

Detection of Power Quality Disturbance of the Best ASD Based on Dynamic PSO Search

Dan Zhao^{1,2}, Shiying Hou¹, Nianrong Zhou^{1,2}, Lijun Tang², Tao Sun¹, Yuan Gong¹

¹State Key Laboratory of Power Transmission Equipment & System Security and New Technology, Chongqing University, Chongqing 400044, China.

²Yunnan Electric Power Test & Research Institute (Group) Co.Ltd. Kunming 650217, China.
2363343725@qq.com

Abstract. This paper mainly studies the power quality disturbance feature detection and optimization method based on atomic sparse decomposition algorithm. In order to solve the problem of large amount of matching pursuit algorithm, this paper proposes a Particle Swarm Optimization dynamic search (PSO-DS) algorithm based on the PSO optimization algorithm, using the prior information provided by the fast Fourier transform and wavelet transform to search for parameters. The range and optimization of the search for the best atom are optimized. The simulation of the example shows that the PSO-DS algorithm can effectively extract the signal features with less decomposition times, avoiding the generation of unrelated and erroneous components, improving the detection accuracy of the disturbance signal and the simplicity and accuracy of the signal representation.

1. Introduction

Signal decomposition is an effective method for signal analysis and processing. In modern digital signal processing, a series of analysis methods that combine time-frequency information such as Fourier transform, short-time Fourier transform, and wavelet transform have emerged. In 1995, Dr. Kennedy and Eberhart proposed a PSO algorithm based on the similarity of behavior rules and optimization problem solving for birds flying to habitats^[1].

The phenomenon of premature convergence or oscillation of the algorithm may occur when the parameters of the PSO algorithm are incorrectly set or the size of the population is unreasonable. The standard PSO algorithm tunable parameters include the inertia factor w and the acceleration factors $c1$, $c2$, w shows the influence of the historical position of the particle on the current position^[2], and determines the local development ability and global exploration ability of the PSO algorithm. At that time, the PSO algorithm was similar to the local search algorithm, and it converged to the local optimal solution with fast speed. When the PSO algorithm has strong global exploration ability, but the algorithm converges slowly or cannot converge, its performance is intermediate. Acceleration factors $c1$ and $c2$ are also known as cognitive factors and social factors respectively^[3, 4]. Ratnaweera proposed a time-varying acceleration factor, that is, at the beginning of the algorithm^[5], set larger cognitive factors and smaller social factors.

Aiming at the phenomenon of “short-sightedness” in the matching pursuit algorithm, many scholars have optimized the PSO algorithm. The idea of windowing the original signal was proposed by[6], and gradually reduced the length of the atom to search for the best time domain of the atom. The time domain segmentation of the original signal was proposed by[7], and the length of the atom



was gradually reduced to search for the best time domain of the atom. The influencing factors of the fundamental wave amplitude in detail was analyzed in [8], also an iterative and based approach was proposed. The analysis shows that the PSO optimization algorithm can effectively reduce the complexity of the algorithm, but at the expense of the extraction accuracy of the parameters, coupled with the short-sighted and cumulative error effects of matching tracking itself, so that the process of decomposition has appeared irrelevant components and error components, interfere with the signal characteristics Effective extraction.

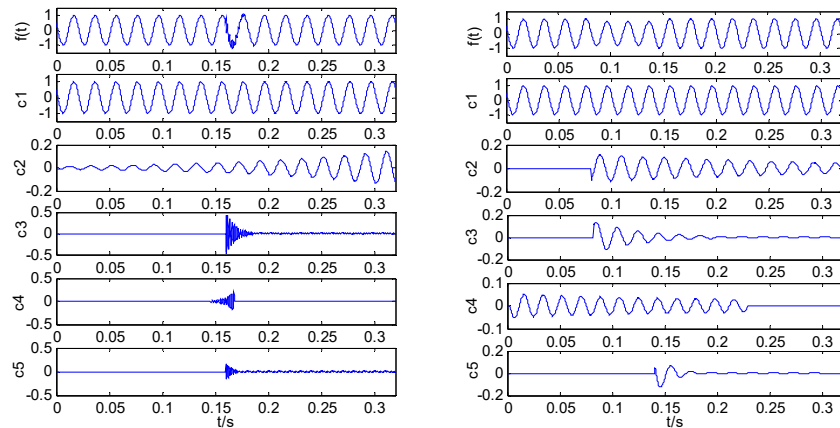
2. Analysis of power quality disturbance characteristics of time-frequency atoms optimized by standard PSO

Transient oscillations and voltage sag is used as an example for simulation analysis in this section. In the next simulation, the sampling frequency of the signal be 6.4 kHz and the sampling data length be 0.32 s. The population of the algorithm is set to 100 and iterates 40 times. Figure 1 shows the decomposition results after five decompositions of transient oscillations and voltage sags, where $f(t)$ is the original signal and $c1(t)$ to $c5(t)$ are atoms for each decomposition, and the ordinate in the figure is the amplitude. The atomic parameters of each decomposition are shown in Table 1. The transient oscillation signal is:

$$f(t) = \cos(100\pi t + \pi/3) + 0.5e^{-100(t-0.16)} \cos(1000\pi t + \pi/4) [u(t-0.16) - u(t-0.32)] \quad (1)$$

The voltage dip signal is:

$$f(t) = \{1 - 0.2 \cdot [u(t-0.08) - u(t-0.14)]\} \cos(100\pi t + \pi/3) \quad (2)$$



(a) Transient oscillation (b) Voltage dips

Fig. 1. Result of the algorithm

TABLE I. ATOMIC DECOMPOSITION PARAMETERS

	Amplitude /p.u.	Frequency f/Hz	Phase ϕ/rad	Decay exponent ρ	Start time t_s/s	Termination time t_e/s
c1	0.9980	49.9235	1.0687	0.0000	0.0000	0.3200
c2	0.1458	50.2350	2.0920	-7.6358	0.0000	0.3200
c3	0.4224	502.5991	-0.6935	119.4448	0.1604	0.3200
c4	0.2135	500.0398	1.5255	-128.4794	0.0171	0.1681
c5	0.1550	600.0000	0.6486	181.6986	0.1601	0.3200

According to the decomposition results of the transient oscillation signal, it can be seen that the PSO optimization algorithm can directly extract the main characteristics of the signal, such as the decomposition waveforms $c1(t)$ and $c3(t)$, which represent the fundamental and oscillatory components of the signal, respectively. The decomposition parameters are not accurate, the maximum amplitude error is 15.52%, and the attenuation parameter error is 19.44%. In the decomposition process, some uncorrelated or erroneous components are generated and the interference signal analysis results are obtained, which further affects the convergence performance of the algorithm. For the

voltage dip signal, the PSO optimization algorithm can effectively extract the fundamental wave component, but cannot extract the disturbance component.

The above causes of error can be summarized as the following three points:

(1) The particle swarm optimization algorithm uses the suboptimal solution generated by the initial population to continuously approach the optimal solution, without traversing the entire atomic library, the optimization result may not be globally optimal.

(2) The matching The tracking algorithm has a short-sighted phenomenon, which decomposes unsuitable atoms during signal decomposition, such as the decomposition waveform $c2(t)$ of the transient oscillation and the decomposition waveform $c2(t)$ of the voltage sag.

(3) The matching pursuit algorithm uses the inner product size of the atom and the signal or residual signal as the evaluation criterion of the best atom. Due to the mutual interference between different disturbances, it is not possible to extract the signal characteristic parameters accurately by one matching, and the matching tracking algorithm has error accumulation. In effect, the previous decomposition error will definitely affect the accuracy of subsequent decomposition.

3. Dynamic power PSO search time-frequency atom power quality disturbance analysis

According to some problems existing in the second quarter PSO optimization algorithm, the following improvement measures are taken in this paper based on the specific application of power quality disturbance detection in the algorithm:

(1) In the improved algorithm, Fast Fourier Transform will be used to detect the frequency and phase information of the signal, the atomic parameters are limited within the smaller range of the optimal value, which improves the convergence and accuracy of the algorithm.

(2) In the improved algorithm, Wavelet Transform will be used to positioning the mutation point of the signal, and finding the best matching atom in each optimization interval.

(3) After the first two optimization measures, the extracted atoms can effectively represent some characteristics of a certain disturbance, and they are superimposed by atoms that do not overlap in the same frequency and in the time domain or in the same frequency and in the time domain. Improve the detection accuracy of single disturbances.

3.1. Atomic Parameter Estimation Based on Fast Fourier Transform

FFT can obtain the amplitude, frequency and phase information of the signal. This paper first obtains the estimated frequency and phase of the signal through FFT transform, and the frequency and phase in the time-frequency atom library is limited to the corresponding estimated values. Moreover, the search range of parameters is reduced to further improve the convergence and accuracy of the algorithm.

Take the voltage oscillation signal as an example. Figure 2 shows the fast Fourier transform spectrogram. According to the spectrogram, it can be predicted that the signal contains 50Hz, 500Hz components, the corresponding phase detection value is 60.0233° , 44.5335° .

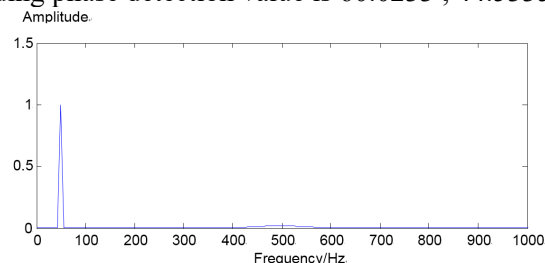


Fig. 2. Spectrum of voltage oscillation

3.2. Disturbance Point Localization Based on Wavelet Transform

The non-stationary power quality disturbance signal has a local mutation point. The wavelet transform $Wf(a,t)$ expresses the first-order reciprocal of the signal smoothed by the function $f(t)$ at the scale a ,

and the corresponding point of the modular maximum of the first-order reciprocal is the mutation point of the function. Therefore, when the basic wavelet is taken as the first-order reciprocal of the smoothing function, the modulus maximum point of the wavelet transform corresponds to the location of the abrupt point of the signal. It can be used to locate the abrupt point of non-stationary power quality disturbance signals.

The voltage oscillation and voltage sags are taken as examples below. The disturbance signal parameters are the same as those in the second section. The db24 wavelet is used to locate the signal, as shown in Figure 3. In the figure (a) is the power quality disturbance signal, the ordinate is the amplitude (p.u.), and (b) is the scale 1 wavelet modulus modulus. The location of the disturbance point is the voltage oscillation starting point 0.1600s, the positioning error 0.00%, the voltage dips starting point 0.07984s, the ending point 0.1400s, and the positioning error of 0.2% and 0%, respectively. It can be seen that the wavelet transform can effectively locate the start and end time of the disturbance.

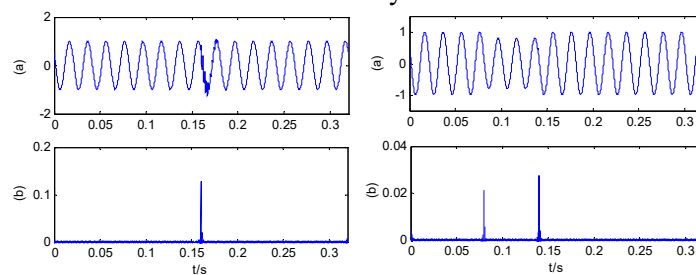


Fig. 3. Disturbance location of signals

3.3. Algorithm Implementation and Performance Comparison of Time-Frequency Atom Dynamic Search for PSO

The specific steps of the PSO Dynamic Search (PSO-DS) algorithm are as follows:

(1) Using wavelet transform to locate the location of the catastrophe of the disturbance signal, and form multiple optimization intervals with the starting and ending moments of $[t_{s1}, t_{e1}], [t_{s2}, t_{e2}] \cdots [t_{sn}, t_{en}]$;

(2) Acquire the spectral maximum value corresponding to the frequency and phase through the Fast Fourier Transform and set the search range of $[f_{\min}, f_{\max}] [\varphi_{\min}, \varphi_{\max}]$;

(3) Search for the best matching atom for the selected optimization interval;

(4) Use the PSO optimization algorithm to search for the best atom. At this time, the particle swarm optimization position consists of three parameters: f, φ and ρ ;

(5) Go back to step 3 until all search optimizations are completed;

(6) Comparing the best fitness function values of each optimization space, and taking the larger one as the best atomic parameter corresponding to the global optimal position as the current decomposition;

(7) Organize the best atoms for each decomposition. If the frequency and the time domain are the same or the frequency and amplitude are the same but the time domain intervals do not overlap, merge them. Otherwise, use the single feature.

(8) It is judged whether the resolution or energy threshold of matching pursuit is reached.

After the implementation steps of the PSO-DS algorithm are given, the convergence performance of the algorithm is further tested. The test results are shown in Figure 4. The ordinate is the residual energy and the abscissa is the number of decompositions. It can be seen from Figure 4 that the convergence performance of the PSO-DS algorithm is significantly better than the PSO optimization algorithm.

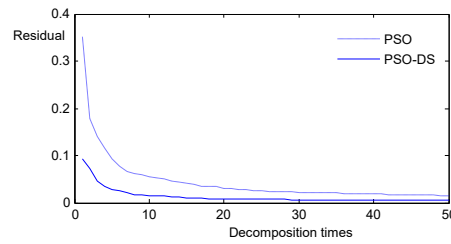


Fig. 4. The convergence of the algorithm

4. PSO-DS search for the best atom ASD power quality disturbance simulation analysis

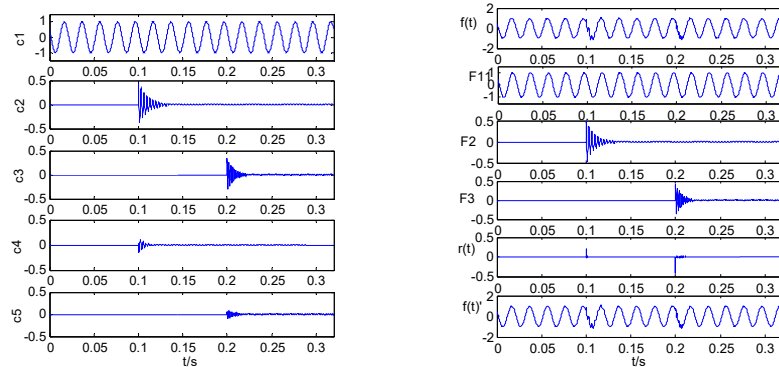
In this paper, three common single power quality disturbance signals (voltage oscillation, voltage dips, voltage interruptions) and complex disturbance signals are taken as examples to verify the algorithm. The signal sampling frequency is 6.4kHz and the data length is 0.32s. The decomposition results of various types of disturbance signals are shown in Table 2 and Figures 5~8. The corresponding waveforms are shown in Fig. 5 to 8 (a). Figures (b) in Figures 5 to 8 extract the characteristics of the perturbation signal, the residuals, and the reconstructed signal. $f(t)$ is the original signal. Feature 1, feature 2 and feature 3 are the extracted signal feature waveforms $r(t)$. For the decomposition of the residual signal, $f(t)$ is the reconstructed signal, and the ordinate is the amplitude.

4.1. Voltage oscillation

$$f(t) = \cos(\omega_0 t + \varphi_0) + ae^{-b(t-t_1)} \cos(c\omega_0 t + \varphi_1)[u(t_1) - u(t_2)] + a'e^{-b'(t-t_1')} \cos(c'\omega_0 t + \varphi_2)[u(t_1') - u(t_2')] \quad (3)$$

Simulation parameters are:

$$a = 0.5, b = 100, c = 6, t_1 = 0.1s, a' = 0.4, b' = 150, c' = 10, t_1' = 0.2s, \varphi_1 = \varphi_2 = \pi/4, t_2 = t_2' = 0.32s$$



(a) Atomic decomposition results

(b) Extraction of characteristic waveforms

Fig. 5. Decomposition result of voltage oscillation

TABLE II. ATOMIC DECOMPOSITION PARAMETERS

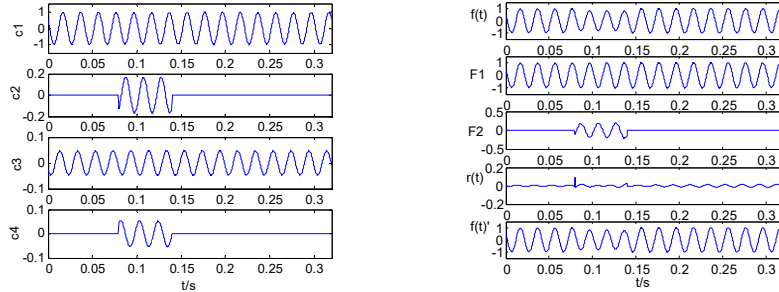
	Amplitude /p.u.	Frequency f/Hz	Phaseφ/rad	Decay exponent ρ	Start time ts/s	Termination time te/s
c1	0.9994	50.0000	1.0477	0.0000	0.0000	0.3200
c2	0.4473	300.4652	0.7827	96.8516	0.1000	0.3200
c3	0.3421	499.6041	0.8177	136.9557	0.2000	0.3200
c4	0.1420	300.3201	-0.4269	90.4494	0.1000	0.3200
c5	0.1526	503.0768	-2.1773	116.6928	0.2000	0.3200

According to the above decomposition results, it can be seen that the PSO-DS algorithm achieves the effective extraction of voltage oscillation signal features through five decompositions, and the parameter extraction accuracy is better than the PSO optimization algorithm, and there is no generation of unrelated or erroneous components in the decomposition process.

4.2. Voltage dips

$$f(t) = \{1 - \alpha \cdot [u(t_1) - u(t_2)]\} \cos(\omega_0 t + \varphi_0), 0.5T < t_2 - t_1 < 30T \quad (4)$$

Simulation parameters are: $\alpha = 0.2, t_1 = 0.08s, t_2 = 0.14s$.



(a) Atomic decomposition results

(b) Extraction of characteristic waveforms

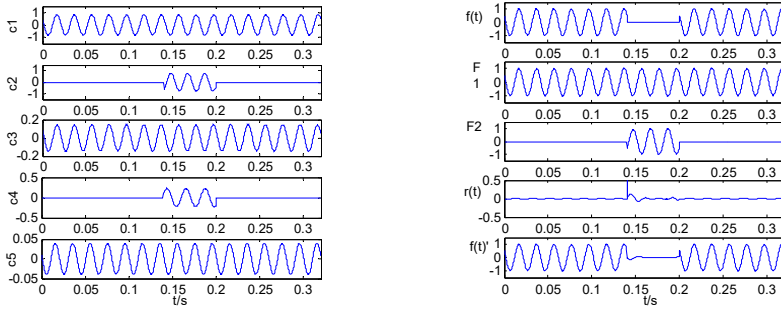
Fig. 6. Decomposition result of voltage sag

Figure 6 shows the breakdown of voltage dips. $c1$ is the fundamental wave component, $c2$ is the disturbance component. Since the voltage sag is a kind of fundamental wave disturbance, the mutual interference between the feature quantities is large, and the complete signal feature cannot be extracted through one match. Therefore, $c3$ and $c4$ are the re-extraction of the active ingredient in the remaining amount. From the above decomposition results, it can be seen that the PSO-DS algorithm extracts the active components in the remaining quantity by cross-extracting different feature quantities, and combines the similar frequencies and the atoms in the same time domain to have greater errors. The eigen-components are modified to make the extracted fundamental and disturbance feature components more accurate. The voltage breakdown and compound disturbance signal are decomposed in the same way as shown in Fig. 7~8.

4.3. Voltage interruption

$$f(t) = \{1 - \alpha [u(t_1) - u(t_2)]\} \cos(\omega_0 t + \varphi_0), 0.5T < t_2 - t_1 < 30T \quad (5)$$

Simulation parameters are: $\alpha = 0.9756, t_1 = 0.14s, t_2 = 0.2s$.



(a) Atomic decomposition results

(b) Extraction of characteristic waveforms

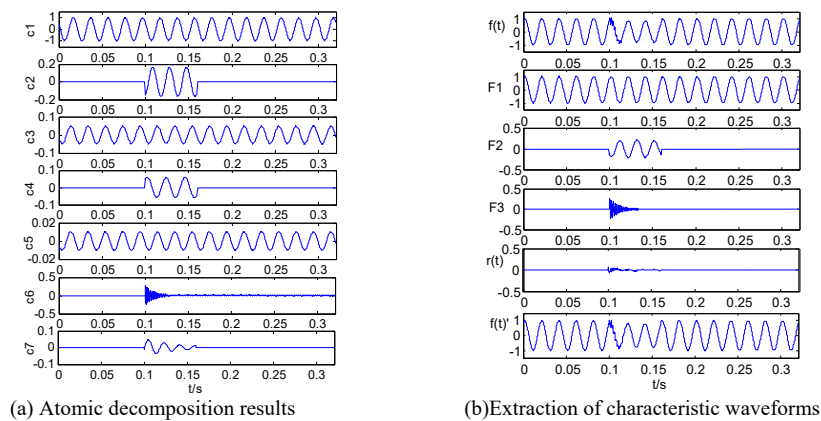
Fig. 7. Decomposition result of complex disturbance

4.4. Compound disturbance

$$f(t) = \{1 - \alpha [u(t_1) - u(t_2)]\} \sin(\omega_0 t + \varphi_0) + ae^{-b(t-t_1)} \sin(c\omega_0 t + \varphi_1) [u(t_3) - u(t_4)] \quad (6)$$

Simulation parameters are:

$$\alpha = 0.2, t_1 = 0.1s, t_2 = 0.16s, \varphi_1 = \pi/4, a = 0.3, b = 100, c = 10, t_3 = 0.1s, t_4 = 0.32s.$$



(a) Atomic decomposition results (b) Extraction of characteristic waveforms

Fig. 8. Decomposition result of complex disturbance

According to the decomposition results of different disturbance signals, we can see that the PSO-DS algorithm can effectively extract the signal features through several decompositions, and realize the alternate extraction of multiple features to make the decomposition results of a single perturbation more accurate. The PSO-DS algorithm improves the extraction accuracy of the perturbation signal's characteristic components, and effectively avoids the generation of unrelated and erroneous components in the initial stage of the algorithm, improving the simplicity and accuracy of the signal representation.

5. Conclusion

This paper mainly studies the power quality disturbance feature detection and optimization method based on atomic sparse decomposition algorithm. Firstly, for the problem that the matching tracking algorithm has a large amount of computation, the PSO algorithm is used to optimize, and the convergence performance of the algorithm is improved by linearly adjusting the inertia factor and the acceleration factor. The analysis shows that the PSO optimization algorithm can effectively reduce the complexity of the algorithm, but at the expense of the extraction accuracy of the parameters, coupled with the short-sightedness and error accumulation effect of the matching tracking itself, so that the uncorrelated components and error components appear in the decomposition process. In this paper, based on the PSO optimization algorithm, the PSO Dynamic Search (PSO-DS) algorithm is proposed, using the prior information provided by the fast Fourier transform and the wavelet transform, the search range of the parameters and the search method of the best atom are optimized. The simulation of the example shows that the PSO-DS algorithm can effectively extract the signal features with less decomposition times, avoiding the generation of unrelated and erroneous components, improving the detection accuracy of the disturbance signal and the simplicity and accuracy of the signal representation.

References

- [1] FUKUYAMA Y, TAKAYAMA S, NAKANISHI Y, et al. A particle swarm optimization for reactive power and voltage control in electric power systems; proceedings of the Conference on Genetic and Evolutionary Computation, F, 1999 [C].
- [2] MIRANDA V, FONSECA N. EPSO-evolutionary particle swarm optimization, a new algorithm with applications in power systems; proceedings of the Transmission and Distribution Conference and Exhibition 2002: Asia Pacific IEEE/PES, F, 2002 [C].
- [3] AL-HINAI A S, AL-HINAI S M. Dynamic stability enhancement using Particle Swarm Optimization Power System Stabilizer; proceedings of the International Conference on Adaptive Science & Technology, F, 2010 [C].
- [4] ZHANG Q, XUE S. An improved multi-objective particle swarm optimization algorithm [J]. Microcomputer & Its Applications, 2017, 186(3): 454-8.

- [5] RATNAWEERA A, HALGAMUGE S K, WATSON H C. Particle Swarm Optimization with Self-Adaptive Acceleration Coefficients; proceedings of the FsdK'02, Proceedings of the International Conference on Fuzzy Systems and Knowledge Discovery: Computational Intelligence for the E-Age, 2 Volumes, November 18-22, 2002, Orchid Country Club, Singapore, F, 2002 [C].
- [6] HOANG T A, NGUYEN D T. Matching pursuit for the recognition of power quality disturbances; proceedings of the Power Electronics Specialists Conference, 2002 Pesc 02 2002 IEEE, F, 2002 [C].
- [7] WANG N. Research on Power Quality Disturbances Analysis Method Based on Correlation Atom Library [D]; Tianjin University, 2013.
- [8] WANG J. Research on Overvoltage Identification Method and Hybrid Overvoltage Decomposition Method in Power System [D]; Chongqing University, 2011.