ISSN 2616-5767 Vol.6, Issue 1: 55-60, DOI: 10.25236/AJETS.2023.060109

Selection of fault selection jump identification algorithms for high-speed railway traction networks

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Abstract: *High-speed railways have become a new business card for China. When power supply faults occur in the electrical traction network of high-speed railways, the practice of sacrificing selectivity to ensure the reliability of the relay protection system often occurs, and a more effective relay protection scheme must be adopted if the reliability and selectivity of the protection system are to be taken into account. Fast and accurate identification of fault types and their removal from the traction network is of great significance for the stable operation of railway power supply systems. Therefore, it is particularly important to identify and locate fault solutions. This paper analyses the commonly used fault identification and location algorithms, determines the fault signal processing principles for fully parallel AT lines, determines which algorithms are used to identify and locate faults, and helps to improve the fault detection efficiency of railway power lines.*

Keywords: *High-speed railway; Traction power supply; Fault selection and jumping; Fault identification*

1. Introduction

As the backbone of the comprehensive transport system and one of the main modes of transport, railways play a vital role in the economic and social development of China. The existing high-speed railways are generally powered by electric traction, with trains drawing current through the contact network. As the national railway is mostly operated outdoors, the climate and environmental conditions are complex and changeable. Under the more severe climate and environmental conditions, high-speed railways operating with electric traction are prone to electrical failures. Therefore, the use of an efficient and reliable relay protection system is essential for the safe operation of high-speed railways. At present, there is a practical problem that insufficient attention is paid to the detection and location of faults in the distribution lines of railway power supply systems, resulting in an impact on the normal and safe operation of the entire railway power supply lines. Based on the analysis of several commonly used signal processing methods, this paper presents practical methods that can characterise the operation of the traction network, and qualitative analysis of the different methods yields a solution for the identification and location of faulty lines.

2. Common signal analysis methods for the identification of fault selective jump signals

2.1 Short Time Fourier Transform (SFFT) algorithm

For the Short Time Fourier Transform (SFFT) algorithm can be seen as an upgraded version of the Fast Fourier Transform (FFT) algorithm to improve the local signal processing ability and make targeted improvements [1], the Short Time Fourier Transform (SFFT) algorithm in processing the local signal, the whole signal is divided into many shorter periods [2], and the signal is assumed to be smooth in each period interval, obviously this This approach artificially approximates part of the smooth signal in the whole unstable signal, which is of course a "pseudo-smooth" signal for the whole signal, but this method also has the effect of localising the time and frequency [3].

The following is an example of signal analysis to illustrate the characteristics of the Short Time Fourier Transform (SFFT) algorithm for signal processing. Figure 1 shows the original waveform of the example signal.

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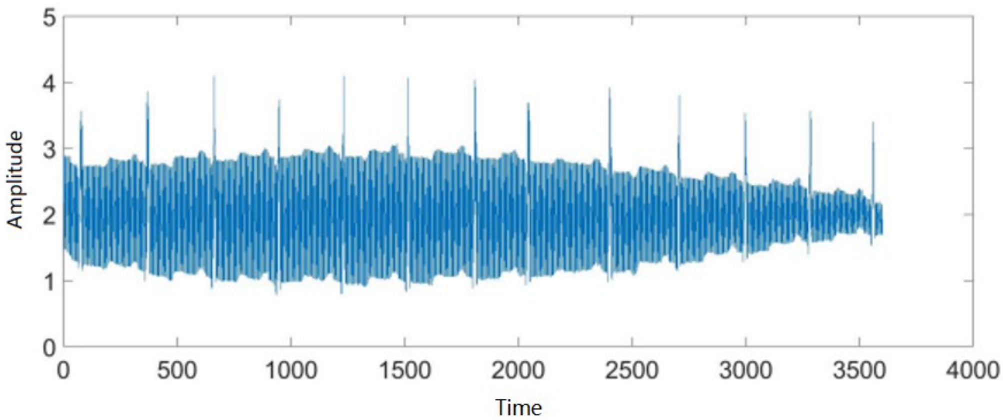

Figure 1: Waveform of the original signal processed by the Short Time Fourier Transform (SFFT) algorithm

From the original signal plot it is relatively easy to see that the signal is roughly at data points at 150, 450, 600, 800, 1250, 1500, 1700, 2100, 2800, 3000, 3250, 3600 with abrupt waveform singularities. By programming the SFFT algorithm to run, Figure 2 shows the results of the analysis of the original waveform.

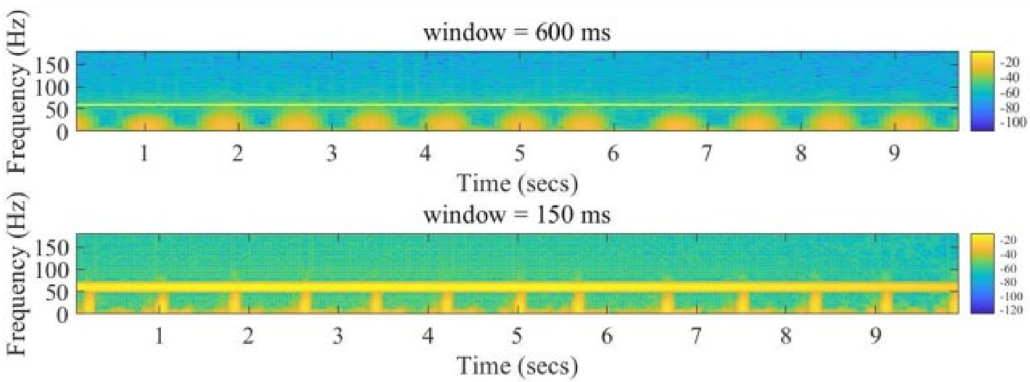

Figure 2: Analysis results of the Short Time Fourier Transform (SFFT) algorithm for different window function widths

As can be seen from the graph of the SFFT algorithm's analysis results, setting different window function widths yields widely varying analysis results. The window function requires a high temporal resolution for violently varying signals, and a high frequency resolution for more subdued waveforms. The Short Time Fourier Transform requires different widths of window functions for the analysis of signals with different characteristics. Once the window function is determined, its shape and size do not change and the resolution of the SFFT is determined. This feature makes it necessary to change the width of the window function according to the situation in order to effectively differentiate the type of short-circuit faults occurring on fully parallel AT lines, while the task of the fault criterion algorithm itself is to differentiate the type of short-circuit faults, so the fault selection scheme for fully parallel AT traction network lines should not use the Fourier transform (SFFT) algorithm as a fault criterion, but only as an auxiliary discrimination method.

2.2 Basic theoretical approach to the Hilbert-Yellow transform

The Hilbert-Huang transform is a newer signal processing algorithm whose basic idea is to sieve the intrinsic mode function obtained by sieving the signal to be processed in order of frequency, step by step. The Hilbert spectrum and the marginal spectrum can be obtained by performing the HHT transform on the intrinsic mode function components. The Hilbert and marginal spectra reflect the spatial and temporal distribution of the signal to be analysed. The Hilbert transform is calculated as

$$H[x(t)] = \frac{1}{\pi}\int_R \frac{x(\tau)}{t-\tau} d\tau \tag{1}$$

where x(t) is the function to be transformed.

Mathematically speaking, the Hilbert transform is a convolution operation on x(t) and 1/t. The Hilbert transform has significant advantages in terms of local characteristics. The Hilbert transform can be used to detect the singularity of a waveform and is significantly better at measuring the degree of singularity, which can be detected in terms of frequency, amplitude, direction etc. The technical approach to waveform singularity analysis using the Hilbert transform is to first perform an empirical modal decomposition of the signal to be analysed to obtain the intrinsic modal function of each order corresponding to the order. As the distribution of signal energy is from high to low frequencies, the higher the energy component of the signal analysed the better the analysis will be in terms of fit to the original signal, so in the analysis that follows the measure of signal singularity is mainly through the high frequency intrinsic mode function, i.e. the intrinsic mode function with the smallest scale. The process of singularity analysis under multiple signals using the Hilbert transform is roughly as follows.

Step 1: Empirical modal decomposition of the original signal, sieved by frequency and energy, to obtain the intrinsic modal function.

Step 2: From the intrinsic mode function, the component with the smallest scale is selected, and the amplitude, frequency and other characteristic quantities of the intrinsic mode function are quantified to compare the degree of singularity of each signal.

As the Hilbert transform requires the analysis of multiple components and is more time consuming to calculate, the Hilbert transform is not used alone in the analysis of fault currents in fully parallel AT lines, but is applied in combination with the wavelet transform.

2.3 Basic theoretical approach to wavelet transform analysis

In principle, the wavelet transform first localises the signal in the time domain using a window of fixed size and variable shape, which is then analysed and processed. The time and frequency windows of the wavelet transform can be adapted to the characteristics of the signal to be analysed. In the process of signal processing, the time resolution and frequency resolution of the wavelet transform are often diametrically opposed in the same frequency band, i.e. when analysing the low frequency range of a signal, it has a high frequency resolution and a low time resolution. When analysing the high frequency range of a signal it has a higher temporal resolution with a lower frequency resolution. This diametrically opposed distribution of temporal and frequency resolution is well suited to the analysis of non-smooth signals and is also very beneficial for extracting local features of the signal [4]. The task of quickly identifying fault locations and fault types for fully parallel AT lines can be accomplished very successfully.

The effect of wavelet analysis on signal processing is also visualized in the following example. Figure 3 shows the original waveform and the modal maximum waveform calculated by wavelet analysis.

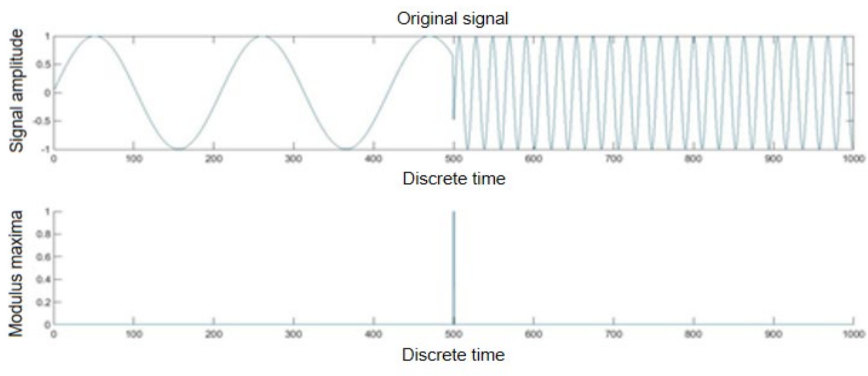

Figure 3: Plot of the original signal waveform analysed by the wavelet analysis algorithm and the analysis results

As can be seen from the example, the wavelet analysis algorithm pinpoints the location of the singularities of the waveform by calculating the mode maxima, although this example is based on an ideal signal. In practical engineering applications, after the wavelet transform has been applied to the signal, it is possible to quickly determine the fault interval where the fault occurs by sorting the obtained mode maxima by size.

Wavelet analysis is well suited to the task of fault type identification and fault location determination

ISSN 2616-5767 Vol.6, Issue 1: 55-60, DOI: 10.25236/AJETS.2023.060109

for fully parallel AT lines. The reason is that the wavelet transform is able to detect local signals of analytical value in both the time and frequency domains, so that sudden changes in the fault current waveform can be effectively identified and the signal singularities can be intuitively obtained by means of modal maxima calculations to determine the fault zone and fault type. The wavelet transform is also "adaptive" and "zoomorphic" in that it automatically adjusts the parameters of the algorithm for different objects, which is why the wavelet transform can play an important role in the analysis of fault current signals in fully parallel AT traction networks. As the choice of different wavelet basis functions has a significant impact on the results obtained by applying wavelet analysis, the next step is to characterise the common wavelet basis functions and discuss their suitability for fault identification on fully parallel AT lines.

2.4 Analytical selection of wavelet analysis basis functions

Fourier transform and wavelet transform have different characteristics, the Fourier transform function is constant, while the wavelet transform using the transform function is according to the research needs of their own selection, the choice of wavelet base can be adjusted according to the different characteristics of the object of analysis, even if the analysis of the same signal, in the choice of different wavelet base, will get very different analysis results. Therefore, the selection of the appropriate wavelet base is the most fundamental and critical step in the process of wavelet analysis in engineering practice. The criteria for determining whether a wavelet base is suitable for a particular project is whether the size of the error is within an acceptable range, i.e. there should not be too much error between the signal results obtained by wavelet analysis and the theoretical analysis results. Commonly used basis functions are Haar, Daubechies, Mexican Hat, Morlet, Meyer wavelets 5 kinds. For the fault identification of the power supply line, the commonly used wavelet analysis basis functions are Morlet wavelet, Meyer wavelet and Daubechies wavelet, which are discussed separately for the fully parallel AT line.

2.4.1 Morlet wavelets and Meyer wavelets

Morlet wavelets are single frequency complex sinusoidal functions under a Gaussian envelope.The Morlet wavelet function, like the Mexican Hat wavelet function, has no corresponding scale function, the difference being that the Morlet wavelet function also has a non-orthogonal decomposition.The Morlet wavelet is defined by the following function.

$$\Psi(t)=Ce^{-\frac{t}{2}}cos(5t) \tag{2}$$

where C is the normalization constant at reconstruction and t is a time domain variable. Figure 4 shows the time and frequency domain plots of the Morlet wavelet.

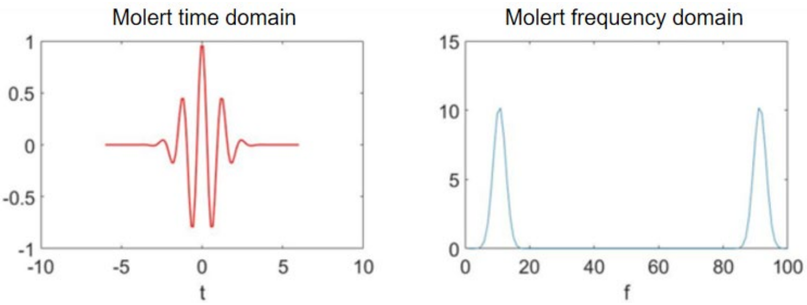

Figure 4: Time and frequency domain plots of Morlet wavelets

Morlet wavelet is a very common wavelet function, Morlet's time domain and frequency domain performance is relatively good, but it does not meet the tolerance conditions, so it is not suitable as a fault determination basis for fault selection jumping scheme for fully parallel AT lines.

Figure 5 shows the time and frequency domain diagrams of the Meyer wavelet, which lacks tight support characteristics and is therefore not chosen as the basis for fault discrimination in the fault selection scheme for fully parallel AT lines.

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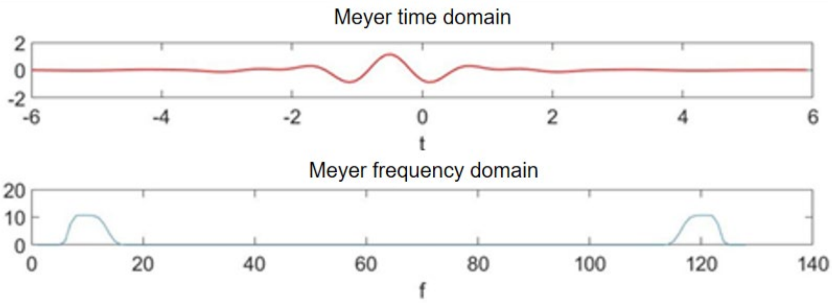

Figure 5: Time and frequency domain plots of Meyer wavelets

2.4.2 Daubechies wavelets

Daubechies wavelets are named after the world-renowned wavelet analyst Daubechies, in honour of his contribution to the creation of this wavelet function. It is generally abbreviated as dbN, with N being the order [5]. Except for the case where N = 1, dbN is not symmetric.

The Daubechies wavelet [6] family is a collective name for a series of binary wavelets, and in practical engineering programming applications, the convention is to use dbN as a notation for such wavelet families. Unlike dbN wavelets, N is not used to denote the order, but rather the order number of the wavelet, with N being desirable in the range 2 to 10.

The Daubechies function relation is

$$\left|\frac{1}{\sqrt{2}}\sum_{k=0}^{2N-1} h_k e^{-jk\omega}\right|^2 = \sum_{k=0}^{N-1} C_k^{N-1+k} y^k (\cos^2\frac{\omega}{2})(\sin^2\frac{\omega}{2}) \tag{3}$$

Daubechies wavelets have the following characteristics.

(i) In the time domain it is finitely supported, i.e. Ψ(t) has finite length.

(ii) In the frequency domain Ψ(t) has Nth order zeros at ω = 0. The wavelet function Ψ(t) can be calculated from the "scale function" φ(t). The scale function is generally a low-pass function with a support domain in the range t=0~(2N-1).

(iii) Ψ(t) and its integer shifts are orthogonally normalized, i.e. $\int \Psi(t)\Psi(t-k)\,\mathrm{d}t = \delta_{\mathrm{k}}$ (4)

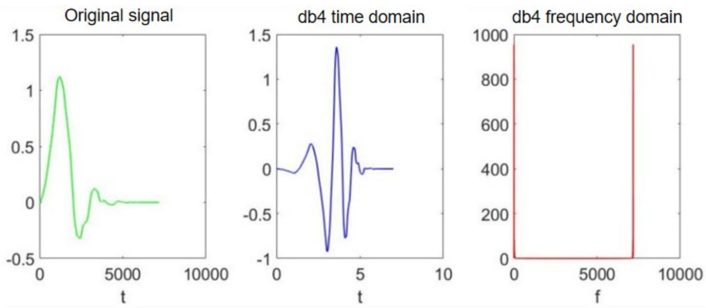

Figure 6: Show the results of the analysis completed by Daubechies wavelet analysis

The dbN wavelet has good regularity and can achieve relatively smooth signal reconstruction. By choosing the appropriate order, better frequency domain localization and frequency band division results can be obtained. Therefore, the dbN wavelet is chosen as the basis function for the wavelet selection criterion of the fault in the fully parallel AT grid (Figure 6).

3. Fault identification solutions

After the analysis and demonstration in this chapter, it was determined that the principle of fault signal processing for fully parallel AT lines is to use a combination of the wavelet transform algorithm and the empirical modal decomposition algorithm under the Hilbert transform. As the empirical modal algorithm requires a longer calculation time compared to the wavelet transform algorithm, in order to enhance the speed of fault determination, the wavelet transform analysis is used to process the fault current of the transformer to divide the fault interval and the empirical modal algorithm to determine the fault line, aided by Fourier signal processing.

4. Conclusion

This paper introduces several mainstream waveform signal processing algorithms, and analyses the characteristics of each in some detail. As the choice of wavelet basis has an important influence on the analysis and processing results obtained through the wavelet transform, a special section is devoted to the analysis of the characteristics of the three commonly used wavelet basis functions in turn, and a judgement is made as to whether they are suitable for application to the processing of fault current waveforms on fully parallel AT traction lines. The principle of fault signal processing for fully parallel AT lines is determined by combining the wavelet transform algorithm with an empirical modal decomposition algorithm under the Hilbert transform. As the empirical modal algorithm takes longer to compute than the wavelet transform algorithm, in order to improve the speed of fault determination, the wavelet transform analysis is used to process the transformer fault currents to delineate the fault interval and the empirical modal algorithm to determine the fault line, aided by Fourier signal processing.

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