Postprint: Anti-Interference Voltage Sag Detection Method Based on Dual Wavelet Transform

Authors: Xu Dan, Huang Lijun, Xiao Hui, Li Xianwei, Wang Yi, Li Bo

Date: 2019-03-05T00:00:00+00:00

Abstract

To address the current issues of poor analysis accuracy and low real-time performance in voltage sag detection arising from interferences such as noise and harmonics, a voltage sag detection method based on dual wavelet transform is proposed. This method first employs the db20 wavelet to perform multi-scale decomposition of the signal, extracting the fundamental component containing sag information. Subsequently, the db10 wavelet is utilized to conduct single-scale decomposition of the fundamental component, detecting the modulus maxima of high-frequency components to achieve voltage sag localization, thereby mitigating the influence of interfering signals such as noise and harmonics and enhancing the detection performance of wavelet analysis.

Full Text

2 Wavelet Analysis Methods

In recent years, with the rapid development of power electronics technology and the large-scale application of computers and automation control equipment in industrial and social domains, people have placed higher demands on power quality in supply systems. Voltage sag represents a major power quality issue. According to China' s national power quality standards, voltage sag refers to the phenomenon where, under power frequency conditions, the root-mean-square voltage value suddenly drops to 0.1–0.9 pu and returns to normal after a brief duration of 10 ms to 1 minute [1]. Voltage sag causes significant harm to sensitive loads, such as PLC malfunctions and computer data loss, resulting in substantial economic losses [2-4], and has therefore attracted widespread attention.

Currently, methods for detecting voltage sag signals primarily include time-domain approaches and coordinate transformation methods. Time-domain methods detect the occurrence time and duration of voltage sag by obtaining difference signals. Coordinate transformation methods include short-time

Fourier transform, dq coordinate transformation, and wavelet transform [5-8]. Among these, wavelet transform exhibits excellent capability for analyzing transient signals and can accurately identify characteristic quantities at voltage mutation points, garnering extensive attention from researchers [9-11]. Reference [12] implemented wavelet transform algorithms using Field-Programmable Gate Array (FPGA) for real-time voltage sag detection, achieving a time delay of 1 ms that meets real-time requirements for engineering applications. However, filtering and denoising are critical to ensuring real-time and accurate voltage sag detection. In practical applications, noise and harmonic interference present in detection signals affect the analytical capability of wavelet transform, leading to increased errors or even misjudgment. Reference [13] proposed a threshold-based method to quantify high-frequency wavelet coefficients for noise elimination, but threshold selection is often difficult to determine in practice. Reference [14] employed multi-scale wavelet decomposition to suppress noise amplitude by fully utilizing high-frequency and sub-high-frequency components, but misjudgment easily occurs under conditions of large noise amplitude and harmonic presence. Reference [15] proposed using weighted least squares estimation algorithms and resetting covariance for rapid voltage sag judgment, but frequent changes in harmonic components cause continuous threshold resetting. Reference [16] presented a method using double wavelets for coarse estimation and precise localization of start and end times to exclude noise interference, but the presence of high-frequency harmonics affects the singularity of modulus maxima, reducing the detection capability of wavelet analysis.

This paper first investigates the propagation characteristics of noise and harmonics across wavelet scales and proposes a double-wavelet detection concept—extracting fundamental wave components at large scales and analyzing voltage mutation information at small scales. Based on this, the paper examines the influence of vanishing moment order on fundamental wave extraction accuracy and sag information localization, selects appropriate wavelet functions, determines the double-wavelet detection scheme, and verifies the method' s feasibility through Matlab/Simulink simulation.

2.1 Wavelet Transform

The wavelet transform window size can be adjusted according to signal frequency. Its essential idea is to represent a signal as an algebraic sum based on wavelet functions and derived scaling functions. For any signal f(t) $L^2(R)$ and wavelet function Ψ(t), its continuous wavelet transform can be expressed as:

WTf(a,b) = f(t), Ψa,b(t) = f(t)Ψ*

where f(t), Ψa,b(t) represents the inner product of f(t) and Ψa,b(t); Ψ* is the complex conjugate of wavelet function Ψ; a is the scale factor, characterizing signal stretching in the frequency domain; and b is the translation factor, characterizing signal shifting in the time domain.

2.2 Multi-Resolution Analysis and Filtering

The center and radius of the wavelet function' s time-frequency window vary with the scale factor. Typically, the scale factor is discretized (a = 2 , where j is an integer) to achieve layer-by-layer binary division in the frequency domain. Performing wavelet transform on a signal is equivalent to decomposing it into different frequency bands, with wavelet coefficients representing component information of each frequency band. Wavelet coefficients from each band can be reconstructed through inverse transform to restore signal components, thereby obtaining fundamental or harmonic information of the signal. [Figure 1: see original paper] shows a schematic diagram of wavelet decomposition at scale 3 (j = 3). After wavelet transform, signal S is expressed as S = A + D + D + D , where A , A , A represent low-frequency approximations of the signal, corresponding to frequency bands 0-f /4, 0-f /8, and 0-f /16 (f being the sampling frequency), and D , D , D represent high-frequency details, corresponding to frequency bands f /4-f /2, f /8-f /4, and f /16-f /8. High-frequency components are analyzed using small-scale short windows, while low-frequency components use large-scale wide windows. By properly setting sampling frequency and decomposition scales, fundamental and harmonic components of the signal can be effectively separated, with fundamental information existing in the lowest frequency band and harmonic information distributed across various high-frequency bands.

2.3 Singularity Detection and Sag Localization

Voltage sag belongs to a class of singular signals, equivalent to superimposing impulse or step functions at signal singularity points. Mallat proved that local signal singularity is closely related to wavelet transform modulus maxima. Singularity points of a signal correspond to modulus maxima points of wavelet coefficients in the time domain and propagate from one scale to another while maintaining maxima across all scales. By detecting modulus maxima points in high-frequency bands of wavelet decomposition, the start and end times of sag in the original signal can be determined. [Figure 2: see original paper] shows single-scale decomposition results of a voltage sag signal, where D is the reconstructed signal component of the high-frequency band. Modulus maxima points can be clearly identified from the high-frequency component D , corresponding to the start and end times of voltage sag. [Figure 3: see original paper] illustrates the propagation characteristics of sag signals across wavelet scales. As can be seen, sag distributes across all high-frequency scales of wavelet transform, presenting modulus maxima at each scale. As decomposition scale increases, modulus maxima gradually increase, reaching maximum values in the high-frequency band D .

3 Double-Wavelet Sag Detection

Wavelet analysis methods achieve voltage sag localization by detecting modulus maxima in the highest frequency band D or sub-high-frequency band D .

In practical applications, however, the presence of noise and harmonics often degrades detection performance or even causes failure.

3.1 Propagation Characteristics

The propagation characteristics of sag signals, noise, and harmonics differ across wavelet scales. Taking a 220 V power frequency signal containing sag as an example, with added 3rd harmonic, 13th harmonic, and white noise interference, this paper investigates the propagation characteristics of sag, noise, and harmonics across wavelet scales. Signal characteristics and analysis conditions are shown in the table below.

[TABLE:N] Signal characteristic parameters and simulation analysis conditions

Voltage amplitude/frequency	Voltage sag (%)	Sag start/end time (s)	Sampling frequency (Hz)	Harmonics	Noise amplitude
220V/50Hz	3rd, 13th harmonics	Maximum amplitude 1V	0.2–0.5		

[Figure 4: see original paper] shows the propagation characteristics of noise across wavelet scales. As can be observed, noise as an interference signal is randomly distributed across various high-frequency scales of wavelet transform, with noise modulus values exhibiting negative singularity characteristics—larger in high-frequency bands and gradually decreasing with increasing scale, essentially non-existent in low-frequency bands.

[Figure 5: see original paper] shows the propagation characteristics of harmonics across wavelet scales. Unlike noise and sag signals, each harmonic component distributes in specific high-frequency bands. The 3rd harmonic mainly distributes in band D , the 13th harmonic mainly in band D , and fundamental information in band A .

In summary, noise, sag, and harmonics exhibit the following propagation characteristics in wavelet transform: noise and sag distribute across all high-frequency scales, while harmonics exist in specific high-order frequency bands of wavelet transform. As shown in [Figure 6: see original paper], noise exhibits singularity characteristics opposite to sag, significantly impacting high-frequency scales, particularly D and D . The presence of noise and harmonics (especially high-order harmonics) weakens modulus maxima, affecting voltage sag localization.

3.2 Detection Principle

Although noise and harmonics distribute in high-frequency bands of wavelet transform and affect maximum detection, they have almost no impact on the lowest frequency band. Based on this, this paper proposes a real-time voltage sag detection method using double wavelet transform—extracting and analyzing voltage fundamental components at large scales while detecting and analyzing voltage mutation information at small scales, thereby accurately locating the start and end times of voltage sag. As shown in [Figure 7: see original paper], the specific steps of double-wavelet detection are as follows:

1. Determine an appropriate scale j, perform multi-scale wavelet decomposition on the original signal to obtain wavelet coefficients at each scale.
2. Perform single-branch reconstruction on the lowest frequency band A to obtain the fundamental component a containing sag information.
3. Perform single-scale wavelet transform on the fundamental component a to obtain the high-frequency component D .
4. Determine the start and end times of voltage sag by detecting the modulus maxima of high-frequency component D .

3.3 Vanishing Moment Order

The key to double-wavelet detection lies in the accuracy of fundamental wave extraction and sag time detection. Vanishing moment order characterizes the convergence rate of wavelet functions approximating signals and represents an important parameter in wavelet analysis. This paper selects db-series wavelet functions for investigation, studying the relationship between fundamental wave extraction accuracy, sag detection accuracy, and vanishing moment order N, providing support for wavelet function selection in double-wavelet detection. Taking a 220 V power frequency signal with 30% voltage sag as an example, sag detection accuracy and fundamental wave detection precision are characterized by time deviation ΔT and error rate Rerror, respectively:

$\Delta T = t - t$ Rerror = (A - A)/A

where t and A are the detected voltage sag time and fundamental amplitude; t and A are the actual sag occurrence time and fundamental amplitude. Analysis results are shown in [Figure 8: see original paper].

As can be seen from [Figure 8: see original paper], when the vanishing moment order is small, db wavelets exhibit large errors in extracting fundamental feature information. As vanishing moment order increases, the extraction precision of db wavelet fundamental feature information improves and errors decrease, showing an obvious inflection point at N = 10. On the other hand, when vanishing moment order is small, sag detection time error is relatively small, but detection accuracy gradually decreases as vanishing moment order increases, with the two showing a basically linear relationship. Considering both time delay and extraction precision, this paper adopts db20 wavelet for fundamental information extraction and db10 wavelet for sag information detection.

4 Simulation Analysis

To verify the feasibility of the double-wavelet detection method, the signal from Section 2 is first analyzed in Matlab. According to the double-wavelet detection principle, db20 wavelet is used for multi-scale decomposition. Signal component information at each scale is shown in [Figure 9: see original paper], with fundamental information components extracted from the lowest frequency band A . Then, the fundamental component A undergoes single-scale decomposition using db10 wavelet, with the resulting high-frequency band information shown in [Figure 10: see original paper]. By detecting the modulus maxima of the secondary wavelet transform' s high-frequency component, the start and end times of voltage sag can be determined with high accuracy, effectively suppressing noise and harmonic interference.

Further, since cascading wavelet transforms may cause certain time delays, the double-wavelet detection model and environment are constructed in Simulink as shown in [Figure 11: see original paper]. The sag source and interference conditions are provided by a programmable three-phase power supply. The double-wavelet analysis method is implemented using the built-in DWT and IDWT modules, where the DWT module achieves multi-resolution decomposition and the IDWT module implements single-branch reconstruction. Phase A voltage signal is selected for double-wavelet analysis to detect voltage sag. Simulation results are shown in [Figure 12: see original paper], where the detected start and end times of voltage sag are 0.202 s and 0.502 s, respectively, with an error of 2 ms, demonstrating good real-time performance.

5 Conclusion

This paper proposes a double-wavelet voltage sag detection method. First, db20 wavelet decomposes the voltage sag signal, and single-branch reconstruction at low-frequency scales obtains the fundamental signal containing sag information. Then, db10 wavelet performs singularity detection on the fundamental signal to precisely determine the start and end times of sag. Matlab/Simulink simulation verification shows that the double-wavelet detection method can effectively suppress noise and harmonic interference, possesses strong anti-interference capability, and can achieve accurate voltage sag localization even under simultaneous noise and harmonic conditions, thereby significantly improving the detection performance of wavelet transform.

References

[1] National Technical Committee for Standardization of Voltage and Current Ratings and Frequencies. GB/T 30137—2013 Power quality—Voltage dips and short interruptions [S]. Beijing: China Electric Power Press, 2013.

[2] Study on the Impact of Voltage Sag on Sensitive Loads and Suppression Measures [D]. Guangzhou: Guangdong University of Technology, 2012.

[3] Tuljapurkar M, Dharme A A. Wavelet based signal processing technique for

classification of power quality disturbances [C]. 2014 Fifth International Conference on Signal and Image Processing (ICSIP), IEEE Computer Society, 2014: 337-342.

[4] Barros J, Diego R I, Apráiz M D. Applications of wavelets in electric power quality: voltage events [J]. Electric Power Systems Research, 2012, 88(1): 130-136.

[5] Xu Dan, Huang Xiaoming, Li Xianwei, et al. The study of self-adapt harmonic detection in power grid based on the wavelet transformation [J]. Electrical Engineering, 2017, 18(8): 37-42.

[6] Latran M B, Teke A. A novel wavelet transform based voltage sag/swell detection algorithm [J]. Electrical Power & Energy Systems, 2015(71): 131-138.

[7] Guo Jifang, Feng Lihong. Analysis of detection methods of voltage sag [J]. Electronic Technology, 2010, 11(4): 28-31.

[8] Xu Yonghai, Zhao Yan. Identification of power quality disturbance based on short-term Fourier transform and disturbance time orientation by singular value decomposition [J]. Power System Technology, 2011, 35(8): 174-180.

[9] Zhang Yan, Yin Lisheng, Ma Ruiqing. Voltage sag detection method based on complex wavelet and RMS algorithm [J]. Electrical Measurement & Instrumentation, 2017, 54(10): 74-79.

[10] Ren Zihui, Liu Haoyue, Xu Jinxia. Power quality disturbance analysis based on wavelet transform and improved Prony method [J]. Power System Protection and Control, 2016, 44(9): 122-128.

[11] Qi Bo, Zou Jinhui, Fan Yugang. Identification of voltage sags source based on Hilbert-Huang transform and wavelet packet energy spectrum [J]. Electric Power, 2013, 46(8): 112-117.

[12] Wang Jianxiong. Design of transient power quality disturbance detection system based on FPGA [D]. Harbin: Harbin University of Science and Technology, 2017.

[13] Pan Congmao, Li Fengting. The detection and identification of transient power quality based on wavelet transform [J]. Electrical Measurement & Instrumentation, 2013, 50(575): 69-72.

[14] Ge Chengyu, Zhu Songyi, Han Xianhe, et al. An anti-noise voltage sag time detection method [J]. Smart Grid, 2017, 5(5): 417-420.