Analysis of resonance data in substations based on WOA-VMD-DWT

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Abstract. Aiming at the problems of low accuracy and sensitivity to noise in existing substation harmonic data analysis methods, a method for analyzing substation resonance data based on WOA-VMD-DWT is proposed in this paper. Firstly, in order to reduce the effect of the subjective judgment uncertainty, the parameters of the VMD (Variational mode decomposition) algorithm are optimized by the WOA (Whale optimization algorithm). Secondly, WOA-VMD is used to decompose the signal into multiple modal components adaptively, and DWT (Discrete wavelet transform) transform is used to extract the instantaneous frequency and amplitude of each harmonic mode. Finally, the accuracy of the method is verified by simulation data. The results show that the method has obvious advantages which could extract each harmonic component accurately with high detection accuracy.

1. Introduction

The gridding of renewable energy is the development trend of modern power grid. It brings uncertainty to the steady operation of substation. So it is critical to analysis the substation resonance data and find out the existing problems in time [1]. There are still many problems in the existing methods of harmonic data analysis. Literature [2] uses Fourier transform to realize the analysis of harmonic data. Fourier transform can detect integer harmonics with high accuracy, but for transient harmonics and inter harmonics and other nonstationary signals, frequency leakage and fence effect caused by asynchronous sampling cannot be avoided. Literature [3] adopts the method of wavelet transform to analysis the resonance data. Although the wavelet transform has good local characteristics, it needs to choose the wavelet base and the number of decomposition layers manually. The choice of different detection may be caused different results, and there will be frequency bands Aliasing. Literature [4] proposes an algorithm combining EMD (Empirical mode decomposition) and Hilbert transform to realize harmonic data analysis. However, under-envelopes and over-envelopes are easy to occur in EMD. For the noisy signals or harmonic signals with similar frequency, modal aliasing will occur, which will lead to wrong results or even unexplained negative frequency.

In the view of the above problems, a method for analyzing resonance data of substations based on WOA-VMD-DWT is proposed in this paper. Firstly, the K value of VMD (Variational mode decomposition) [5] needs to determine, which makes the decomposition result uncertain. The WOA (Whale optimization algorithm) is used to optimize the parameters of VMD algorithm to determine the optimal model number in this paper. Secondly, instead of EMD, WOA-VMD is used to decompose the resonance signals. Different from the circular screening stripping method by using EMD, the VMD...
determines the bandwidth and center frequency by iteratively searching for the optimal solution of the mode in the framework of variation. Finally, the time-frequency analysis of the modal components obtained by DWT (Discrete wavelet transform) decomposition of WOA-VMD is carried out, and the high-precision harmonic data analysis is realized by combining the advantages of the two noises robustness.

2. K value determination method based on whale optimization algorithm

The WOA is a bionic intelligent optimization algorithm that imitates the unique foraging behavior of humpback whales. It assumes that the current optimal individual is prey, and other individuals in the population approach to the optimal individual. The WOA algorithm is mainly divided into three stages: searching for foraging, shrinking the enclosing, and updating the spiral position. The searching and foraging stage is a process in which whales search for food randomly. Whale individuals search randomly according to each other's positions, corresponding to the global exploration stage of the algorithm. Its mathematical model can be expressed as [6]

\[ D = | CX_{rand}(t) - X(t) | \]  
\[ X(t + 1) = X_{rand}(t) - A [ CX_{rand}(t) - X(t) ] \]

In equation (1), \( X_{rand}(t) \) is a whale individual randomly selected from the current whale population, \( X(t) \) is the current whale individual position, and \( t \) is the number of iterations. In equation (2), \( A \) and \( C \) are coefficient vectors, defined as

\[ A = 2 \alpha r1 - \alpha \]  
\[ C = 2 r2 \]

Among them, \( r1 \) and \( r2 \) are random numbers between \([0,1]\), and \( \alpha \) is the control parameter expressed as

\[ \alpha = 2 - \frac{2t}{Max_{iter}} \]

Among them, \( Max_{iter} \) is the maximum number of iterations.

When \( |A| \geq 1 \), the whale enters the search and foraging stage, and whale individual will perform random search according to their phase position. The bubble net predation behavior of whale individual includes two mechanisms, which are shrinking enclosing and spiral updating position, corresponding to the local development stage of the algorithm. When \( |A| < 1 \), it enters the contraction phase.

In the stage of helix renewal, when whales are close to the best whale individuals, they will swim in a spiral way to search for the best possible solution between them. The initial point of spiral renewal is the position of the current whale individual, and the target end point is the position of the current best whale individual. Its mathematical model can be expressed as

\[ D' = | X_{best}(t) - X(t) | \]  
\[ X(t + 1) = D' e^{bl} \cos(2\pi t) + X_{best}(t) \]

In equation (6), \( D' \) represents the distance between the current whale individual and the best whale. In equation (7), \( b \) is a constant coefficient, \( t \) is a number between \([-1,1]\).

In the whale optimization algorithm, the update position is determined by the probability factors \( p \) and \( |A| \). When \( p \geq 0.5 \), it enters the spiral update position stage; when \( p < 0.5 \), it enters the search and foraging stage and the contraction and encircling stage.

3. Analysis method of substation harmonic data based on WOA-VMD-DWT

In view of the problems in the existing harmonic data analysis methods, this paper puts forward the specific steps of the substation harmonic data analysis method based on WOA-VMD-DWT as follows:
1) Obtain the original resonance current or voltage signal;
2) Use the WOA to optimize parameters the VMD and ensure the accuracy of results.
3) Input the initial signal into WOA-VMD and decompose the signal into K IMF (Intrinsic Mode Function);
4) Use DWT to further decompose each IMF to obtain the time-frequency curve and time-amplitude curve of the fundamental wave and each harmonic component, then analysis them.

The specific flow of the algorithm proposed in this paper is as follows:

Figure 1. WOA-VMD-DWT algorithm flow.

4. Example analysis

In order to verify the accuracy of the proposed method in resonance data analysis, a simulation signal is constructed as the input data for WOA-VMD-DWT decomposition, and the harmonic content is analysis. In order to show the superiority of the proposed algorithm in dealing with harmonic data, compare the decomposition results with the existing HHT (Hilbert-Huang transform) harmonic decomposition method based on EMD. Now the simulation signals including fundamental wave, 2.2nd harmonic, 3rd harmonic, 5th harmonic and 7th harmonic:

\[ s(t) = \sin(100\pi t) + 0.9\sin(220\pi t) + 0.7\sin(300\pi t) + 0.45\sin(500\pi t) + 0.32\sin(700\pi t) \] (8)

4.1 WOA accuracy verification

In order to verify the accuracy of the WOA optimization algorithm in optimizing the K value, taking equation (8) as input data, use WOA-VMD、GA-VMD(General Algorithm) and PSO-VMD((Particle Swarm Optimization) to decompose them respectively and compare the accuracy of the results. The optimization results of the three algorithms are shown as Table 1.

Table 1. Comparison of parameter optimization results.

| Parameter optimization times | WOA optimization Results | GA optimization Results | PSO optimization Results |
|------------------------------|--------------------------|------------------------|-------------------------|
| 1                            | 5                        | 7                      | 5                       |
| 2                            | 5                        | 6                      | 5                       |
| 3                            | 5                        | 8                      | 8                       |
| 4                            | 5                        | 9                      | 6                       |
| 5                            | 5                        | 6                      | 6                       |
| 6                            | 5                        | 5                      | 4                       |
| 7                            | 5                        | 5                      | 6                       |
| 8                            | 5                        | 7                      | 6                       |
| 10                           | 5                        | 8                      | 7                       |
| Average value                | 5                        | 7                      | 6                       |

From Table 1, it can be seen that there are some differences in the parameter optimization results of the three algorithms. The final decomposition results are shown in Fig.2:
It can be seen from the decomposition result in Fig. 2 that the WOA-VMD decomposition result is optimal. And, when K=5, the signal is completely decomposed without modal aliasing. The decomposition results include 5 different frequency waveforms, which completely correspond to the number of harmonic content in the initial signal described above. The decomposition results of pso-vmd and ga-vmd are relatively poor, and significant over decomposition phenomenon appears, which are shown in the 2.2 and 3 harmonics respectively. So it can be concluded that compared with the traditional PSO and GA optimization algorithm, WOA has stronger parameter optimization ability and more accurate results.

4.2 WOA-VMD-DWT accuracy verification

In order to verify the accuracy of the algorithm proposed in this paper, the simulation data of equation (8) is used as the input to analyze the resonance data, and the results are compared with the results of the existing resonance data analysis method HHT. Due to space limitations, some of the results are shown below, as shown below:

Figure 2. WOA-VMD, PSO-VMD, GA-VMD decomposition results.

Figure 3. Comparison of WOA-VMD and EMD decomposition results.
Fig. 3 shows the comparison of WOA-VMD and EMD decomposition results. Obviously, when the input data is the same, the WOA-VMD decomposition result is the same as the number of harmonics contained in the initial data. In contrast, EMD does not include the harmonics contained in them. The wave is decomposed and only 3 kinds of harmonics are decomposed. It can be seen that the decomposition accuracy of EMD is poor in the decomposition of the initial data, modal aliasing occurs, and WOA-VMD can achieve the best decomposition effect. The final running results of the two algorithms are shown in Fig.4:

![Figure 4](image_url)

**Figure 4. Comparison of decomposition results.**

It can be seen from Table 2 that the average amplitude detection error of the algorithm proposed in this paper is 0, and the average error of frequency detection is 0.41%, which has higher detection accuracy for steady-state harmonics. In contrast, there is a large error in the amplitude and frequency detection of HHT, which cannot be used as a basis for judgment.

| Harmonic frequency | WOA-VMD-DWT | HHT |
|--------------------|-------------|-----|
|                    | Frequency   |      |
|                    | Amplitude   | Error (%) | Frequency   | Amplitude   | Error (%) | Frequency   | Amplitude   | Error (%) |
| Kibo               |             |           |             |             |           |             |             |           |
| 1/1                | 50.49/63    | 0.74      | 100         | 0           | 0.76      | 150/220.16  | 46.77      |
| 2.2                | 0.9/0.9     | 0.51      | 100         | 0           | 0.71      | 150/250.67  | 14.01      |
| 3                  | 150/151.13  | 0.75      | 100         | 0           | 0.71      | 150/250.67  | 14.01      |
| 5                  | 250/250.07  | 0.02      | 155.55      | 0.45/1.15   | 0.41     | 250/250.67  | 14.01      |
| 7                  | 350/349.91  | 0.03      | 40.62       | 0.32/0.45   | 0.41     | 350/300.97  | 14.01      |

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5. Conclusions

This paper proposes a method of substation harmonic data analysis combining WOA-VMD and DWT. After analyzing the examples data, the following conclusions are obtained:

(1) The WOA optimization algorithm effectively reduces the K value determination method based on the instantaneous frequency mean quantization analysis, which can accurately determine the number of decomposition modes K, effectively reduces the data processing workload, and significantly reduces the instability of traditional parameter optimization algorithms and subjectivity based on artificial judgment alone.

(2) WOA-VMD can effectively extract modal components, suppress modal aliasing, and decomposition is actually multiple filtering processes, and has strong ability to resist noise interference.

(3) DWT filters out some small wavelet coefficients according to the set threshold before transformation, which improves the overall noise robustness of the algorithm. The average error of the amplitude detection algorithm proposed in this paper is 0, and the average error of the frequency detection is 0.41%. It has extremely high accuracy in the analysis of harmonic data.

In addition, VMD will inevitably have endpoint effects when it is decomposed, and iterative update calculations are large and the real-time performance is not high. In the future, research can be conducted on accelerating the algorithm's convergence speed and on-line harmonic monitoring and improvement, providing strong theoretical support for practical applications.

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