity of the power system frequency variation correction is $O(L/\mathrm{N}) + O(L) + O(L) + O(L) = O(L)$.

2) THE ABNORMALITY OF VOLTAGE WAVEFORMS DETECTION

The complexity of detecting the voltage waveforms abnormality depend on steady-state components estimation, residual voltage waveform determination, and KLD calculation. Thus, the complexity of the abnormality of voltage waveforms detection is $O(Q)^*O(L^* \log L) + O(L)^*O(L) + O(L^2) = O(L^2)$.

3) THE MONITORED VOLTAGE WAVEFORM DATA PRE-PROCESSING

The complexity of pre-processing the monitored voltage waveform data depends on the wavelet packet decomposition, wavelet packet's energy calculation, voltage waveform reconstruction, and mean square error calculation. Thus, the complexity of pre-processing the monitored voltage waveform data is $O(L^* \log L) + O(2^{j*}j) + O(2^j) + O(L^2) = O(L^2)$.

4) VOLTAGE TRANSIENT DISTURBANCE DETECTION

The complexity of voltage transient disturbance detection depends on positive zero-crossing point determination, segmented RMS values of the reference waveform calculation, and segmented RMS values of the differential waveform calculation. Thus, the complexity of the voltage transient disturbance detection is $O(L) + O(K^*L/K) + O(L)^*O(L)^*O(K^*L/K) = O(L^3)$.

In total, the complexity of the proposed voltage transient disturbance detection method is $O(\mathrm{L}) + O(L^2) + O(L^2) + O(L^3) = O(L^3)$, which depends on the length of the voltage waveform.

C. LIMITATIONS OF THE PROPOSED METHOD

As seen from the above section, the proposed method has clear physical meaning, thus its result can be trusted. However, it should be mentioned that there are three practical issues which may limit its application.

1) The segment-differential-waveform-based method developed in this paper focuses on the voltage transient disturbance, thus is not applicable to the case where two or more disturbances occurring simultaneously or immediately after another. However, it is believed that the occurrence probability of the latter case is relatively low.

2) The proposed detection method is based on the monitored voltage waveform. As the monitor always installed at the substation, the proposed method may not work well for the case where the transient disturbance location is far away from the measurement point. But this is in fact the challenge faced by all the measurement-based method.

3) So far, the proposed voltage transient disturbance detection method is used offline, but it is possible to develop its online application with further researches needed. Not only the sampling rate should be considered, but also the frequency response, ratio of detected disturbances versus those actually occurred, sensitivity of the detection instrument to the occurrence of transient disturbances, influence of the input transducers, the interaction between the employed detection algorithm and the employed hardware structure.

III. VOLTAGE TRANSIENT COMPONENT EXTRACTION

Voltage transient disturbances can be detected based on the RMS values of segmented differential waveforms proposed in Section II. The recorded waveforms are original disturbance waveforms containing transient components, which cannot be directly used to characterize the transient disturbance features. However, the extraction of the transient components is the precondition to describe the transient disturbance characteristics. Therefore, this section will propose the extraction method of the voltage transient components.

The real sampling location in the reference cycle has already been determined in Section II.A. The transient component is obtained by the subtraction between the samples and the corresponding real samples in the reference cycle, as shown in equation (12).

$$\Delta v(k) = v(k) - v'(k) \tag{12}$$

It is worth noting that the steady-state waveform between pre-disturbance and post-disturbance may not be the same, for example, the bus voltage will rise due to capacitor energization. If a pre-disturbance steady-state cycle is taken as the reference cycle, the extracted transient component will not decay to zero. The non-zero component is the steady-state voltage difference between pre-disturbance and post-disturbance, and the non-zero component cannot be regarded as a part of the transient component. Therefore, the post-disturbance steady-state cycle is usually taken as the reference cycle. Hence, in general, the last cycle of the stored original disturbance waveform is taken as the reference cycle, which can effectively solve the problem that the transient component cannot decay to zero due to the different steady-state voltage before and after the disturbance. The extracted transient components are shown in Figure 5, when taking the steady-state waveforms before and after the disturbance as reference cycles, respectively.
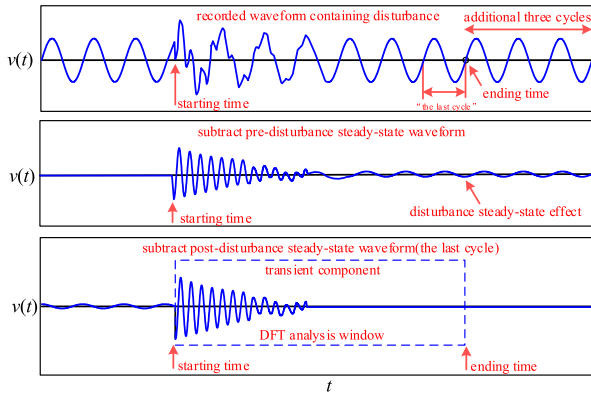
FIGURE 5. The extracted transient component by using the pre-disturbance and post-disturbance as a reference cycle, respectively.

IV. VOLTAGE TRANSIENT CHARACTERIZATION

There is no unified standard for the characterization of voltage transient disturbances in current power systems. In this paper, four indicators are proposed to characterize the voltage transient disturbance: dominant frequency, polarity, magnitude and duration. Of these, the dominant frequency is mainly for oscillatory transient, while the polarity is mainly for impulsive transient.

A. DOMINANT FREQUENCY

Fast Fourier transform is applied to the extracted voltage transient component. According to the spectrum diagram, the frequency corresponding to the spectrum component with the largest amplitude is called the dominant frequency f_d of the transient component.

Impulsive transient and oscillatory transient can be distinguished by the dominant frequency of the transient disturbance. For the 60Hz power system, the following conditions can be obtained:

1) If $f_d < 60$Hz, the disturbance is impulsive transient.

2) If $f_d > 180$Hz, the disturbance is oscillatory transient.

On the one hand, when the largest frequency spectrum component appears in the DC component (<60Hz), the transient disturbance is impulsive transient. On the other hand, when the transient waveform contains high frequency components (>180Hz), the transient disturbance must have the form of oscillation, which is the oscillatory transient disturbance.

B. POLARITY

Polarity is an important feature to characterize impulsive transients, reflecting whether the transient disturbance exceeds the peak value of steady-state waveform. If the absolute value of any sample of the original disturbance waveform is larger than the peak value of the steady-state waveform, the impulsive transient has a positive polarity, otherwise, the polarity is negative, as shown in Figure 6.
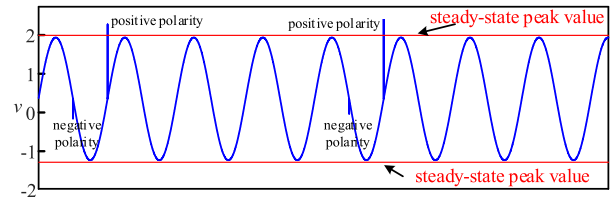

FIGURE 6. Definition of polarity of impulsive transients.

C. MAGNITUDE

Magnitude of voltage transient disturbance is defined as the superposition of peak value of steady-state waveform and peak value of transient component [34], shown in (13).

$$M = V_p + V_{nominal} \qquad (13)$$

where, M is the magnitude of voltage transient disturbance, V_p is the peak value of transient component, which refers to the maximum absolute value of the extracted transient component. $V_{nominal}$ is the peak value of steady-state voltage waveform.

It should be noted that the magnitude of voltage transient disturbance defined in (13) is the sum of the peak value of the transient component and the peak value of the steady-state waveform, which are based on the assumption that the transient disturbance exactly occurs at the peak point of the waveform, referring to the most serious case.

D. DURATION

The basic idea to determine the duration of the voltage transient disturbance is to use the standard waveforms [47], [48] defined in IEEE C62.41.2 to fit the extracted transient component and calculate the duration of transient disturbance based on the principle of energy equivalence [49].

1) DURATION OF IMPULSIVE TRANSIENT

When the transient disturbance is impulsive transient, the standard double exponential waveform defined in IEEE C62.41.2, as shown in equation (14), is used to fit the extracted transient component, as shown in Figure 7.

$$v(t) = V_m \left(e^{-At} - e^{-Bt} \right) \qquad (14)$$

where, V_m, A and B are the parameters to be determined, so that the double exponential function can "maximally" fit the transient component waveform, as shown in Figure 7. Specifically, the following boundary conditions should be applied:

a) The peak voltage of the double exponential waveform is assumed to occur at T_r, which is also called the rise time. In general, the value of T_r is 1.5 μs, which meets the following requirements:

$$\frac{dv(t)}{dt}\Big|_{t=T_r} = 0 \qquad (15)$$

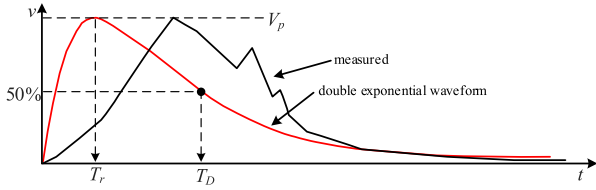b) The peak voltage of the double exponential waveform should be equal to the peak value of the transient

FIGURE 7. Fitting an impulsive transient using a double exponential waveform.

component, as follows:

$$V_p = V_m \left(e^{-AT_r} - e^{-BT_r} \right) \quad (16)$$

c) The energy of the double exponential waveform should be equal to the energy of the transient component, as follows:

$$E = \Delta t \sum_k \frac{v_k^2 + v_{k+1}^2}{2}$$

$$= E_{double} = \int_{t=0}^{\infty} \left[V_m \left(e^{-At} - e^{-Bt} \right) \right]^2 dt \quad (17)$$

where, v_k is the k-th sampling point of the extracted transient component waveform.

The duration of the voltage transient disturbance is defined as the time when the magnitude of transient component drops to γV_p, which satisfies equation (18). γ is a user-defined input parameter, which is used to remind the user that the duration of transient disturbance is a function of the input parameter. Generally, γ is taken as 50%. T_D is the duration to be determined.

$$\gamma V_p = V_m \left(e^{-AT_D} - e^{-BT_D} \right) \quad (18)$$

An iterative process is used to solve equations (15) to (18), and the results are shown as follows:

$$V_{m(k+1)} = \frac{V_p}{e^{-A_k T_r} - e^{-B_k T_r}}$$

$$A_{k+1} = \frac{B_k V_{mk}^2 (A_k + B_k)}{2EB_k (A_k + B_k) + V_{mk}^2 (3B_k - A_k)}$$

$$B_{k+1} = A_k - \frac{\ln(A_k) - \ln(B_k)}{T_r}$$

$$T_{D(k+1)} = -\frac{1}{A_k} \ln \left(\gamma \frac{V_p}{V_{mk}} + e^{-B_k T_{Dk}} \right) \quad (19)$$

where, k is the iteration number. The iterative process is ended when the difference of parameters is less than 0.01 between two successive iterations.

2) DURATION OF OSCILLATORY TRANSIENT
When the transient disturbance is oscillatory transient, the standard ring waveform defined in IEEE C62.41.2, as shown in equation (20), is used to fit the extracted transient component, as described in Figure 8.

$$v(t) = \begin{cases} \dfrac{V_m}{T_r} t, & 0 \le t \le T_r \\ V_m e^{-A(t-T_r)} \cos\left[f(t - T_r) \right], & t \ge T_r \end{cases} \quad (20)$$

where, V_m is the peak value of the ring waveform, which should be equal to the peak value of the transient component waveform, i.e., $V_m = V_p$. T_r is the rise time and the typical value is 0.5 μs. f is the oscillatory frequency, which is equal to the dominant frequency of the transient component, i.e., $f = f_d$. A is the time constant, which is the parameter to be determined.
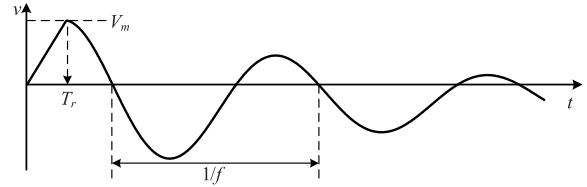

FIGURE 8. Standard ring waveform of IEEE C62.41.2.

The energy of the ring waveform should be equal to the energy of the oscillatory transient component, as follows:

$$E = \Delta t \sum_k \frac{v_k^2 + v_{k+1}^2}{2}$$

$$= E_{ring} = \int_{t=0}^{\infty} [v(t)]^2 dt = V_m^2 \left[\frac{T_r}{3} + \frac{2A^2 + f^2}{4A(A^2 + f^2)} \right] \quad (21)$$

By solving (22), the parameters A, K_1 and K_2 can be obtained, as follows:

$$A = \frac{1}{6K_1} \left[1 + K_2 + \frac{12 f_d^2 K_1^2 - 1}{K_2} \right]$$

$$K_1 = \frac{E}{V_p^2} - \frac{T_r}{3}$$

$$K_2 = \sqrt[3]{1 + 9 f_d^2 K_1^2 + 3\sqrt{3} f_d K_1 \sqrt{64 f_d^4 K_1^4 - 13 f_d^2 K_1^2 + 2}} \quad (22)$$

The duration of the oscillatory transient disturbance is defined as the time when the magnitude of transient component drops to γV_p, denoted as T_D, and shown in equation (23).

$$T_D = \frac{-\ln(\gamma)}{A} + T_r \approx \frac{-\ln(\gamma)}{A} \quad (23)$$

E. FLOWCHART TO EXTRACT AND CHARACTERIZE THE VOLTAGE TRANSIENT DISTURBANCE
Combine with Section III, the flowchart to extract and characterize the voltage transient disturbance is shown in Figure 9. First, considering the power system frequency variation, the transient component is extracted by the subtraction between the recorded voltage waveform and the post-disturbance waveform. Then, the dominant frequency can be determined by applying fast Fourier transform to the extracted transient component. Based on the dominant frequency, the type of the transient disturbance can be determined. Finally, determine the magnitude and duration if the transient disturbance is oscillatory transient. If the transient

disturbance is impulsive transient, determine the polarity, magnitude and duration.
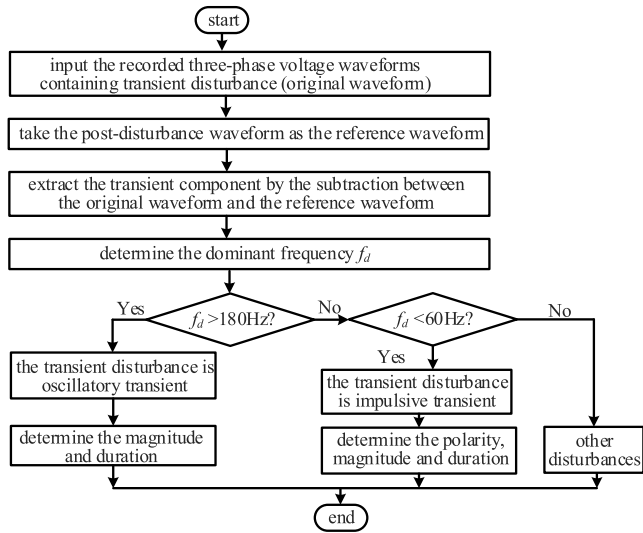

FIGURE 9. Flowchart to extract and characterize the voltage transient disturbances.

V. SIMULATION AND EXPERIMENTAL ANALYSIS

In order to verify the accuracy and effectiveness of the proposed voltage transient disturbance detection method based on the RMS values of segmented differential waveforms, an improved IEEE-13 node test system shown in Figure 10 is used for simulation analysis. The sampling rate is 7680 Hz, i.e., the number of sampling points is 128 per cycle for 60 Hz system. Several main aspects have been considered, as follows:

1) A capacitive load and an inductive load are energized at node 652, respectively. Using the data recorded at node 650 to detect voltage transient disturbances.

2) The detection accuracy of the proposed voltage transient disturbance detection method is evaluated.

3) The effect of frequency variation on transient disturbance detection is studied.

4) Voltage transient disturbances start at different instants are simulated. The starting time of the disturbance obtained by the algorithm is compared with that of the actual simulation.

5) Different locations, capacities, and instants of the voltage transient disturbances are considered. The effect of the measurement noise on the detection accuracy is also investigated.

6) A comparison between the proposed method and the methods of RMS, DWT (discrete wavelet transform) [10], and HHT (Hilbert Huang transform) [18] is discussed.

Furthermore, an actual laboratory experiment is done to generate the voltage transient disturbances, and the monitored voltage waveform is used to detect the voltage transient disturbance.
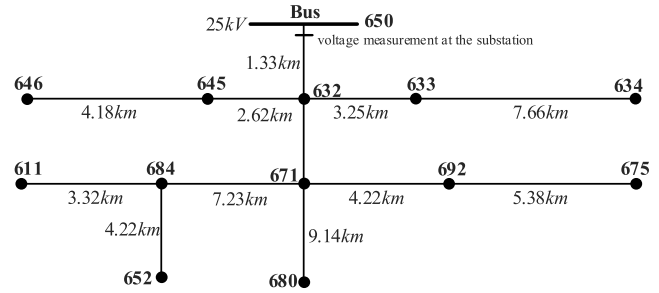

FIGURE 10. The modified IEEE-13 node test system.

A. VOLTAGE TRANSIENT DISTURBANCE DETECTION

In order to verify the effectiveness of the proposed voltage transient disturbance detection and extraction method, a 2MVAr capacitive load and a 3.32MW inductive load is energized at node 652 in the test system, respectively. As voltage transient disturbances include both impulsive transient and oscillatory transient disturbances, the voltage waveforms generated by capacitor energization represent the oscillatory transient disturbance, while the voltage waveforms generated by an inductive load energization represent the impulsive transient disturbance. The monitored three-phase voltage waveforms at node 650 are shown in Figure 11. The corresponding extracted three-phase transient components by using the proposed method are shown in Figure 12. What's more, the extracted voltage transient disturbance features are included in Table 2 and 3.
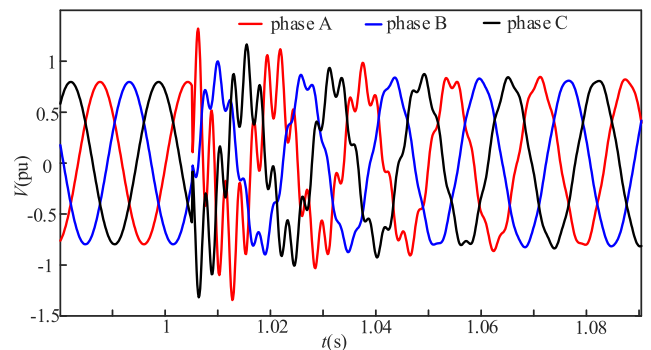
(a) The monitored three-phase voltage waveforms at node 650 generated by capacitor energization (oscillatory transient).
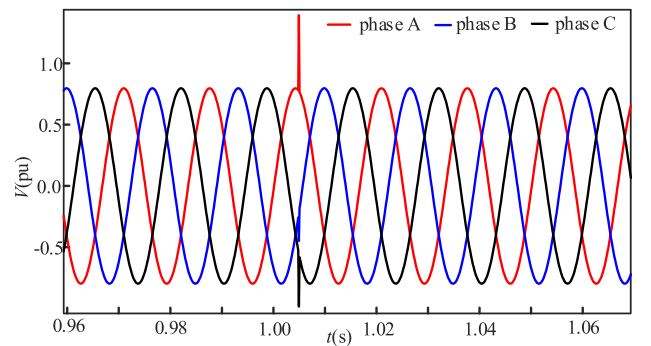
(b) The monitored three-phase voltage waveforms at node 650 generated by an inductive load energization (impulsive transient).

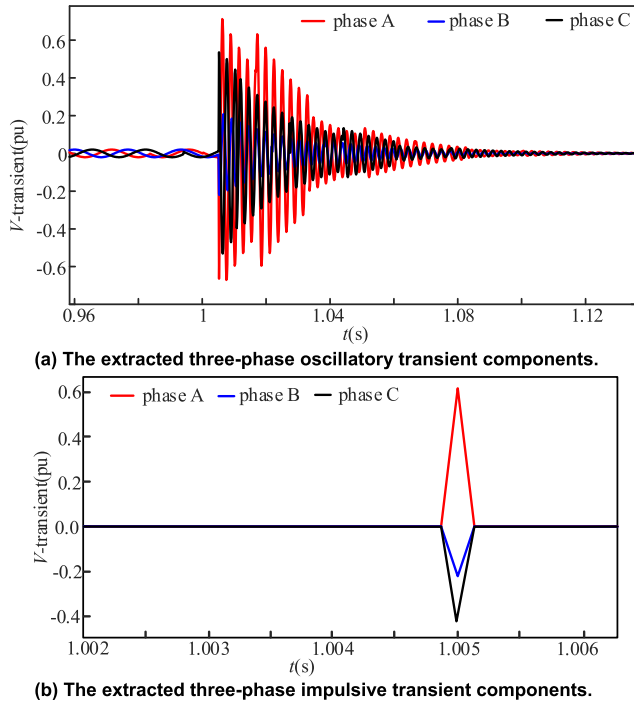**FIGURE 11.** The monitored three-phase voltage waveforms at node 650.

(a) The extracted three-phase oscillatory transient components.

(b) The extracted three-phase impulsive transient components.

FIGURE 12. The extracted three-phase transient components.

TABLE 2. Extracted oscillatory transient disturbance features.

three-phase	f_d (Hz)	T_D (s)	M (pu)
phase A	385.7143	0.0016	1.3205
phase B	372.2567	0.0016	0.9995
phase C	380.3329	0.0016	1.3180

TABLE 3. Extracted impulsive transient disturbance features.

three-phase	polarity	f_d (Hz)	T_D (s)	M (pu)
phase A	positive	59.4434	1.5607×10^{-4}	1.4166
phase B	negative	59.4434	1.5607×10^{-4}	1.0266
phase C	negative	59.4434	1.5607×10^{-4}	1.2266

As shown in Figure 11(a) and 12(a), the proposed method can effectively detect the oscillatory transient disturbance and extract the oscillatory transient components. It can be seen from Table 2 that the dominant frequency of the three-phase is larger than 180 Hz, indicating that the voltage transient disturbance is oscillatory transient, which is in consistence with the actual simulations.

Similarly, as shown in Figure 11(b) and 12(b), the proposed method can also effectively detect the impulsive transient disturbance and extract the impulsive transient components. In addition, it can be seen from Table 3 that the dominant frequency of the three-phase is smaller than 60Hz, indicating

that the voltage transient disturbance is impulsive transient, which is in consistent with the actual simulations.

What's more, both Figure 11 and 12 show that phase A has undergone the most serious voltage transient disturbance, compared with the other two phases. The results can also be revealed in Table 2 and Table 3 that phase A has the largest magnitude of voltage transient disturbance, i.e., 1.3205 p.u. and 1.4166 p.u.

In order to further illustrate the proposed segment-differential-waveform-based detection method, the segmented voltage RMS values of the steady-state three-phase voltage waveforms (V_{RMS}), and the segmented RMS values of the three-phase differential waveforms (ΔV_{RMS}) for oscillatory transient disturbance in Figure 11(a) and impulsive transient disturbance in Figure 11(b) are calculated and plotted, shown in Figure 13 and Figure 14.

(a) V_{RMS} and ΔV_{RMS} for phase A (oscillatory transient).

(b) V_{RMS} and ΔV_{RMS} for phase B (oscillatory transient).

(c) V_{RMS} and ΔV_{RMS} for phase C (oscillatory transient).
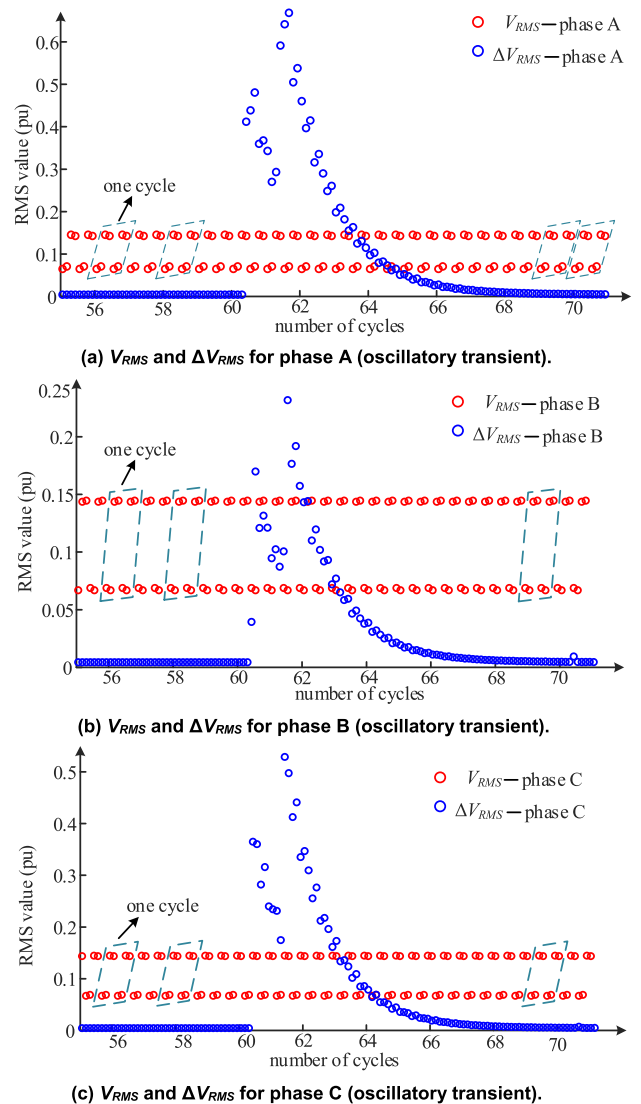
FIGURE 13. V_{RMS} and ΔV_{RMS} for three-phase voltage waveform (oscillatory transient).

As seen from Figure 13 and 14, the difference between the steady-state voltage waveforms' segmented RMS values
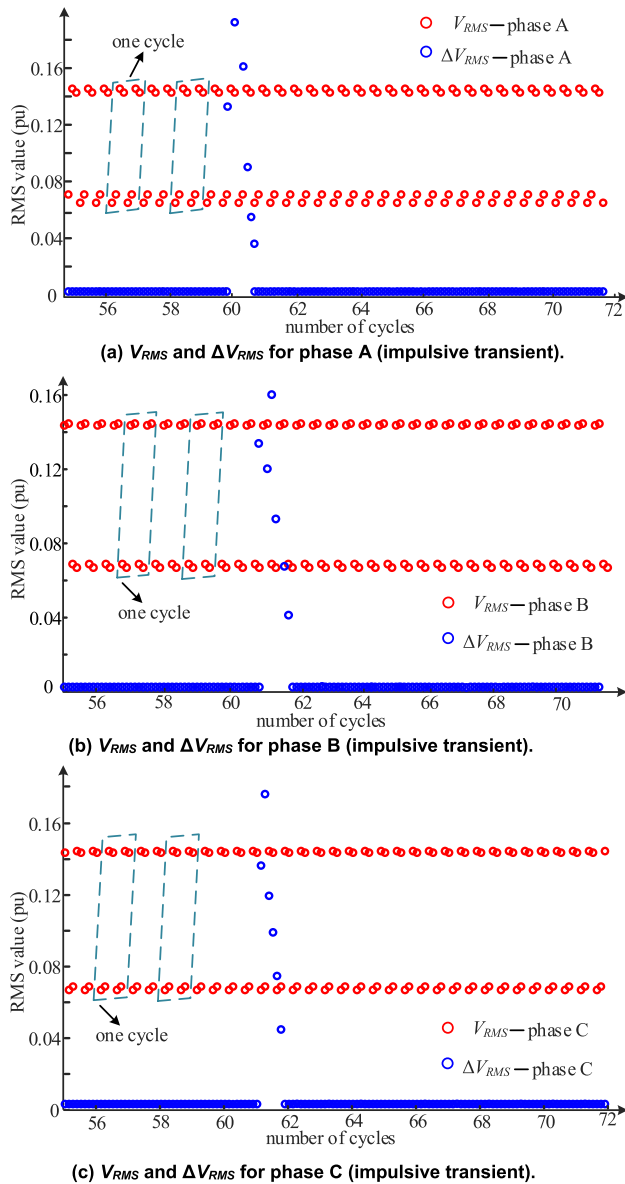
(a) *V_{RMS}* and *ΔV_{RMS}* for phase A (impulsive transient).

(b) *V_{RMS}* and *ΔV_{RMS}* for phase B (impulsive transient).

(c) *V_{RMS}* and *ΔV_{RMS}* for phase C (impulsive transient).

FIGURE 14. *V_{RMS}* and *ΔV_{RMS}* for three-phase voltage waveform (impulsive transient).

and the differential waveforms' segmented RMS values is obvious, indicating that the proposed method can be applied to effectively detect the voltage transient disturbances.

B. DETECTION ACCURACY EVALUATION

The detection accuracy of the proposed method can be evaluated by calculating the error of the starting time and ending time between the simulation and the proposed method, shown in equation (24).

$$\eta = 1 - \left| \frac{t_{i,sim} - t_{i,pro}}{t_{i,sim}} \right| \times 100\% \qquad (24)$$

In equation (24), $i = 1,2$, where $i = 1$ means starting time, and $i = 2$ means ending time. $t_{i,sim}$ and $t_{i,pro}$ refer to

the starting time or the ending time of the simulation and the proposed method, respectively.

Based on the monitored three-phase voltage waveforms at node 650 in Figure 11, the starting time and ending time of the simulation and the proposed method, as well as the detection accuracy are shown in Table 4.

TABLE 4. Starting time, ending time and detection accuracy.

disturbance type		simulation	proposed method	detection accuracy
oscillatory transient	starting time	1.0051s	1.0036s	99.85%
	ending time	1.0716s	1.1336s	94.21%
impulsive transient	starting time	1.0048s	1.0030s	99.82%
	ending time	1.0051s	1.0657s	93.97%

As seen from Table 4, for both the oscillatory transient and impulsive transient, the detection accuracy is larger than 93%. For the starting time, the detection accuracy can even reach 99.8%, and the starting time of the proposed method is a little bit smaller than that of the simulation. The reason is that the waveform is segmented, and the corresponding segment's first sampling point's instant is the starting time, while the transient disturbance occurs in the corresponding segment. On the other hand, the ending time of the proposed method is larger than that of the simulation. The reason is that three consecutive cycles not satisfying equation (11) are recorded and the last sampling point's instant for the third cycle is the ending time, while the simulation does not consider the three consecutive cycles. Therefore, it is reasonable that the starting time of the proposed method is smaller, and the ending time of the proposed method is larger.

C. EFFECT OF FREQUENCY VARIATION ON TRANSIENT DISTURBANCE DETECTION

Take the monitored three-phase voltage waveforms in Figure 11(a) as an example. The extracted three-phase voltage transient components without considering system frequency variation correction are shown in Figure 15.

Compared with Figure 12(a), voltage transient disturbances cannot be effectively detected and extracted without considering the system frequency variation correction, which could not lead engineers to further identify the root cause and take measures.

D. EFFECT OF STARTING TIME ON TRANSIENT DISTURBANCE DETECTION

Voltage transient disturbances start at different instants are simulated in the test system shown in Figure 10. The disturbance starting time detected by the proposed method and the simulation results are compared in Table 5. It should be noted that the peak value and zero-crossing point in Table 5 are all taking phase A as the reference phase.

In Table 5, it is observed that the disturbance starting time detected by the proposed method is almost the same as the
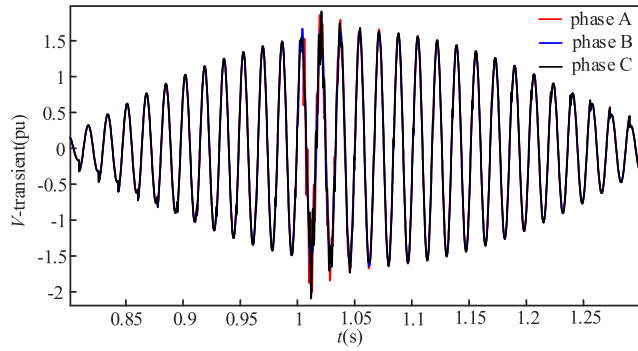
FIGURE 15. Extracted three-phase voltage transient components without considering system frequency variation correction.

TABLE 5. Starting time comparison between detection results and simulation results.

	positive peak	negative peak	positive zero-crossing	negative zero-crossing	arbitrary
simulation	1.0042s	1.0125s	1.1667s	1.1750s	1.3355s
detection	0.9829s	0.9913s	1.1583s	1.1667s	1.3168s
error	2.1211%	2.0938%	0.7200%	0.7064%	1.4002%

simulation result. The errors, which are mainly caused by the number of waveform segments K, are small.

E. DETECTING THE VOLTAGE TRANSIENT DISTURBANCES RECORDED AT VARIOUS LOCATIONS

The impact of different locations, capacities, and instants on the detection accuracy of the voltage transient disturbances are investigated. A capacitive load or an inductive load is selected randomly to be energized to simulate the voltage transient disturbance. The switching locations cover all the 13 nodes. On the basis of the load size, the capacitive size ranges from 0.5MVAr to 4MVAr, and the inductive load size ranges from 0.47MW to 4.15MW. The switching angle ranges from 0° to 360°. As a result, the proposed detection method is applied to over a total of 1327 simulation scenarios. The errors between the simulated disturbance starting time and the detected disturbance starting time are calculated. Figure 16 shows the errors for all the cases, in which the abscissa represents the errors within certain range and the ordinate represents the number of the corresponding cases.
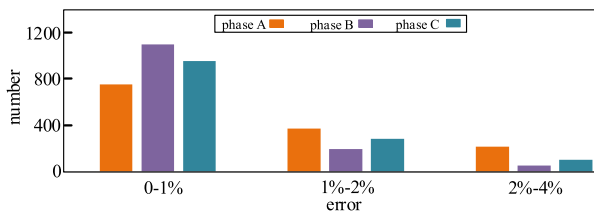

FIGURE 16. Errors between the simulated disturbance starting time and the detected disturbance starting time for all the 1327 simulation scenarios.

As observed in Figure 16, all the errors are less than 5%, indicating that the proposed method can detect the voltage transient disturbance accurately regardless of the disturbance locations, switching angles, and capacity sizes.

Additionally, in order to further study the effect of the measurement noise on the proposed method, different signal-to-noise ratio (SNR) are applied to the above 1327 cases. The average error between the detected starting time and the simulated starting time is calculated in Figure 17. As observed, the lower the SNR, the larger the average errors, and the average errors can be even larger than 10%. Thus, in order to further improve the accuracy of the detection method, wavelet packet energy denoising method is applied to the voltage waveforms whose SNR are 50. The corresponding average error between the simulated starting time and the detected starting time is also shown in Figure 17. It is shown that after applying the denoising method, the errors are greatly reduced, which are almost the same as that of the no noise case.
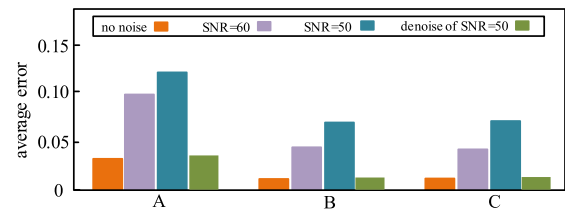

FIGURE 17. Average error between the simulated disturbance starting time and the detected disturbance starting time for all the 1327 cases with different SNR.

F. COMPARISON BETWEEN THE PROPOSED METHOD AND THE METHODS OF RMS, DWT, AND HHT

To illustrate the advantages and accuracy of the proposed voltage transient detection method, the RMS method, the discrete wavelet transform (DWT) method [10], the Hilbert Huang transform (HHT) method [18], and the proposed method are applied to the generated 1327 simulation scenarios in Section V.E. The number of the detected transients and the total detection time are summarized in Table 6.

TABLE 6. The number of the detected transients and the total detection time of different detection methods.

method	detected number	total detection time (min)
proposed method	1327	7.91
RMS method	1053	7.62
DWT in [10]	581	12.92
HHT in [18]	1327	15.34

As seen from Table 6, the proposed method and the HHT method can accurately detect all the generated voltage transients, however, the detection time of the HHT method is about twice of the proposed method. As for the RMS method, although the detection efficiency is higher than the proposed method, the detection accuracy is lower. As the DWT method is mainly developed for the stationary signal, the accuracy and

efficiency of the voltage transient detection are relatively low compared to the proposed method.

In Table 6, the RMS method has the highest detection efficiency, which directly compares the voltage waveform's RMS values with that of the steady-state voltage waveforms. Compared to the RMS method, the advantages of the proposed method are summarized as follows.

(1) The proposed method is based on segmented differential waveforms, and the shortest disturbance duration that can be detected is $1/K$ of a cycle (K is the segmented number.). However, the RMS method compares the whole cycle of the waveform, i.e., the detected shortest disturbance duration is one cycle. As the duration of the voltage transient disturbance is short, which is usually less than a cycle, the proposed method can determine the starting time and duration of the voltage transient disturbance more accurately.

(2) The proposed method compares the segmented differential waveform's voltage RMS value with the segment RMS value of a healthy cycle, while the RMS method directly compares voltage waveform's RMS value with the healthy cycle's RMS value. If the magnitude of the transient component is small, there will be little difference between the voltage waveform's RMS value and the healthy cycle's RMS value. However, the RMS value of the differential waveform is comparable to the RMS value of the healthy cycle. That is, the proposed method can detect the voltage transient disturbance effectively, even if the magnitude of the transient component is small.

(3) The differential waveforms are robust to the noise. As stated in [32], test results in an actual 120V~500kV grid showed that the difference between two consecutive waveform cycles would effectively reduce the impact of noise on the detection results.

Finally, we want to state that we only focus on the voltage transient disturbance, thus we only use the voltage waveforms. But the proposed method can also be applied to the current transient disturbance detection. What's more, the voltage waveform and current waveform can be combined to detect the transient disturbance.

In total, the proposed time-domain segment-differential-waveform-based detection method is more accurate, effective, and robust to noise, which can accurately and efficiently detect the voltage transient disturbances.

G. LAB MEASURED SIGNAL DETECTION

In order to further validate the accuracy of the proposed detection method, a capacitor energization test is done in the lab. The equivalent test circuit is shown in Figure 18(a), and the actual power network topology is in Figure 18(b). In the figure, the three-phase voltage source is 120 V, and each capacitor capacity is $50\mu F$. The number of sampling points N per cycle is 1024. The PQPro power quality analyzer, from CANDURA Instruments, is used to record the voltage waveform at the power source, which is shown in Figure 19(a). The extracted transient component of phase A is shown in Figure 19(b). It should be noted that in real power system,

power quality monitor devices should be installed at the substation where power quality disturbances need to be analyzed. The sampling rate of the power quality monitor devices are higher than that of the PMU, which can reach 61440 Hz, i.e., the number of sampling points is 1024 per cycle for 60 Hz power system.

The magnitude, dominant frequency, and duration of the transient disturbance in Figure 19 is 1.1084pu, 1060Hz, and 8056.4μs, respectively. The lab test results are in line with the theoretical analysis.
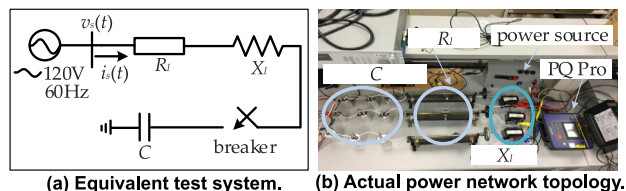

(a) Equivalent test system.   (b) Actual power network topology.

FIGURE 18. Equivalent circuit and the photo of lab test.

(a) Recorded phase A voltage waveform.

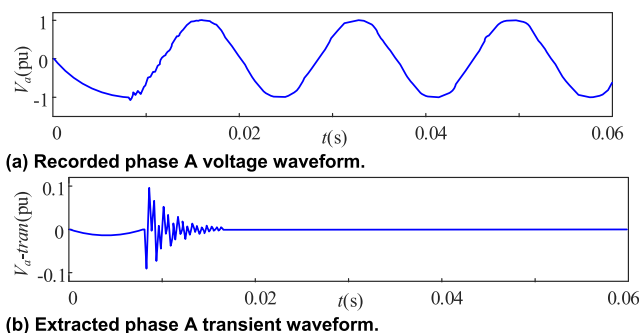

(b) Extracted phase A transient waveform.

FIGURE 19. Phase A voltage waveform monitored at the power source and the extracted transient component waveform.

VI. CONCLUSION

This paper has proposed a voltage transient disturbance detection method based on the RMS values of segmented differential waveforms, and considering the system frequency variation correction, the transient components are extracted as well. Based on the extracted transient components, four indicators (dominant frequency, polarity, magnitude and duration) are proposed to characterize the voltage transient disturbances. The accuracy and effectiveness of the proposed method are verified not only by a simulation analysis but also by a lab test. The proposed method is simple and intuitive, which can guide the technicians to detect and analyze voltage transient disturbances.

Besides the proposed time-domain segment-differential-waveform-based voltage transient detection method, four interesting directions are worth to be further researched.

1) A premise to implement the proposed detection method is to detect the positive zero-crossing point. A more precise method to detect the positive zero-crossing point is needed to further improve the accuracy of the transient detection results.

2) Identify the root cause of the transient disturbance is helpful for technicians to take measures. Thus, not only should the transient disturbance be detected, the root cause identification method should also be explored in the future.

3) Voltage waveform and current waveform may contain different disturbance information. A more comprehensive detection method will be developed by making full use of both voltage and current data.

4) An advanced machine learning based detection scheme can be developed to ensure better detection accuracy with low computational time for transient disturbances detection.

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