Feature Extraction Method for DC Charging Signal of Electric Vehicle

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Abstract. The high-power DC charging of electric vehicle charging stations leads to a large amount of ripple and unsteady waves in the power grid, which seriously affects power quality. The existing algorithms cannot accurately identify the signal characteristics of the fundamental wave, ripple, and the unsteady wave, and it is urgent to develop a comprehensive signal feature extraction method. Aiming at the time-varying characteristics of fundamental and non-steady-state waves in DC charging signals, the layered parameters of wavelet transform are modified, a multi-resolution method is established, and the fundamental and unsteady wave signals are identified and separated. Based on the amplitude-frequency and phase-frequency characteristics of DC charging signal, Fourier transform (FFT) is used to identify the amplitude and frequency of each sub-ripple, and a signal feature recognition method based on Fourier/wavelet transform is proposed to extract the signal characteristics of the DC charging process. The experimental results show that the signal feature recognition method based on Fourier/wavelet transform can identify the DC charging signal characteristics of electric vehicle with high accuracy, and can separate the unsteady state signal from the steady state signal.

1. Introduction

For the special environment of DC charging of electric vehicles, it is urgent to carry out research on signal feature extraction methods. The related classic algorithms are Fourier transform, band-pass filtering, wavelet analysis, instantaneous power theory, neural network and so on [1,2]. The Fourier analysis method can decompose multiple ripples, but it cannot accurately identify the non-steady-state waves, and the detection accuracy of the ripples is easily affected by the DC fundamental wave and the unsteady state signals, and it is difficult to meet the reality extraction characteristics of DC charging signals of electric vehicles. Wavelet transform uses local and temporal transforms in time and frequency domain to accurately detect unsteady signal characteristics, but local accurate detection reduces the accuracy of multiple ripple recognition and cannot accurately extract all the signal characteristics of DC charging in electric vehicles [3].

According to the DC charging load and signal characteristics of electric vehicles, a method of extracting DC charging signals of electric vehicles using Fourier/wavelet transform is proposed. The characteristics of all signals in DC charging process of electric vehicles are identified and extracted. Simulation and experimental results show that this method can separate the fundamental and unsteady
wave signals from the electrical signals, and accurately identify the frequency and amplitude of multiple ripples. The accuracy of signal characteristics is higher in both time domain and frequency domain.

2. DC Charging Load and Signal Characteristics of Electric Vehicles

The fast charging mode of electric vehicles adopts high-power DC power supply. Since the batteries of electric vehicles and charging devices, such as distribution transformers and chargers, have many nonlinear components [4], the voltage and current signals in the charging system of electric vehicles contain multiple ripple components that are integral multiples of the fundamental frequency and the signal's frequency drifts. Figure 1 is a partial enlarged view of the DC charging voltage curve collected at a certain electric vehicle charging station.

![Figure 1. Enlarged DC charging voltage curve of electric vehicle](image)

The FFT algorithm uses spectrum analysis, which has the advantages of fast response speed, high data processing capability, and good real-time performance [5]. However, the Fourier transform is mainly used to decompose periodic signals. For unsteady waves with indefinite amplitude and frequency, especially, it is an impact signal that cannot be quickly and accurately identified [6-8], and the detection accuracy of the ripple is easily affected by the non-steady-state signal, and it is difficult to meet the actual demand for feature extraction of the DC charging signal of the electric vehicle.

Based on the DC charging load and signal characteristics of EVs, combined with the FFT algorithm and wavelet transform to detect the advantages of different types of signals, this paper proposes a DC/DC signal feature extraction method for electric vehicles using Fourier/wavelet transform to realize the DC charging of electric vehicles. Seamless measurement of the process.

For the DC charging signal of an electric vehicle, it is decomposed into a low-frequency characteristic approximation signal and a high-frequency characteristic detail signal [9-11]. The j-scale decomposition will be performed according to the following formula

$$f(t) = \sum_k c_{j,k} 2^{-j/2} \phi(2^{-j}t - k) + \sum_k d_{j,k} 2^{-j/2} \psi(2^{-j}t - k)$$

(1)

where $\phi(*)$ is the scale space function, $\psi(*)$ is the wavelet mother function, $\sum_k c_{j,k} 2^{-j/2} \phi(2^{-j}t - k)$ is the projection on the scale, and the decomposition of the low-frequency part of the signal is realized, $\sum_k d_{j,k} 2^{-j/2} \psi(2^{-j}t - k)$ is the projection of the wavelet space, and the decomposition of the high-frequency part of the signal is realized [12].
The multi-resolution decomposition divides the frequency band of each layer, and the approximation parameters and local feature parameters can be obtained by

\[ c_{j+1,k}(k) = \sqrt{2} \sum_{m} h(m-2k)c_{j,m} \]  
\[ d_{j+1,k}(k) = \sqrt{2} \sum_{m} g(m-2k)c_{j,m} \]

where \( c_{j,k} \) is an approximation parameter on the \( j \) scale, \( d_{j,k} \) is a local feature parameter in the \( j \) wavelet space; \( k \) is the number of the signal in each layer; \( \psi_{a,\tau}(*) \) is a wavelet basis function, \( a \) is a scale factor, \( \tau \) is a translation factor; \( m \) is a discrete dimension Power series; \( h(*) \) is a scale-space filter function, which reflects the low-pass characteristics of the signal; \( g(*) \) is a wavelet spatial filter function, which embodies the signal high-pass characteristics.

After decomposition, each frequency band contains different signal components, and each frequency band is reconstructed to obtain fundamental and unsteady wave signal feature extraction. The reconstruction formula is

\[ f_1(t) = \sum_{a} \sqrt{2} c_{j,a} h(m-2a) + \sum_{a} \sqrt{2} d_{j,a} g(m-2a) \]
\[ f_2(t) = \sum_{a} \sqrt{2} c_{j,a} h(m-2b) + \sum_{a} \sqrt{2} d_{j,a} g(m-2b) \]
\[ x(t) = \sum_{a} \sqrt{2} c_{j,a} h(m-2c) + \sum_{a} \sqrt{2} d_{j,a} g(m-2c) \]

where \( f_1(t) \) is the extracted fundamental wave signal, \( a \) is the level number of the fundamental wave, \( f_2(t) \) is the extracted non-stationary wave signal, \( b \) is the non-steady-state wave at the hierarchical number; \( x(t) \) is the superimposed ripple signal.

The formula for the number of decomposition layers is

\[ p = \log_2 \left[ \frac{f_s}{(f_0 \sqrt{k})} \right] + 0.5 \]

where \( f_s \) is the sampling frequency and \( f_0 \) is the greatest common divisor of the frequency of the ripple signal.

The FFT algorithm decomposes the periodic ripple signal in the form of a Fourier series into the superposition of different frequency components, and then uses the separated signal to calculate the relevant features.

The ripple signal is represented by a periodic function as

\[ x(t) = x(t + kT) \quad (k = 0, 1, 2, \ldots) \]
\[ x(\omega_0 t) = a_0 + \sum_{n=1}^{\infty} (a_n \cos n\omega_0 t + b_n \sin n\omega_0 t) \]

where \( a_0 \) is the DC component, \( a_n \) is the cosine term coefficient of the secondary ripple, and \( b_n \) is the sine term coefficient of the n-order ripple.

To analyze the characteristics of the DC charging ripple signal of the electric vehicle, it is necessary to make a transition from the theoretical Fourier series analysis to an exponential form using the Fourier series to obtain the magnitude and phase of each ripple and obtain the corresponding characteristic values.

According to Euler's theorem, formula (7) is transformed into
\[ x(t) = a_0 + \sum_{n=1}^{\infty} \left( a_n - \frac{j b_n}{2} e^{j\omega_0 t} + \frac{a_n + j b_n}{2} e^{-j\omega_0 t} \right) \]  

(8)

3. Simulation
The DC charging data of electric vehicles collected in the test platform is preprocessed to obtain the characteristics of ripple and unsteady wave signals, then, modeling and simulation analysis are performed to verify the accuracy of the DC signal extraction algorithm for electric vehicles using Fourier/wavelet transform. Considering the case of multiple ripples, intermittent waves, and unsteady waves, the analysis wavelet db40 and five-layer wavelet transform are used to decompose the ripple. Since the even-number ripple and the odd-numbered ripples more than 19 times during the charging of the electric car are too small to be ignored.
Ripple of incomplete decomposition
Transient attenuation wave and unsteady wave
Fundamental wave

Figure 4. The sub components of the wavelet transform of the voltage signal

Fundamental wave
Transient attenuation wave and unsteady wave
Ripple of incomplete decomposition

Figure 5. The sub components of the wavelet transform of the current signal

Figures 2 to 5 show that when there are too many ripple times, the wavelet transform cannot restore the multiple ripples one by one, but it can accurately identify the non-steady and fundamental waves. Comparing the energy calculations of fundamental and unsteady wave electrical signals, it can be known from comparison that the feature extraction algorithm for DC charging signals of electric vehicles using Fourier/wavelet transform can extract the characteristics of fundamental and non-steady state signals, and eliminate non-stationary waves. After the influence of the ripple, the amplitude and frequency of multiple ripples are more accurately identified. The DC charging ripple content of electric vehicles is shown in Table 1.

Table 1. The DC charging ripple content of electric vehicles

| Ripple Times | Voltage Ripple Factor (%) | Current Ripple Factor (%) | Frequency(HZ) |
|--------------|---------------------------|---------------------------|---------------|
| 1            | 2.6                       | 2.4                       | 50            |
| 5            | 2.8                       | 2.8                       | 250           |
| 9            | 2.3                       | 1.6                       | 450           |
| 13           | 2.4                       | 2.6                       | 650           |
| 17           | 2.1                       | 1.2                       | 850           |
| 19           | 1.5                       | 1.4                       | 950           |
4. Experiments
According to the architecture of the electric vehicle charging system, a hardware experiment platform was set up, and the ripple effect on the measurement error was designed and tested. The accuracy of the feature extraction algorithm of the DC charging signal of the electric vehicle using the Fourier/wavelet transform was verified. The experiment increases the given ripple effect according to GBT 17215.321-2008, 3 official prototypes (No.1, No.2, and No.3) and 3 comparative prototypes of the same model specification under the specified reference conditions for testing.

The Fourier transform/wavelet transform of the electric vehicle's DC charging signal feature extraction algorithm significantly reduces the amount of error in the prototype compared to the comparison prototype. When the applied ripple current varies within the range of 0.02In ~ 1.2In, the test results of the official prototype meet the requirements of the error change limit under the influence of ripple. The error change amount is less than 0.2, which is only about 1/2 of the comparison prototype. Experiments show that the feature extraction algorithm of DC charging signal of electric vehicle using Fourier/wavelet transform has obvious advantages in the data extraction ability of fundamental wave, ripple and unsteady wave signal, and has higher accuracy.

5. Conclusions
Due to the effects of non-linear loads and concentrated charging, there are a large number of ripples and unsteady waves in the DC charging process of electric vehicles. Fourier transform is difficult to identify the frequency of intermittent wave and cause spectral leakage. It is very inaccurate to extract the features of unsteady wave signal, and it is easily affected by the non-steady state signal in the process of identifying the ripple signal. The wavelet transform can effectively extract the characteristics of non-steady-state signals and fundamental signals are more accurate, but they have limited ability to identify multiple ripple signals. Experiments show that the synthesis algorithm formed by the combination of the two makes up for the inaccuracy of the FFT algorithm for non-steady-state and interharmonic energy measurements, and has obvious advantages over the existing FFT algorithm for extracting the DC charging signal characteristics of electric vehicles. The shortcomings of the FFT algorithm in identifying the non-steady-state wave are solved, the detection accuracy is improved, and the entire extraction process of the DC charging signal characteristic of the electric vehicle is more complete and reliable. The electric energy metering and filter circuit improvement for DC charging of electric vehicles has important reference significance.

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7. References
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