Application of Empirical Mode Decomposition in EAST Superconducting Coil Voltage Signal Analysis (Postprint)

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Abstract

During a quench event in the poloidal field superconducting coils of the Experimental Advanced Superconducting Tokamak (EAST), the weak voltage signal variation induced by resistance changes in the superconducting coils is submerged in strong noise. To address this problem, Fast Fourier Transform analysis is employed to investigate the time-frequency characteristics of the coil voltage signal. Based on the analysis results, the Empirical Mode Decomposition (EMD) method is proposed for analyzing the voltage signal across the superconducting coil, yielding several Intrinsic Mode Functions and a residual component, and it is revealed that the energy of the weak signal is primarily distributed in the residual component. This method can eliminate environmental influences and detect weak variations in the voltage signal.

Full Text

Application of Empirical Mode Decomposition to Voltage Signal Analysis in EAST Superconducting Coils

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Abstract: In the Experimental Advanced Superconducting Tokamak (EAST) device, during the quench process of a superconducting coil, the voltage variation caused by resistance changes is extremely small and becomes submerged in strong background noise. To address this problem, we analyze the time-frequency characteristics of coil voltage signals using fast Fourier transform.

Based on the analysis results, we propose applying Empirical Mode Decomposition (EMD) to analyze the voltage signals across superconducting coils, obtaining several intrinsic mode components and a remainder term. We find that the energy of the weak signal is mainly distributed in the remainder term. This method can eliminate environmental influences and detect subtle variations in voltage signals.

Keywords: weak signal, empirical mode decomposition, coil voltage, remainder term

1 Introduction

The Experimental Advanced Superconducting Tokamak (EAST) is a fully superconducting, large-scale, non-circular cross-section tokamak device independently designed by China. Its poloidal field magnet system consists of 14 superconducting coils that must provide sufficiently large alternating currents and extremely rapid magnetic flux changes to control plasma breakdown and configuration [1-4]. To ensure safe operation of the device, it is necessary to detect the weak voltage signal changes caused by resistance variations in the early stages of superconducting coil quench.

Quench is a critical phenomenon in superconductor operation. The poloidal field coils are made of CICC-type conductors, and when quench occurs, resistance appears suddenly in the superconducting coil and gradually increases. Since resistance changes directly cause voltage changes, voltage detection is more direct and faster among various quench detection methods. However, poloidal field superconducting coils operate in extremely complex and variable electromagnetic environments, where the coupled voltage across the coil terminals is very strong, and the voltage change caused by resistance variation becomes submerged in coupled noise voltage. Therefore, eliminating voltage signal noise and accurately detecting voltage variation trends is crucial for quench signal detection.

Over the past decades, domestic and international experts have conducted extensive research on weak signal detection. From traditional techniques such as curve fitting and smoothing, lock-in amplification, statistical averaging of discrete quantities, correlation detection, and adaptive noise cancellation, to emerging methods like stochastic resonance, chaotic oscillators, empirical mode decomposition, and blind source separation, the development of computer technology and modern power electronics has created the material conditions for implementing these methods [5-6]. Reference [7] introduces the principle of curve fitting; reference [8] compares several different smoothing and denoising methods; reference [9] constructs a lock-in amplifier and applies it to multi-frequency time-varying signal processing; reference [10] discusses the principle of sampling integration in detail; reference [11] proposes an optimal segmentation method for time-domain averaging to eliminate periodic truncation errors;

reference [12] introduces the use of autocorrelation functions to suppress noise and extract weak periodic signals; references [13-14] apply cross-correlation detection to echo signals in laser ranging and gear crack fault signals, respectively, effectively improving the success rate and accuracy of weak signal extraction; reference [15] proposes a variable step-size adaptive filtering algorithm; and reference [16] presents an improved energy detection algorithm for generalized Gaussian noise backgrounds, with simulation results demonstrating significantly reduced error probability under low signal-to-noise ratio conditions.

This paper employs the Empirical Mode Decomposition (EMD) algorithm to process voltage signals across superconducting coils before and after adding quench signals, obtaining intrinsic characteristic functions and a remainder term of different frequencies. Through Hilbert-Huang transform, we calculate the spectrum and marginal spectrum of each component to obtain the time-frequency distribution of the signal. Analysis reveals that weak voltage variations can be reflected in the remainder term of EMD decomposition.

2.1 Principle of Empirical Mode Decomposition Algorithm

The Empirical Mode Decomposition algorithm, proposed by Norden E. Huang et al., is based on the concept of Intrinsic Mode Functions (IMF) and decomposes any signal into several IMF components. Each IMF component represents local characteristics of the original signal, and instantaneous frequency can be obtained by deriving the phase of its analytic signal. Compared with Fourier transform, its adaptive time-frequency analysis feature allows the frequency characteristics of components to vary with time, making it more suitable for analyzing non-stationary, non-linear signals. However, the EMD algorithm also has limitations:

(1) **Endpoint effect phenomenon**: When using spline functions to process extreme points, fitting errors occur at the endpoints, and error accumulation can "pollute" the entire sequence.

(2) **Envelope fitting problems**: Cubic spline functions exhibit overshoot and undershoot phenomena when fitting data.

(3) **Mode mixing**: Abnormal signal variations cause multiple different characteristic time scales to exist in one mode component after decomposition, causing IMF components to lose specific physical meaning.

2.2 Steps of Empirical Mode Decomposition Algorithm

The steps of the EMD algorithm are as follows:

(1) Identify the maxima and minima of the original signal and fit the upper and lower envelope curves using cubic spline interpolation.

(2) Calculate the mean of the upper and lower envelope curves and subtract this value from the original signal to obtain a new sequence.

(3) Determine whether this sequence meets the two criteria of an intrinsic mode function. If satisfied, it can serve as an IMF; otherwise, treat it as the original signal and repeat the first two steps until the first IMF component is obtained.

(4) Calculate the residual signal and treat it as a new signal, repeating steps (1) and (2) until all IMF components are extracted.

The original signal can be expressed as:

$$x(t) = c_i(t) + r_n(t)$$

where $c_i(t)$ represents the i-th intrinsic mode function and $r_n(t)$ represents the remainder term.

3.1 Generation of Superconducting Coil Voltage

The poloidal field power supply is one of the subsystems of the tokamak device and plays a crucial role in plasma current generation and control. It consists of 12 sub-power supply systems, each composed of corresponding control, measurement, protection, and drive units. By controlling current changes, it provides extremely rapid magnetic flux changes to maintain plasma current magnitude and configuration. The structure of each power supply system is shown in [Figure 1: see original paper].

During each operation cycle, the current in the coils goes through a rising phase, flat-top phase, and feedback stage for plasma current control. The voltage and current across the coils are measured by Hall elements and transmitted to a Windows platform. [Figure 2: see original paper] shows the voltage signal collected by Hall voltage sensors and current signal collected by Hall current sensors during a normal discharge experiment, with a sampling frequency of 10 kHz and 230,000 sampling points. The coupled voltage across the coil terminals reaches up to 300 V, while the voltage change during initial quench is only a few volts, with the detected trend change accounting for only about 1% of the noise voltage.

For superconducting coils, due to their zero-resistance characteristic, if current is applied without interference, the voltage across their terminals is close to zero, enabling rapid quench judgment through voltage amplitude monitoring.

However, in the poloidal field power supply system, there are 14 parallel superconducting coils with magnetic flux coupling between them; plasma current generates interfering magnetic fields during generation or disruption; and induced eddy currents in the device shell produce magnetic flux coupling interference. Therefore, during device operation, substantial coupled voltages exist across superconducting coil terminals, which pose significant interference for quench signal detection.

3.2 Amplitude-Frequency Characteristics Analysis of Voltage Signals

To understand the amplitude-frequency characteristics of voltage signals and quench signals, we performed analysis using fast Fourier transform. The results are shown in [Figure 3: see original paper], revealing six large-amplitude frequency components in the voltage signal corresponding to significant harmonic components in the rectifier bridge output current, along with numerous stray components, particularly abundant low-frequency signals.

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4 EMD Analysis of Voltage Signals

Fourier analysis shows that the voltage signal across the coil terminals has a wide frequency band with rich low-frequency components, making it a non-stationary signal. During quench, coil resistance increases linearly, and quench events may occur at any time during device operation. To simulate quench phenomena, we selected data from the 5–7 s time period and added an artificially constructed quench signal to the original voltage signal, calculated as the resistance value multiplied by the real-time current value. Taking the quench occurrence moment as time zero, the resulting quench signal is shown in [Figure 4: see original paper].

The quench signal is non-periodic, approximating a ramp signal with amplitude gradually increasing from 0 V to 5 V and linearly superimposed on the original signal. Following the steps described in Section 2, we performed EMD analysis on the voltage signals before and after adding the quench signal to extract IMF components and trend terms of different frequencies.

[Figure 5: see original paper] shows the EMD decomposition results before and after adding the quench signal. [Figure 5a: see original paper] demonstrates that the original signal is decomposed into 11 IMF components, with slight frequency aliasing effects in low-frequency components caused by abrupt changes in the voltage signal, though this does not affect trend term extraction. [Figure 5b: see original paper] shows that after adding the quench signal, the voltage is decomposed into 12 IMF components, indicating that the added signal energy is not entirely concentrated in the trend term but partially extracted into components. Subtracting each IMF component from the original signal yields the voltage variation trend. [Figure 6: see original paper] shows the spectra of EMD decomposition results. From the final decomposition layer, under normal conditions, the voltage trend range during the selected time period is 116–118 V, while after adding the quench signal, the voltage trend value increases correspondingly, reaching a maximum of 121 V. Comparing the trend term variation with the added quench signal, as shown in [Figure 7: see original paper], the variation of the trend term extracted by EMD decomposition tracks the quench signal superimposed on the original voltage signal well.

5 Conclusion

To address the problem of excessive coupled noise voltage in EAST poloidal field superconducting coils submerging quench signals, we analyzed the time-frequency characteristics of voltage signals and proposed using the EMD algorithm to decompose voltage signals and extract voltage variations from the trend term. The analysis yields the following conclusions:

(1) The main components of coupled voltage across superconducting coil terminals are distributed in the 0–1,000 Hz range, as revealed by fast Fourier analysis.

(2) EMD decomposition can extract voltage signals with different frequency characteristics. From the spectra of each component, the decomposition results roughly match the time-frequency analysis of the original signal. The extracted remainder term has deviations at the endpoints but overall can effectively reflect voltage trends after adding the quench signal.

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Note: Figure translations are in progress. See original paper for figures.