

Article

A Hybrid Identification Method for Subsynchronous Oscillation in Power Systems

Jinping Liang ^{1,*}, Yi Zheng ¹  and Xiangde Mao ² 

¹ School of New Energy and Power Engineering, Lanzhou Jiaotong University, Lanzhou 730070, China; z_y_01@126.com

² Shaanxi Railway Institute, Weinan 714000, China; maoxiangde@163.com

* Correspondence: l_j_p_1@126.com

Abstract

The increasing proportion of wind power integration in the power systems and the dynamic interaction of power electronic equipment lead to frequent subsynchronous oscillation, which seriously threatens the safety and stability of the system. Therefore, it is urgent to develop a high-precision and robust identification method. Traditional standalone identification methods are vulnerable to wind speed fluctuations and noise, resulting in unsatisfactory accuracy and robustness. To accurately extract the oscillation parameters from the active power signal, this paper proposes a hybrid method for identifying subsynchronous oscillation in power systems. First, the active power signal is preprocessed using the wavelet threshold denoising strategy, which effectively filters out noise through multi-scale decomposition and signal reconstruction. Second, VMD is applied to the preprocessed signal to decompose it into intrinsic mode functions, thereby achieving effective separation of different oscillatory characteristics. Finally, the fast Fourier transform is used to perform spectral analysis on each IMF to accurately capture the dominant frequency and amplitude of each oscillating component. On the four-machine two-area system with DFIG, the verification is carried out under the wind speeds of 9 m/s, 10.5 m/s and 12 m/s and the no noise, 60 dB and 40 dB noise conditions. SSO is excited by inserting 20 Hz, 30.5 Hz or 40 Hz subsynchronous oscillation components into the external part of the mechanical power input of the generator. The results show that the relative error of frequency identification of the proposed method is less than 0.0426% under all test conditions. The relative error of amplitude identification is less than 1.4155%. Compared with different methods, the proposed method exhibits excellent performance under noise conditions and has robustness to wind change and noise interference.

Keywords: subsynchronous oscillation; wavelet transform; variational mode decomposition; fast Fourier transform; power systems stability



Academic Editors: Pedro J. Villegas and Zhongyong Zhao

Received: 3 May 2026

Revised: 3 July 2026

Accepted: 9 July 2026

Published: 11 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Power systems are developing rapidly. Ultra-high voltage, heavy load and long-distance grid transmission have become a trend [1]. The increasing probability of subsynchronous oscillation (SSO) poses challenges to power systems' stability [2]. To suppress the occurrence of SSO, identifying SSO in power systems is of great significance.

When oscillations emerge in power systems, accurate and prompt identification of SSO parameters such as frequency and amplitude is a prerequisite for formulating effective suppression countermeasures [3,4].

Traditional frequency-domain methods, which rely on Fourier analysis and its variants, offer simple implementation and high computational efficiency. The identification method based on synchronous phasors could effectively extract the frequency and amplitude of oscillation [5], yet its calculation process introduced inherent system errors. Discrete Fourier transform (DFT) was prone to spectrum leakage during parameter estimation [6]. To mitigate this issue, reference [7] adopted an improved interpolation DFT based on the Hanning window to realize SSO identification within a 2 s data window. Nevertheless, the short window length limited the estimation accuracy. By contrast, the combination of interpolation DFT and filtering technology [8], as well as an improved interpolation all-phase FFT method [9], achieved higher identification accuracy. In addition, Prony analysis was applied for frequency and amplitude estimation [10], but this method was highly sensitive to noise. Adaptive bandpass filters were also adopted for oscillation parameter identification [11], but the noise robustness of the algorithm was not fully considered. Overall, traditional frequency-domain methods perform well under ideal conditions but degrade significantly in noisy and multi-mode scenarios.

Adaptive decomposition methods, which decompose signals to separate oscillatory components, exhibit anti-noise capability and mode separation. Reference [12] combined compressed sensing with ensemble empirical mode decomposition to enhance noise robustness, but the method suffered from complex computation and long processing time. Furthermore, an improved multi-synchrosqueezing wavelet transform integrated with an automatic identification algorithm was proposed in [13]. It raised identification speed without compromising accuracy, yet its performance relied heavily on threshold selection. It tended to misclassify modes with similar damping ratios. To make full use of multi-channel information, multivariate variational mode decomposition was adopted to extract SSO features from multiple PMU channels simultaneously [14]. This method improved positioning accuracy and noise immunity, but it increased measurement costs and system complexity. Moreover, the fixed window function limited its ability to distinguish closely spaced SSO modes. In addition, the combination of variational mode decomposition (VMD) and Prony-GSO produced modal aliasing and signal distortion in oscillation identification [15]. A beluga whale optimization VMD combined with wavelet threshold denoising and the Teager–Kaiser energy operator was proposed to suppress modal aliasing [16], whereas it increased computational complexity. Reference [17] presented a hybrid method integrating heuristic-optimized VMD and regularized total least squares Prony for doubly fed induction generator (DFIG) systems. The method reduced estimation errors under low signal-to-noise ratios at the cost of high computational complexity. Direct integration of VMD and Prony analysis worked well under low-noise conditions [18], but it was sensitive to the model order. Compressed sensing combined with adaptive VMD was adopted for wideband multi-modal identification [19], which reduced the computational burden but introduced reconstruction approximation errors. Reference [20] combined empirical wavelet transforms based on adaptive Fourier segmentation with the Hilbert transform for PMU-based SSO recognition. This approach ensured high efficiency but was vulnerable to spectral segmentation and generated physically ambiguous instantaneous frequencies for non-smooth modes. In general, the adaptive decomposition method is superior to the traditional frequency domain method in anti-noise and modal separation, but the computational complexity of some algorithms is too high.

Data-driven methods automatically extract oscillation features and adapt to complex nonlinear signals. A VMD–CNN-based wideband oscillation recognition method was presented in [21]. In this method, VMD extracted dominant modes and CNN directly estimated frequency and amplitude, and it achieved high accuracy for mode-superimposed signals. However, this approach required a large volume of labeled data, which was

difficult to acquire in practical engineering. Reference [22] proposed a two-stage SSO evaluation method for DFIG systems, which adopted deep Q network and Hanning-window interpolated FFT in sequence. It achieved strong anti-interference capability but required abundant training data and computational resources. Overall, the data-driven method has advantages in adaptive feature extraction, but it is dependent on the label data and has a long calculation time.

To solve the above problems, this paper proposes a hybrid method to identify SSO in power systems. At the same time, a four-machine two-area system (FMTAS) with DFIG is built to verify the reliability and robustness of the proposed method. First, the active power signal of the transmission line is collected, and wavelet transform (WT) is employed for multi-scale denoising to suppress noise in the acquired data. Then, VMD decomposes the denoised signal into intrinsic mode functions (IMFs) with diverse oscillatory characteristics, effectively separating aliased oscillation modes. Finally, fast Fourier transform (FFT) is used to accurately calculate the frequency and amplitude of each IMF. In terms of innovation, this paper has the following characteristics:

(1) By comparing the frequency error and calculation time calculated by different modal numbers in VMD, the optimal K value is selected. There is no need to traverse optimization and many iterations to optimize the key parameters of VMD.

(2) WT suppresses noise to mitigate VMD mode mixing, while VMD isolates oscillation components to reduce spectral leakage in FFT analysis. This synergistic cascade enhances both anti-noise robustness and mode separation capability.

(3) It avoids the high complexity of optimized VMD or deep learning-based approaches, outperforming traditional frequency-domain and single-stage decomposition methods in reliability and stability.

The remaining organizational structure is as follows. The Section 2 introduces FMTAS with the DFIG system and its oscillation mechanism. The Section 3 introduces the identification strategy for SSO. The Section 4 evaluates the reliability of this method through the simulation platform. The Section 5 is the conclusion.

2. System Description and Oscillation Analysis

2.1. System Description

The topology of the FMTAS with DFIG is shown in Figure 1. The system comprises two similar areas connected by a 220 km interconnection line [23]. Each area contains two synchronous generators. Area 1 contains generators G1 and G2, while Area 2 contains generators G3 and G4. Area 1 includes an aggregated wind farm equivalent to 18 wind turbines. The system load model consists of constant impedance loads L2, L7 and L9, which are connected to busbar 2, busbar 7 and busbar 9, respectively. Shunt capacitors C7 and C9 are installed on bus 7 and bus 9 to supply reactive power to the system. The two areas are connected to the main system via transmission lines through busbar 6.

The parameters of synchronous generators G1, G2, G3, and G4 in Area 2 are essentially identical to those in Area 1, the difference being the settings of other equipment parameters. The inertia coefficients of G1 and G2 are $H = 6.5$, while those of G3 and G4 are $H = 6.175$. The transformer model connected to G1, G2, G3, and G4 has a transformation ratio of 20/230 kV; the transformer connected after the wind turbine has a transformation ratio of 575 V/20 kV. The reactive compensation capacitor C7 has a nominal phase-to-phase voltage of 230 kV, an inductive reactive power $Q_L = 0$ and a capacitive reactive power $Q_C = 200$ MVar; C9 has a nominal phase-to-phase voltage of 230 kV, $Q_L = 0$ MVar and $Q_C = 350$ MVar. The parameters of load L7 include an active power $P = 967$ MW, $Q_L = 100$ MVar and $Q_C = 187$ MVar; the parameters of heavy load L9 include $P = 1767$ MW, with Q_L and Q_C set as the same as those of L7. The parameters of load L2 include an active

power $P = 100$ W, $Q_L = 0$ MVar and $Q_C = 0$ MVar. This tiny load L_2 is adopted to eliminate numerical singularity and ensure stable operation of the simulation model.

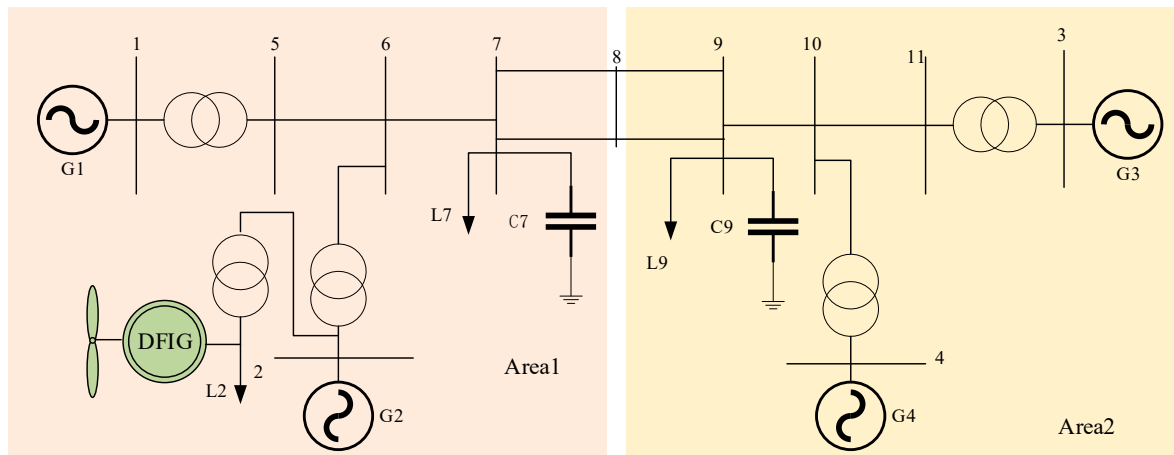


Figure 1. The topological structure of FMTAS with DFIG.

2.2. Oscillation Analysis

In the FMTAS connected to DFIG, the power system stabilizer provides good damping for low frequency oscillation. However, its control loop may produce undesirable components at the subsynchronous torsional vibration frequency of the shafting, which is transmitted to the excitation winding of the generator and excites the SSO of the shafting.

When a significant disturbance occurs in the system (such as a short circuit or sudden load change), electromagnetic torque is applied to the generator rotor, causing the generator shaft section to bear torque pressure and thus generating SSO. Additionally, the generator rotor oscillates at a torsional frequency, which leads to a subsynchronous frequency component in the armature voltage. When the subsynchronous frequency component approaches the electrical resonance frequency, the armature current generates a magnetic field that can produce torque that enhances the oscillation of the generator rotor. This allows the subsynchronous torque caused by the subsynchronous voltage component to be sustained. When the phase of the subsynchronous frequency component is the same as the increment of rotor speed and is equal to or exceeds the inherent mechanical damping torque of the rotor, the oscillation of the shaft system intensifies.

3. The Proposed Oscillation Identification Method

3.1. The Proposed Oscillation Identification Strategy

The SSO identification consists of four steps: signal acquisition and extraction, preprocessing of noisy signals, decomposition of processed signals, identification of the frequency and amplitude of characteristic signals. The main steps are shown in Figure 2.

Step 1: Add interference to the input power of each generator in the FMTAS with DFIG to collect the active power of the transmission line.

Step 2: The active power is decomposed by WT. The noise is filtered out and the signal is reconstructed.

Step 3: The reconstructed signal is decomposed by VMD to obtain the IMF.

Step 4: Use FFT to calculate the main IMF frequency and amplitude.

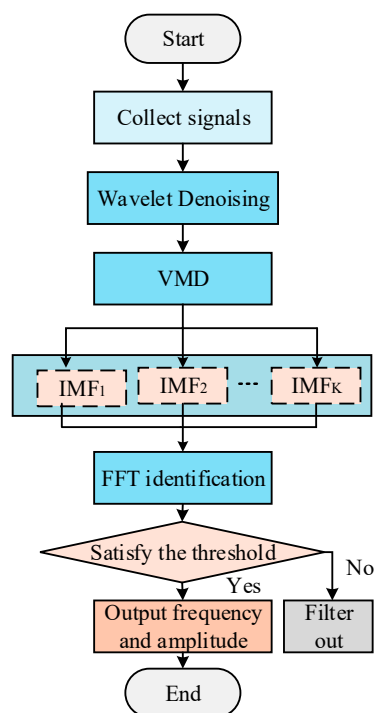


Figure 2. SSO identification flowchart.

3.2. Signal Preprocessing Based on WT

The WT is used to filter out noise [24]. The mathematical formula of the WT is as follows:

$$\psi_c(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} S(t) \psi^* \left(\frac{t-b}{a} \right) dt \quad (a > 0) \quad (1)$$

where a is the scaling factor and b is the translation factor; $\psi(t)$ is the wavelet basis function. Daubechies 4-order wavelet (db4) is selected as the mother wavelet. It can ensure that the signal reconstruction is non-redundant and the tight support feature makes its computational efficiency high. ψ^* denotes the complex conjugate. $S(t)$ is the active power.

The actual acquisition signal is a discrete sequence $S[n]$. $L = 5$ discrete wavelet decomposition using the Mallat algorithm. A higher number of layers will lead to loss of details, and a lower number of layers may have residual noise.

$$S[n] = A_5[n] + \sum_{l=1}^5 D_l[n] \quad (2)$$

$A_5[n]$ is the approximate coefficient of the fifth layer and $D_l[n]$ is the detail coefficient of the l layer. The soft threshold function is applied to each layer of detail coefficients:

$$\hat{D}_l[n] = \begin{cases} \text{sgn}(D_l[n]) \cdot (|D_l[n]| - \lambda_l), & |D_l[n]| \geq \lambda_l \\ 0 & |D_l[n]| < \lambda_l \end{cases} \quad (3)$$

The threshold λ_l is a general threshold, σ_l is the standard deviation estimation of the noise in the first layer, and the median absolute deviation estimation is commonly used:

$$\lambda_l = \sigma_l \sqrt{2 \ln(N)} \quad (4)$$

$$\sigma_l = \frac{\text{median}(|D_l|)}{0.6745} \quad (5)$$

The denoised signal is reconstructed by inverse wavelet transform and the length is still N :

$$\hat{S}[n] = A_5[n] + \sum_{l=1}^5 \hat{D}_l[n] \quad (6)$$

3.3. Signal Feature Extraction Based on VMD

VMD decomposes the data and extracts characteristic signals, which can reflect the characteristics of each frequency band signal [25]. The principle of this method is to establish a constraint model and introduce Lagrange multipliers and penalty factors into the model. Subsequently, the center frequency and bandwidth of each mode are continuously updated alternately.

The construction of the variational problem: VMD decomposes the denoised signal into K intrinsic mode functions $u_k(t)$ and each mode is an amplitude modulation and frequency modulation signal.

$$u_k(t) = A_k(t) \cos(\phi_k(t)) \quad (7)$$

A_k is an instantaneous amplitude; $\phi_k(t)$ is the instantaneous phase. Each sub-signal has a center frequency; the corresponding variational constraint model is established:

$$\begin{cases} \min_{\{u_k\}, \{\omega_k\}} \left\{ \sum_{k=1}^K \left\| \frac{\partial}{\partial t} \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \\ \text{s.t. } \sum_{k=1}^K u_k = \hat{S}(t) \end{cases} \quad (8)$$

ω_k is the center frequency of mode k . $\delta(t)$ is the Dirac distribution with respect to time t . $*$ is the convolution, $\partial/\partial t$ is the partial derivative of time. The solution to variational problems: Further construct the augmented Lagrange function:

$$L(\{u_k\}, \{\omega_k\}, \lambda) = \alpha \sum_{k=1}^K \left\| \frac{\partial}{\partial t} \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| \hat{S}(t) - \sum_{k=1}^K u_k(t) \right\|_2^2 + \left\langle \lambda(t), \hat{S}(t) - \sum_{k=1}^K u_k(t) \right\rangle \quad (9)$$

$\alpha = 2000$, which represents the quadratic penalty factor; λ represents the Lagrange multiplier. It is used to iteratively update the variables $\mu_k^{n+1}, l_k^{n+1}, l_k^{n+1}$ to find the optimal solution:

$$\hat{\mu}_k^{n+1}(\omega) = \frac{\hat{S}(\omega) - \sum_{i=1}^K \hat{u}_i^{n+1}(\omega) - \sum_{i=k+1}^K \hat{u}_i^n(\omega) + \frac{\hat{\lambda}^n(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k^n)^2} \quad (10)$$

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega |\hat{u}_i^{n+1}(\omega)|^2 d\omega}{\int_0^\infty |\hat{u}_i^{n+1}(\omega)|^2 d\omega} \quad (11)$$

$$\hat{\lambda}^{n+1}(\omega) = \hat{\lambda}^n(\omega) + \zeta \left[\hat{S}(\omega) - \sum_{k=1}^K \hat{u}_k^{n+1}(\omega) \right] \quad (12)$$

$\hat{\mu}_k^{n+1}(l)$ is the Wiener filter of the current signal; $\hat{\cdot}$ is Fourier transform (FT); ξ is the fidelity coefficient. When the mode number $K = 5$, the center frequency of each mode is stable and does not overlap. The convergence judgment condition is

$$\sum_{k=1}^K \frac{\|\hat{u}_k^{n+1} - \hat{u}_k^n\|_2^2}{\|\hat{u}_k^n\|_2^2} < \varepsilon = 10^{-6} \quad (13)$$

Taking the addition of the 40 Hz interference with 40 dB at G1 as an example, the frequency error and calculation time of different modal numbers are compared to quantitatively support the final selection. The results are shown in Table 1.

Table 1. The calculation results of different K values.

K	Frequency/Hz	Frequency Error	Time
3	39.4478	0.5522	2.2403 s
4	38.7979	1.2021	2.3138 s
5	39.9978	0.0022	2.4411 s
6	41.7977	1.7977	2.7322 s

The results in Table 1 show that the frequency error is only 0.0022 Hz when $K = 5$, which is less than other values of K . The calculation time of $K = 5$ is 0.2008 s longer than that of $K = 3$ and 0.2911 s less than that of $K = 6$. It is shown that $K = 5$ can effectively avoid the modal aliasing and frequency offset caused by over-decomposition or under-decomposition and ensure recognition accuracy while considering a certain computational efficiency. Therefore, $K = 5$ is the optimal mode number selection.

3.4. Oscillation Identification Based on FFT

FFT is an efficient algorithm for calculating the DFT [26]. Each mode $u_k[n]$ is symmetrically extended and the length after extension is $T = 2N$. The extension rules are as follows:

$$x_k[m] = \begin{cases} u_k(\frac{N}{2} - 1 - m), & 0 \leq m < \frac{N}{2} \\ u_k(m - \frac{N}{2}), & \frac{N}{2} \leq m < \frac{3N}{2} \\ u_k(2N - 1 - m), & \frac{3N}{2} \leq m < 2N \end{cases} \quad (14)$$

The extended sequence $x_k[m]$ is subjected to discrete Fourier transform:

$$X_k[v] = \sum_{m=0}^{T-1} x_k[m] e^{-j \frac{2\pi}{T} vm}, v = 0, 1, \dots, T-1 \quad (15)$$

For the convenience of frequency analysis, *fftshift* is used to shift the zero frequency to the center of the spectrum:

$$X_k^{shift}[v] = \text{fftshift}(X_k[v]), v = -\frac{T}{2}, \dots, \frac{T}{2} - 1 \quad (16)$$

The dominant frequency corresponds to the position of the maximum spectrum amplitude:

$$v_{\max}^{(k)} = \arg\max_v |X_k^{shift}[v]| \quad (17)$$

f_s is the sampling frequency. The frequency and amplitude of the k th mode are

$$f_{osc}^{(k)} = \frac{v_{\max}^{(k)}}{T} \cdot f_s \quad (18)$$

$$A_{osc}^{(k)} = \frac{2}{T} |X_k^{shift}[v_{max}^{(k)}]| \quad (19)$$

The mode with the largest energy is selected from the K modes as the output of the main oscillation mode as the final identification result:

$$\hat{f}_{osc} = f_{osc}^{(k*)}, \hat{A}_{osc} = A_{osc}^{(k*)}, k* = \operatorname{argmax}_k \left(\sum_m |x_k[m]|^2 \right) \quad (20)$$

4. Simulation Results and Analysis

4.1. Simulation Test Platform

In this section, the FMTAS model with DFIG is established using the MATLAB R2018a version of Simulink; the computer configuration is 11th Gen Intel Core i5-1135G7. The model is shown in Figure 3. The main parameters are listed in Table 2.

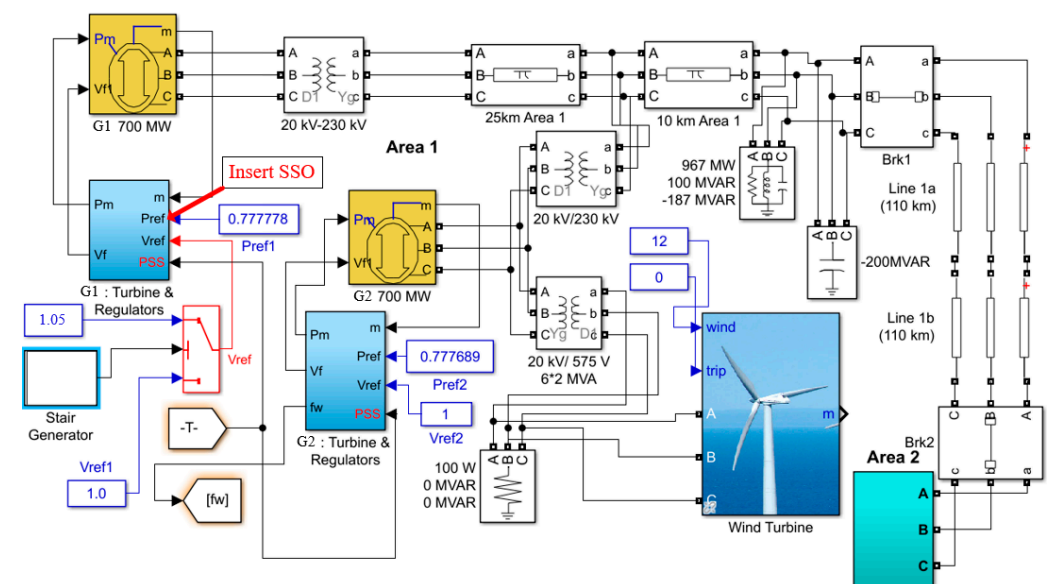


Figure 3. Schematic diagram of FMTAS with DFIG.

Table 2. Main parameters of the power systems.

Parameter	Value
DFIG rated power	1.5 MW
DFIG line voltage	575 V
Frequency	60 Hz
G1–G4 rated power	700 MW/generator
G1–G4 line voltage	20 kV

According to the main parameters of each generator shown in Table 2, the power generation model is established by using MATLAB. In the real working conditions of power systems, SSO also contains non-integer frequency, which is prone to spectrum leakage. To verify the reliability and robustness of the identification method for non-integer identification, 20 Hz, 30.5 Hz and 40 Hz periodic disturbances are introduced at the mechanical power input of different generators. To ensure the robustness of noise, white noise with signal-to-noise ratio of 60 dB and 40 dB is added to the signal.

Figure 3 shows the schematic diagram of the FMTAS with DFIG. The system consists of four synchronous generators, each with a rated power of 700 MW, wind farms and constant power loads. The wind farm comprises 18 wind turbines with a rated capacity of 5 MW each and a rated wind speed of 12 m/s. Before reaching the rated wind speed, the active

power output from G2 gradually decreases with increasing wind speed. The simulation model introduces SSO disturbance at the mechanical power input of four synchronous generators in two areas, with an amplitude of 0.2 per unit.

4.2. Active Power Acquisition

The active power signal is collected on the FMTAS transmission line. When the system runs stably for a period, the disturbance is introduced at 90 s. The continuous oscillation 10 s data is used. Taking the wind speed of 9 m/s as an example, the results are shown in Figure 4. The addition of interference in (a) and (b) breaks the instantaneous power balance between the prime mover and the generator, resulting in an unbalanced torque shock on the rotor shaft and a sudden increase in the amplitude of the active power. With the system damping and rotor inertia, the amplitude decreases slowly until it enters stable oscillation. In addition, the SSO of 40 Hz in (b) has stronger electrical negative damping than the SSO of 20 Hz in (a). The stabilization time will be longer.

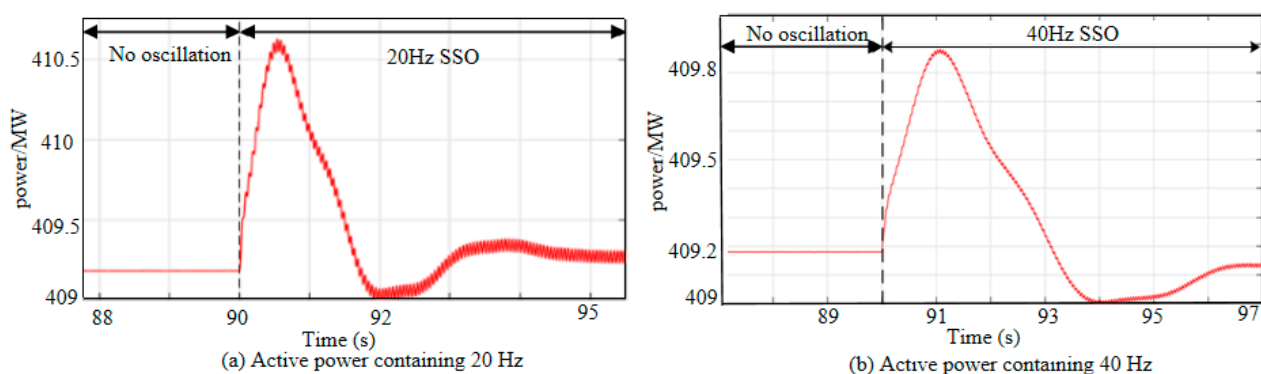


Figure 4. Active power waveforms under SSO disturbances.

In Figure 5, the mechanical power at G1 is disturbed at 90 s, and a stable oscillation occurs after 95 s. In (a), non-attenuated SSO with large amplitude appears in G1 waveform. G2 has slight coupling fluctuation, and G3 and G4 remain stable.

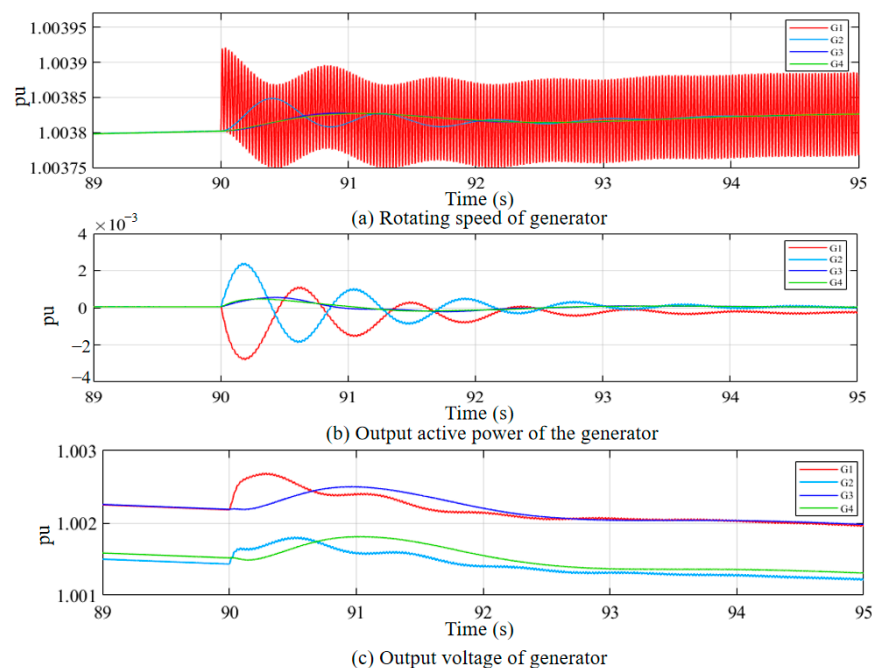


Figure 5. Generator output 20 Hz oscillating signal waveform.

In (b), G1 and G2 generate out-of-phase active power oscillation through grid coupling, forming inter-area oscillation; the G3 and G4 oscillations decay faster.

In (c), the terminal voltage of the G1 machine rises briefly, and the subsynchronous fluctuation is small, but there is no continuous oscillation, indicating that the disturbance energy is mainly concentrated in the electromechanical power coupling channel, and the influence on the voltage control channel is weak. The disturbance excites the subsynchronous mode of weak damping in the disturbed G1 and is transmitted to G2 through the electrical coupling between areas, which leads to oscillation across the generator.

4.3. Feature Extraction

To reduce the influence of noise on the result, WT is used to preprocess the active power. The results after processing are shown in Figure 6.

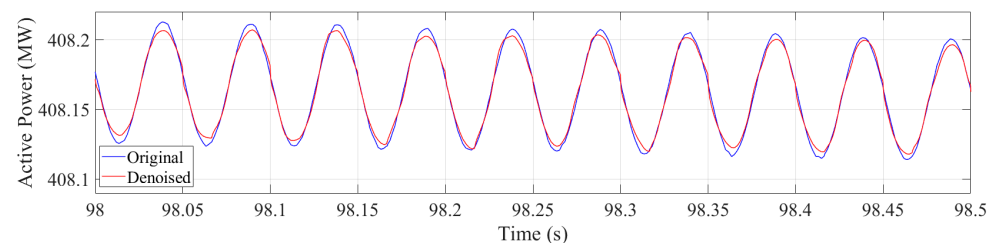


Figure 6. The original signal and the preprocessing signal.

From the waveform of Figure 6, the periodic disturbance of 20 Hz with 40 dB noise is introduced into G1 and the edge of the active power signal waveform is irregularly offset. After wavelet denoising, signal burrs are effectively removed, and the waveform becomes smooth and regular. The oscillation period before and after denoising is completely consistent and the oscillation amplitude is highly consistent with the phase change trend, indicating that the adopted wavelet denoising strategy can completely retain the key characteristics of SSO while suppressing noise.

VMD is used to extract features from the denoised signal. The decomposition result at 9 m/s is shown in Figure 7.

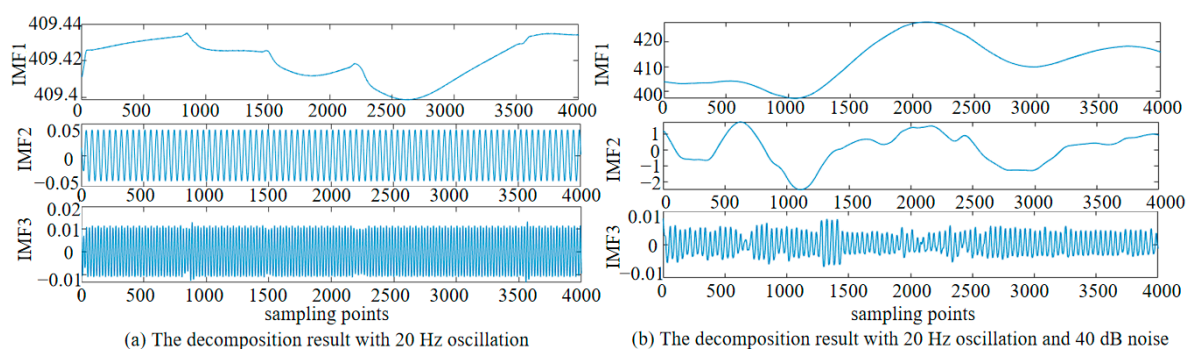


Figure 7. The decomposition diagrams of the SSO signal.

In Figure 7, VMD can effectively decompose the denoised signal into IMF components and each IMF component dominates near its center frequency. In contrast, the IMF component mode aliasing of 20 Hz oscillation decomposition with 40 dB noise in (b) is more serious. The no noise signal in (a) is well separated.

4.4. Result Analysis

For the active power signal of the transmission line, the theoretical amplitude is calculated by using the eigenvalue. The theoretical amplitude directly depends on the amplitude of the periodic disturbance superimposed on the mechanical power input of the generator. The IMF components are analyzed by using FFT to calculate the amplitude and frequency of the main oscillation. Figure 8 presents the theoretical amplitude, identified values and relative errors (ERs) of G1 and G2 in Area 1 at a wind speed of 9 m/s, with the corresponding results for G3 and G4 in Area 2 listed in Table 3. Figure 9 illustrates the results at 10.5 m/s for G1 and G2, while Table 4 provides the relevant data for G3 and G4 under the same wind speed. Similarly, Figure 10 and Table 5 show the results of G1 to G4 at 12 m/s.

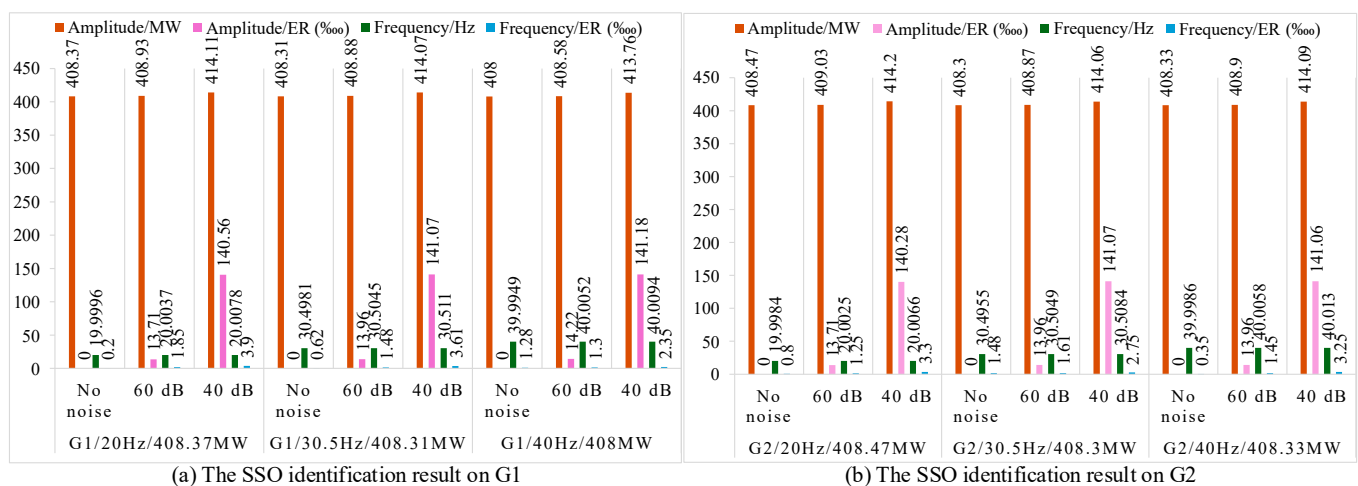


Figure 8. Different noise SSO results in Area 1 (9 m/s).

Table 3. The SSO identification results in Area 2 at 9 m/s.

Oscillation Type	Working Condition	Amplitude/MW	ER (%)	Frequency/Hz	ER (%)
G3/20 Hz/408.24 MW	No noise	408.24	0	19.9979	0.0105
	60 dB	408.81	0.1396	20.0021	0.0105
	40 dB	414	1.4109	20.0062	0.031
G3/30.5 Hz/408.32 MW	No noise	408.32	0	30.5	0
	60 dB	408.89	0.1396	30.5065	0.0213
	40 dB	414.09	1.4131	30.513	0.0426
G3/40 Hz/408.33 MW	No noise	408.33	0	40	0
	60 dB	408.91	0.142	40.0072	0.018
	40 dB	414.11	1.4155	40.0145	0.0363
G4/20 Hz/408.35 MW	No noise	408.35	0	19.9996	0.002
	60 dB	408.93	0.142	20.0037	0.0185
	40 dB	414.13	1.4155	20.0078	0.039
G4/30.5 Hz/408.32 MW	No noise	408.32	0	30.4974	0.0085
	60 dB	408.89	0.1396	30.5039	0.0128
	40 dB	414.09	1.4131	30.5103	0.0338
G4/40 Hz/408.42 MW	No noise	408.42	0	39.9942	0.0145
	60 dB	409	0.142	40.0054	0.0135
	40 dB	414.2	1.4152	40.0087	0.0218

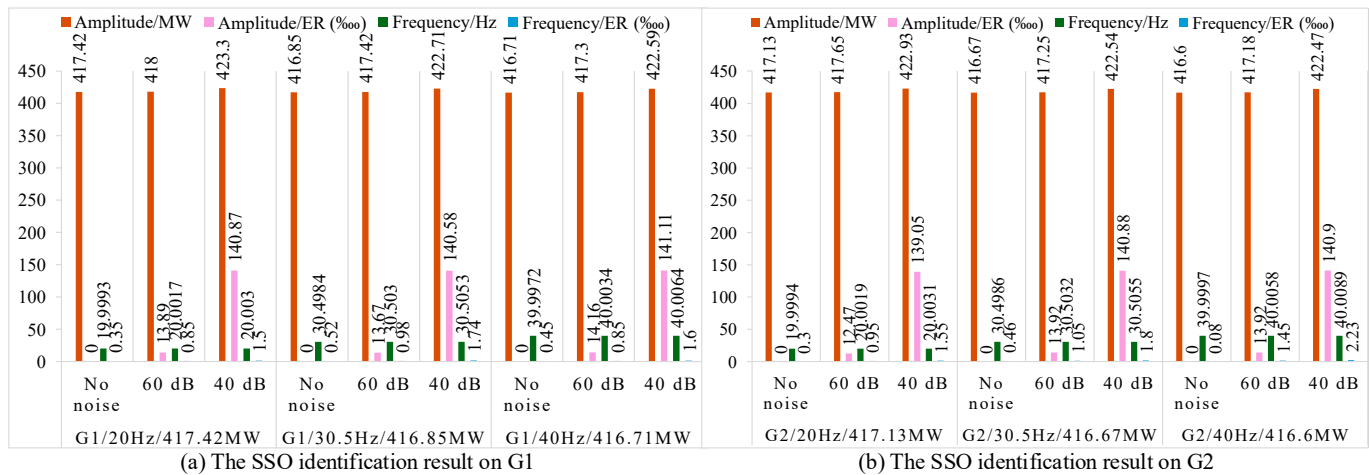


Figure 9. Different noise SSO results in Area 1 (10.5 m/s).

Table 4. The SSO identification results in Area 2 at 10.5 m/s.

Oscillation Type	Working Condition	Amplitude/MW	ER (%)	Frequency/Hz	ER (%)
G3/20 Hz/416.76 MW	No noise	416.76	0	20	0
	60 dB	417.35	0.1416	20.0025	0.0125
	40 dB	422.64	1.4109	20.0037	0.0185
G3/30.5 Hz/416.44 MW	No noise	416.44	0	30.4982	0.0059
	60 dB	417.02	0.1393	30.5028	0.0092
	40 dB	422.32	1.412	30.5051	0.0167
G3/40 Hz/416.05 MW	No noise	416.05	0	39.9997	0.0008
	60 dB	416.64	0.1418	40.0058	0.0145
	40 dB	421.93	1.4133	40.0089	0.0223
G4/20 Hz/416.71 MW	No noise	416.71	0	19.9999	0.0003
	60 dB	417.3	0.1416	20.0024	0.012
	40 dB	422.59	1.4111	20.0036	0.018
G4/30.5 Hz/416.45 MW	No noise	416.45	0	30.4986	0.0046
	60 dB	417.03	0.1393	30.5032	0.0105
	40 dB	422.33	1.4119	30.5055	0.018
G4/40 Hz/416.06 MW	No noise	416.06	0	39.9979	0.0053
	60 dB	416.65	0.1418	40.004	0.01
	40 dB	421.93	1.4109	40.007	0.0175

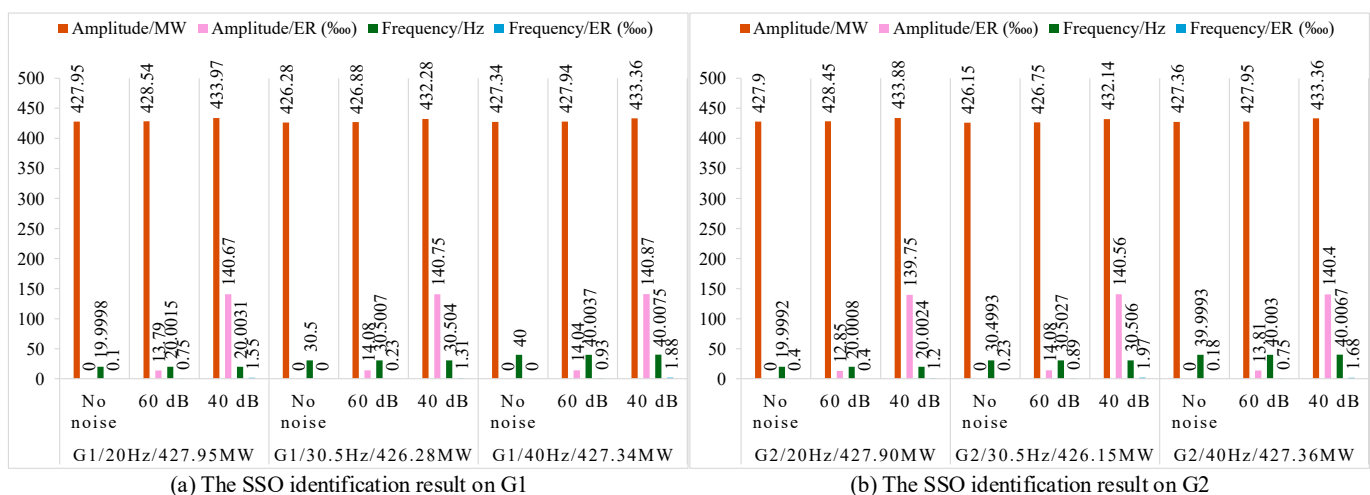


Figure 10. Different noise SSO results in Area 1 (12 m/s).

Table 5. The SSO identification results in Area 2 at 12 m/s.

Oscillation Type	Working Condition	Amplitude/MW	ER (%)	Frequency/Hz	ER (%)
G3/20 Hz/427.77 MW	No noise	427.77	0	19.9989	0.0055
	60 dB	428.36	0.1379	20.0015	0.0075
	40 dB	433.78	1.405	20.0021	0.0105
G3/30.5 Hz/425.96 MW	No noise	425.96	0	30.4973	0.0089
	60 dB	426.55	0.1385	30.5037	0.0121
	40 dB	431.96	1.4086	30.504	0.0131
G3/40 Hz/427.17 MW	No noise	427.17	0	39.9996	0.001
	60 dB	427.77	0.1405	40.0033	0.0083
	40 dB	433.19	1.4093	40.007	0.0175
G4/20 Hz/427.97 MW	No noise	427.97	0	20	0
	60 dB	428.54	0.1332	20.0016	0.008
	40 dB	433.97	1.402	20.0032	0.016
G4/30.5 Hz/425.96 MW	No noise	425.96	0	30.4973	0.0089
	60 dB	426.55	0.1385	30.5007	0.0023
	40 dB	431.96	1.4086	30.504	0.0131
G4/40 Hz/427.42 MW	No noise	427.42	0	39.9996	0.001
	60 dB	428.02	0.1404	40.0033	0.0083
	40 dB	433.45	1.4108	40.0069	0.0173

The amplitude and frequency of the active power are identified under no noise, 60 dB and 40 dB conditions. In Figure 8, when the wind speed is 9 m/s, the calculation results of Area 1 are G1 in (a) and G2 in (b). In the absence of noise, the oscillation frequency identification ER of G1 and G2 is controlled within 1.48 ‰. The amplitude identification ER is 0. Under conditions of noise, the frequency identification ER is controlled within 3.9 ‰ and the amplitude identification ER is controlled within 141.18 ‰.

In the wind speed of 10.5 m/s, Figure 9 shows the SSO identification results of G1 and G2 under three conditions of no noise, 60 dB and 40 dB. Under the condition of no noise, the frequency identification ER of the two generators is controlled within 0.52 ‰ and the amplitude identification ER is 0. After the introduction of noise, the frequency identification ER is still less than 2.23 ‰ and the amplitude identification ER is not more than 141.11 ‰. This shows that the identification method can stably output high-precision results under different noise levels and show robustness under the condition of 10.5 m/s wind speed.

Figure 10 shows the SSO identification results of G1 and G2 in no noise, 60 dB and 40 dB noise environments at 12 m/s wind speed. The results show that the frequency identification ER of the two generators is controlled within 0.4 ‰ under the condition of no noise, and the frequency ER does not exceed 1.97 ‰ even under the noise interference of 40 dB. In terms of amplitude identification, the maximum ER under all operating conditions is 140.87 ‰. The SSO identification method can still maintain stable and high-precision identification capabilities.

Table 3 shows the error results of SSO parameter identification under 9 m/s wind speed. With the increase in noise, the relative error of amplitude increases gradually. Under the condition of 40 dB noise, the amplitude ER ranges from 1.4109% to 1.4155%. The relative frequency ER is less than 0.05% under all working conditions; the maximum is only 0.0426%. This shows that the identification method has high accuracy in frequency estimation and is less affected by noise, but noise enhancement will reduce the accuracy of amplitude identification.

In Table 4, at the wind speed of 10.5 m/s, the amplitude ER ranges from 0 to 1.4133%. The relative frequency ER is less than 0.03% under all working conditions; the maximum is

only 0.0223%. This shows that the identification method still maintains a high accuracy of frequency at high wind speed, and the influence on wind speed and noise is reduced.

In Table 5, under the wind speed of 12 m/s, the ER of the amplitude of each working condition is the smallest, the minimum value is 0, and the maximum value reaches 1.4108%, which is lower than the error level at 9 m/s and 10.5 m/s. The relative frequency ER is less than 0.02%, but the frequency ER reaches 0.0175% at 40 dB noise at G3/40 Hz. In general, at higher wind speeds, the amplitude recognition accuracy of the method increases slightly and maintains a high accuracy.

The results show that the scheme proposed in this study has high accuracy for the signal identification results without noise. The change in wind speed and noise will lead to a decrease in the accuracy of the identification results, but the error rate of the identification results is still within the acceptable range. It further shows that the method used in this paper has certain robustness to the change in wind speed and noise.

To intuitively show the influence of wind speed and noise, this paper compares the ER of the average amplitude under different conditions. Figure 11 shows the variation trend of ER with wind speed under the conditions of no noise, 60 dB and 40 dB.

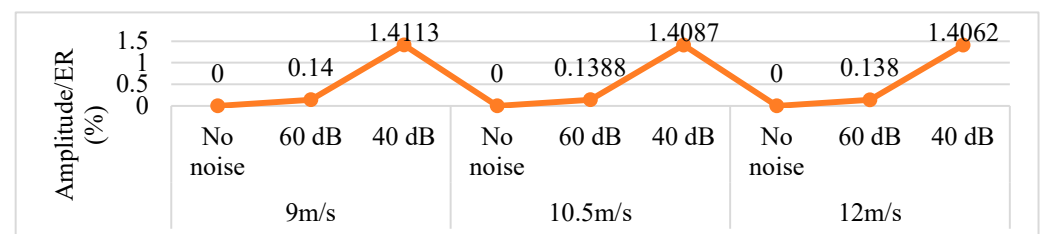


Figure 11. Average amplitude ER under different wind speeds and noise.

Figure 11 presents the average amplitude ER under different wind speeds and noise conditions. The average amplitude ER is 0 across all working conditions in the absence of noise. When noise is inserted, the average amplitude ER increases significantly with rising noise levels, reaching above 1.4% at 40 dB noise. This trend remains consistent across different wind speeds, indicating that noise intensity is the dominant factor affecting amplitude estimation error, while wind speed exhibits no significant impact under the tested conditions.

4.5. Comparative Analysis

To verify the necessity of preprocessing and decomposition, only FFT is employed for SSO parameter identification. Empirical mode decomposition (EMD) enables automatic modal separation but suffers from severe mode mixing. In contrast, VMD can eliminate such modal aliasing and improve oscillation identification accuracy. Meanwhile, the Prony algorithm and Hilbert–Huang transform (HHT) are adopted as post-processing identification methods, and their precision of SSO parameter identification is compared with that of FFT. The results are shown in Table 6.

Table 6. Identification results of different methods.

Method	Oscillation Type	Working Condition	Run Time	Frequency/Hz	ER (%)
FFT	G3/30.5 Hz	40 dB	1.00 ms	30.5268	0.0879
WT + EMD + FFT			637.77 ms	30.5186	0.0610
WT + VMD + Prony			1258.36 ms	30.5393	0.1289
WT + VMD + HHT			1270.76 ms	30.5497	0.1630
WT + VMD + FFT			522.56 ms	30.5130	0.0426

In the EMD, the standard deviation threshold is set to 0.05, the residual energy to 1×10^{-8} , and the maximum number of IMFs to 10. HHT shares the same EMD parameter setup. For the Prony analysis, the model order is chosen as 8, with the relative singular value threshold fixed at 1×10^{-10} . All other algorithm parameters in Table 6 are consistent with this paper.

In Table 6, the frequency identification ER of the WT + VMD + FFT method is only 0.0426% at a wind speed of 9 m/s, which is the highest accuracy among all comparison methods. In contrast, the ERs of FFT and WT + EMD + FFT are 0.0879% and 0.0610%, respectively. The identified frequencies of WT + VMD + Prony and WT + VMD + HHT are 30.5393 Hz and 30.5497 Hz, respectively. Meanwhile, the run time of this method is only 522.56 ms. Its speed is second only to traditional FFT, with some differences. The slowest method, WT + VMD + HHT, takes 1270.76 ms. These results demonstrate that the proposed method achieves high accuracy while maintaining a reasonable level of computational efficiency.

5. Conclusions

This paper focuses on the SSO problem in the FMTAS with DFIG. It proposes a hybrid identification method that combines WT, VMD and FFT.

Wavelet denoising reduces modal aliasing caused by noise in VMD. The VMD separates oscillation components to reduce the spectral leakage in the FFT, thereby achieving accurate frequency and amplitude estimation under noisy conditions. The simulation results on the FMTAS with DFIG show that the frequency estimation error of the proposed method is less than 0.0426% and the amplitude error is within 1.4155% under most operating conditions. Under noisy conditions, it is significantly better than the traditional FFT, Prony and HHT-based methods. Compared with other methods, this method also achieves high computational efficiency.

Looking ahead, the next research focus is to locate and suppress the SSO of the power systems.

Author Contributions: Conceptualization, J.L.; Methodology, J.L.; Software, Y.Z.; Validation, J.L.; Formal analysis, J.L.; Investigation, X.M.; Resources, J.L.; Data curation, X.M.; Writing—original draft, Y.Z.; Writing—review & editing, Y.Z.; Visualization, X.M.; Supervision, J.L.; Project administration, J.L.; Funding acquisition, J.L. All authors have read and agreed to the published version of the manuscript.

Funding: Project funded by the Youth Science and Technology Fund of Gansu Province (24JRR266).

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding author.

Conflicts of Interest: All authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Baltensperger, D.; Dobrowolski, J.; Obushevs, A.; Segundo Sevilla, F.R.; Korba, P. Scaling Version of Kundur's Two-Areas System for Electromechanical Oscillations Representation. In Proceedings of the International Symposium on Power Electronics, Electrical Drives, Automation and Motion, Virtual, 24–26 June 2020; pp. 243–249.
2. Shair, J.; Li, H.; Hu, J.; Xie, X. Power System Stability Issues, Classifications and Research Prospects in The Context of High-Penetration of Renewables and Power Electronics. *Renew. Sustain. Energy Rev.* **2021**, *145*, 111111. [\[CrossRef\]](#)
3. Chen, Q.; Bu, S. Impedance-Based Stability Analysis of Power System Wideband Oscillations: A Bridge Between S Domain and Frequency Domain. *IEEE Trans. Power Syst.* **2024**, *39*, 5854–5868. [\[CrossRef\]](#)

4. Chen, X.; Wu, X.; Yang, H.; Wu, C.; Wang, B. Sub-Synchronous Modal Energy-Based Method for Locating SSO Sources in Power Systems with DFIGs. *IEEE Trans. Power Deliv.* **2023**, *38*, 3712–3728. [\[CrossRef\]](#)
5. Zhang, F.; Wang, X. Synchrophasors-Based Identification for Subsynchronous Oscillations in Power Systems. *IEEE Trans. Smart Grid* **2018**, *10*, 2224–2233. [\[CrossRef\]](#)
6. Choi, J.-H.; Shim, K.; Lee, D.-G.; Kang, S.-H.; Nam, S.-R. Parameter Estimation Method of Low-Frequency Oscillating Signals Using Discrete Fourier Transforms. *J. Electr. Eng. Technol.* **2012**, *7*, 163–170. [\[CrossRef\]](#)
7. Luo, J.; Xie, Z.; Xie, M. Interpolated DFT algorithms with zero padding for classic windows. *Mech. Syst. Signal Process.* **2016**, *70*, 1011–1025. [\[CrossRef\]](#)
8. Derviskadic, A.; Romano, P.; Paolone, M. Iterative-interpolated DFT for synchrophasor estimation: A single algorithm for P-and M-class compliant PMUs. *IEEE Trans. Instrum. Meas.* **2018**, *67*, 547–558. [\[CrossRef\]](#)
9. Sun, B.; Wu, X.; Chen, X.; Zou, Z.; Li, Q.; Ren, B. Parameter Estimation of Sub-/Super-Synchronous Oscillation Based on Interpolated All-Phase Fast Fourier Transform with Optimized Window Function. *J. Mod. Power Syst. Clean Energy* **2024**, *12*, 1031–1041. [\[CrossRef\]](#)
10. Hauer, J.F.; Demeure, C.J.; Scharf, L.L. Initial Results in Prony Analysis of Power-System Response Signals. *IEEE Trans. Power Syst.* **1990**, *5*, 80–89. [\[CrossRef\]](#)
11. Zhong, T.; Yang, H.; Sun, C.; Liu, C.; Chen, J. Adaptive Band-Pass Filter and VMD-Esprit Based Multi-Mode Monitoring Method for Broadband Electromagnetic Oscillation in “double High” Power Systems. *Energies* **2023**, *16*, 3110. [\[CrossRef\]](#)
12. Gao, J.G.; Dong, H.Y.; Xu, H.L.; Yang, Y.; Zhang, X.J.; Mao, X.D. A Multi-Mode Recognition Method for Broadband Oscillation Based on Compressed Sensing and EEMD. *Appl. Sci.* **2024**, *14*, 11484. [\[CrossRef\]](#)
13. Lin, Q.; Zhang, Y.F.; Xue, F.; Yu, G. Parameter Identification Method for Sub-Synchronous Oscillation Signals in Power Systems Based on Improved Multi-Synchrosqueezing Transform and Automatic Recognition Algorithm. *Neural Comput. Appl.* **2025**, *37*, 3719–3732.
14. Jiang, T.; Liu, B.H.; Xue, L.; Mazza, A.; Li, G.Q.; Pons, E.; Huang, T. Subsynchronous Oscillation Source Location in Power System with High Penetration of Wind Power Using Multivariate Variational Mode Decomposition. *IEEE Trans. Power Syst.* **2025**, *40*, 4971–4983. [\[CrossRef\]](#)
15. Wang, M.H.; Li, K.C.; Liu, C.; Wang, W.; Chen, X.Y. Prony-GSO combined harmonic detection method based on VMD de-noising. *Electr. Meas. Instrum.* **2020**, *57*, 101–107. [\[CrossRef\]](#)
16. Pan, Y.; Chen, L.; Li, Y.D. Modal Parameter Identification of Wide-Band Oscillations at the Grid Connection Point in Photovoltaic Power Stations Based on Improved VMD-TKEO. In *Proceedings of the 14th International Conference on Renewable Power Generation (RPG 2025), Shanghai, China, 24–26 October 2025*; Institution of Engineering and Technology: London, UK, 2026; Volume 2025, pp. 954–961.
17. Chen, Y.Z.; Wu, F.; Shi, L.J.; Li, Y.; Qi, P.; Guo, X. Identification of Sub-Synchronous Oscillation Mode Based on HO-VMD and SVD-Regularized TLS-Prony Methods. *Energies* **2024**, *17*, 5067. [\[CrossRef\]](#)
18. Oscullo Lala, J.; Orozco Garzón, N.; Carvajal Mora, H.; Echeverria, D.; Vega-Sánchez, J.; Ohishi, T. Characterization of Power System Oscillation Modes Using Synchrophasor Data and a Modified Variational Decomposition Mode Algorithm. *Energies* **2025**, *18*, 2693. [\[CrossRef\]](#)
19. Zaman, T.; Syed, M.; Feng, Z.; Burt, G. A Realigned Instantaneous Frequency Approach for SSCI Oscillation Localization in Power Networks. *IEEE Trans. Power Syst.* **2025**, *40*, 2217–2229. [\[CrossRef\]](#)
20. Philip, J.G.; Jung, J.; Onen, A. Empirical Wavelet Transform Based Method for Identification and Analysis of Sub-Synchronous Oscillation Modes Using PMU Data. *J. Mod. Power Syst. Clean Energy* **2024**, *12*, 34–40. [\[CrossRef\]](#)
21. Lyu, L.X.; Ma, J.J.; Tan, S.S.; Peng, X. A VMD-CNN Based Mode Identification Method for Broad-band Oscillation of Power System. In *Proceedings of the 2025 IEEE 3rd International Conference on Power Science and Technology (ICPST), Kunming, China, 16–18 May 2025*; pp. 146–149.
22. Liu, G.; Liu, J.; Liu, A.D. A Two-Stage Subsynchronous Oscillation Assessment Method for DFIG-based Wind Farm Grid-Connected System. *Sci. Rep.* **2024**, *14*, 22290. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Kundur, P. *Power System Stability and Control; Example 12.6*; McGraw-Hill: New York, NY, USA, 1994; p. 813.
24. Tian, C.; Zheng, M.; Zuo, W.; Zhang, B.; Zhang, Y.; Zhang, D. Multi-stage Image Denoising with the Wavelet Transform. *Pattern Recognit.* **2023**, *134*, 109050. [\[CrossRef\]](#)
25. Dragomiretskiy, K.; Zosso, D. Variational mode decomposition. *IEEE Trans. Signal Process.* **2014**, *62*, 531–544. [\[CrossRef\]](#)
26. Zhang, D.; Wang, H.; Feng, Y.; Wang, X.; Liu, G.; Han, K.; Gong, X.; Liu, J.; Zhan, X.; Chen, J. Fast Fourier Transform (FFT) Using Flash Arrays for Noise Signal Processing. *IEEE Electron Device Lett.* **2022**, *43*, 1207–1210. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.