

Article

CWT-PSDT-Based Identification of Electromagnetic-Related Stator Vibration Frequency Components in a Hydro-Generator

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Abstract

Accurate identification of electromagnetically induced stator vibration frequency components is essential for the online condition monitoring of hydro-generators, particularly for assessing the dynamic state of the stator core under normal operating conditions. In engineering practice, the fast Fourier transform (FFT) is widely used for vibration spectrum analysis; however, because the measured vibration response is simultaneously affected by electromagnetic excitation, mechanical rotation, hydraulic disturbance, and external harmonic interference, FFT-based spectra often contain multiple frequency components whose structural relevance is difficult to determine directly. To address this issue, this paper proposes a coupled continuous wavelet transform and power spectral density transmissibility (CWT-PSDT) method for identifying key vibration frequency components with stable time-frequency energy and inter-sensor transmissibility in hydro-generator stator vibration signals. In the proposed framework, the analytic Morlet wavelet is first employed to localize dominant energy bands in the time-frequency domain, and PSDT is then used to screen frequency components with relatively stable inter-sensor transmissibility characteristics, thereby reducing the ambiguity caused by excitation-dominated spectral components. A clamped-clamped beam model is first used for numerical validation, and the maximum identification error of the first five natural frequencies is 4.22%. Experiments on a Francis turbine-generator test rig under five operating conditions further show that the proposed method can distinguish the mechanical rotational component near 10.3 Hz from the electromagnetic-related component near 50.8 Hz, while retaining higher-order electromagnetic-related components around 150 Hz and 250 Hz. The results demonstrate that the proposed CWT-PSDT method provides a physically interpretable and data-efficient approach for extracting stator-core-related spectral features, and offers a theoretical basis for spectrum-based online monitoring and future abnormal-condition comparison of hydro-generator stator responses.



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1. Introduction

With the global transition toward low-carbon energy systems, hydropower continues to play an important role in power generation because of its high operational flexibility, mature technology, and strong capability for peak regulation and grid support [1–6].

As the core electromechanical component of a hydropower unit, the hydro-generator directly affects energy conversion efficiency, operational stability, and power supply reliability. In practical operation, the vibration behavior of the generator is one of the most important indicators reflecting its structural and electromagnetic operating state. In particular, stator vibration has attracted increasing attention because it is closely related to electromagnetic force distribution, air-gap condition, and the mechanical integrity of the stator support system [7–11]. Therefore, accurate identification of stator vibration frequency components under normal operating conditions is of great significance for understanding the dynamic characteristics of hydro-generators and for supporting online monitoring of stator-core condition.

Under actual operating conditions, the stator vibration response of a hydro-generator is jointly influenced by multiple excitation sources, including electromagnetic force, shaft rotational motion, hydraulic fluctuation, and environmental disturbances [7,8]. Among them, electromagnetically induced vibration is particularly important because it is directly associated with unbalanced magnetic pull, phase asymmetry, installation error, air-gap non-uniformity, and structural defects in the stator support system [9,10]. As unit capacity and structural scale continue to increase, low-frequency vibration and local resonance of the stator system have become more prominent engineering concerns, which may accelerate insulation aging, weaken structural reliability, and even trigger severe resonance-related failures [11]. From the perspective of engineering monitoring, the key issue is not merely to observe spectral peaks in vibration responses, but to distinguish which frequency components are truly related to the structural-electromagnetic characteristics of the stator system and which are mainly caused by external harmonic interference or non-structural excitation. This is exactly the prerequisite for establishing reliable frequency-based monitoring criteria for hydro-generator stator cores.

At present, the fast Fourier transform (FFT) is still the most widely used tool in engineering vibration spectrum analysis of hydro-generators [12]. FFT can decompose time-domain signals into discrete frequency components and is effective for identifying dominant peaks such as rotational frequency and electromagnetic harmonics. However, FFT is essentially a global frequency-domain transform based on the assumption of stationarity, and therefore it cannot describe the temporal evolution of frequency components [12]. For hydro-generator vibration signals, which are often non-stationary and nonlinear due to load adjustment, coupling effects, and transient disturbance, FFT-based analysis may suffer from spectral leakage, frequency aliasing, and peak mixing, making it difficult to determine whether an observed spectral component originates from structural characteristics or from excitation-related harmonics. To improve time-frequency resolution, the short-time Fourier transform (STFT) has been introduced [13]. However, because of the fixed window width constrained by the Heisenberg uncertainty principle, STFT still faces an inherent trade-off between time resolution and frequency resolution, which limits its effectiveness in simultaneously identifying low-frequency structural components and high-frequency transient responses [14]. EMD [15] adaptively decomposes time-domain signals into oscillatory components, and the resulting oscillatory modes are referred to as intrinsic mode functions (IMFs). An IMF is defined as a function with only one extremum between successive zero crossings and a zero mean. Despite these advantages, EMD suffers from several drawbacks, including mode mixing, interpolation errors, and endpoint effects [16]. Variational mode decomposition (VMD) is a non-recursive algorithm that iteratively determines the center frequency and bandwidth of each band-limited component, thereby achieving adaptive spectral partitioning and mode separation of the signal [17]. The rigorous mathematical foundation of VMD enables superior performance in suppressing mode mixing and noise interference [18]. However, the effectiveness of VMD is highly dependent on precise

parameter selection, particularly the number of modes and the bandwidth control parameter [19]. Improper parameter settings can reduce computational efficiency and lead to information loss.

In the field of fault diagnosis for rotating machinery, several scholars and experts have adopted attention-mechanism [20,21]-based or deep-learning-based approaches [22,23] to assess the health condition of rotating machinery. However, these methods are confronted with a number of inherent issues: they demand large quantities of high-quality labeled data, exhibit limited interpretability, incur substantial computational resource and deployment costs, and rely heavily on architectural hyperparameter tuning. Improper parameter selections can not only reduce computational efficiency but also lead to loss of critical information, among other related concerns.

To overcome the limitations of conventional Fourier-based methods, continuous wavelet transform (CWT) has been widely studied in the field of non-stationary vibration analysis because of its multi-resolution capability [24]. Newland systematically established the theoretical foundation and application framework of wavelet analysis in vibration research [25–27]. Subsequent studies have demonstrated the effectiveness of wavelet-based methods in machinery condition monitoring and fault feature extraction. For example, Wang et al. verified the robustness of wavelet methods in gear damage monitoring [28]; Wang et al. applied wavelet analysis to fault identification of radial swing signals in hydroelectric generators [29]; Zhang et al. used analytic wavelet enveloping for spindle defect diagnosis [30]; He et al. combined optimized Morlet wavelets with sparse coding shrinkage for early bearing fault detection [31]; and Li et al. extracted multi-scale features for bearing diagnosis under varying operating conditions [32]. More recently, hybrid methods integrating CWT with VMD, CNN, SVM, and Transformer-type models have been developed to improve fault recognition performance in rotating machinery and electrical equipment [33–35]. These studies indicate that CWT is highly effective for locating dominant energy bands and enhancing fault-related features in non-stationary signals. Nevertheless, CWT outputs are still essentially time-frequency energy maps. When the signal contains strong load-related or excitation-dominated components, the resulting scalograms may become difficult to interpret quantitatively, and structurally meaningful frequency components can still be submerged in complex background energy distributions [36,37]. Therefore, CWT alone is more suitable for energy localization than for final discrimination of structurally relevant frequency components.

In parallel with time-frequency analysis, another important research direction has focused on extracting structural dynamic characteristics from response relationships between measurement points. Structural dynamics studies have shown that modal frequencies, mode shapes, and damping ratios can be identified through appropriate response-based analysis under operational excitation [38]. In this context, transmissibility-based methods have received increasing attention. Brincker et al. proposed frequency domain decomposition for modal parameter estimation [39]. Devriendt et al. introduced transmissibility into operational modal analysis and proved that the transmissibility at system poles is related to the ratio of mode shapes at different output points [40–42]. On this basis, Yan et al. further proposed the power spectral density transmissibility (PSDT) method, showing that in the vicinity of system poles, the PSDT value is theoretically independent of the reference output and excitation location, which makes it possible to identify structural modal parameters from operational data under a single loading condition [43]. Araujo et al. extended this idea through PSDTM-SVD for identifying natural frequencies and mode shapes in operating structures [44], and ter Meulen et al. demonstrated the applicability of PSDT-based operational modal analysis in offshore wind turbine systems under non-white-noise excitation [45]. Compared with single-point spectral peak value analysis, PSDT provides a structural-transmission perspective and is therefore useful for screening

frequency components with stable inter-sensor transmissibility, rather than relying only on single-point spectral peak values. This advantage is especially valuable for hydro-generator vibration signals, where electromagnetic harmonics, shaft rotation, and other disturbances are often superposed.

The main contributions of this work are summarized as follows. First, a coupled CWT-PSDT framework is proposed for identifying electromagnetic-related stator vibration frequency components in hydro-generators under normal operating conditions. Second, by combining the time-frequency localization capability of CWT with the transmissibility-based screening capability of PSDT, the proposed method enables more physically interpretable identification of frequency components with stable inter-sensor transmission characteristics from complex vibration spectra than conventional FFT-based analysis. Third, the effectiveness of the method is validated through both numerical simulation and hydro-generator experiments, demonstrating its capability to distinguishing the mechanical rotational component from electromagnetic-related forced vibration response components and to retain higher-order electromagnetic-related frequency features. These results provide a theoretical and methodological basis for spectrum-based online monitoring of hydro-generator stator cores.

2. Methodology

2.1. Continuous Wavelet Transform (CWT)

The wavelet transform (WT) is a signal analysis method with adaptive time-frequency resolution and is particularly suitable for non-stationary vibration signals [46]. Unlike conventional Fourier-based methods, WT uses scalable and translatable basis functions to analyze a signal at different resolutions. For a given signal $x(t)$, the continuous wavelet transform (CWT) is defined as follows.

$$W(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t) \cdot \psi^* \left(\frac{t-b}{a} \right) dt \quad (1)$$

where a is the scale parameter, b is the translation parameter, ψ is the mother wavelet, and ψ^* denotes complex conjugation. Through continuous variation of a and b , the one-dimensional time signal can be mapped into a two-dimensional time-scale representation, which can further be converted into a time-frequency representation for practical interpretation.

Different mother wavelets provide distinct time-frequency localization characteristics [47–49]. In this study, the analytic Morlet wavelet is selected as the mother wavelet due to its exceptional suitability for extracting narrow-band, harmonic-like features from complex hydro-generator vibration signals. Mathematically, the analytic Morlet wavelet is constructed by modulating a complex exponential (sinusoidal) carrier wave with a Gaussian envelope. This structural formulation is highly advantageous for two main reasons. First, the Gaussian envelope inherently provides the optimal mathematical trade-off between time and frequency resolution (reaching the lower bound of the Heisenberg-Gabor uncertainty limit), which ensures excellent frequency concentration for narrow-band components. Second, as an “analytic” wavelet, it possesses strictly positive frequency components, which effectively eliminates the aliasing interference from negative frequencies and allows for the precise, independent extraction of instantaneous peak value and phase information [50]. These properties are particularly important for the present engineering scenario, in which the stator vibration response is a complex superposition of dominant electromagnetic harmonics, mechanical rotational components, and transient disturbances. The analytic Morlet wavelet inherently acts as a set of adaptive bandpass filters, cleanly

isolating these dense harmonic-like components while maintaining sufficient temporal resolution to track non-stationary fluctuations.

The primary role of CWT in the proposed framework is to intuitively identify the dominant energy bands of the stator vibration signal and to reveal the macroscopic time-frequency distribution of various spectral components. Specifically, CWT serves as a powerful energy-localization tool to pinpoint which frequency regions contain the most intense vibration responses, thereby screening candidate frequencies that require further structural discrimination. However, because CWT essentially reflects only the spatial energy distribution of the measured response, it cannot autonomously determine whether a highly energetic spectral component is an intrinsic structural property or merely an artifact dominated by strong external excitations. To address this fundamental limitation, PSDT is subsequently introduced to evaluate the inherent structural transmission characteristics of these CWT-identified frequency bands.

2.2. Power Spectrum Density Transmissibility (PSDT)

Power spectral density transmissibility (PSDT) extends the concept of transmissibility from deterministic response ratios to the spectral domain and provides a response-based tool for identifying structural dynamic characteristics under operational excitation [43,51]. Compared with direct spectral peak index analysis, PSDT emphasizes the transmission relationship between measurement points and is therefore more suitable for distinguishing frequency components associated with intrinsic structural characteristics from those mainly dominated by common excitation.

For responses at any two output Points i and j , the PSDT with respect to a reference point p is defined as the ratio of the cross-power spectrum $S_{ip}(\omega)$ to $S_{jp}(\omega)$:

$$T_{ij}^p(\omega) = \frac{S_{ip}(\omega)}{S_{jp}(\omega)} \quad (2)$$

If the reference point is changed to q , the PSDT relative to reference q becomes:

$$T_{ij}^q(\omega) = \frac{S_{iq}(\omega)}{S_{jq}(\omega)} \quad (3)$$

Furthermore, $T_{ij}^p(\omega)$ can be expressed in terms of the Frequency Response Function (FRF) $H(\omega)$ and the input PSD matrix $G(\omega)$:

$$T_{ij}^p(\omega) = \frac{\sum_{n=1}^{N_r} \sum_{k=1}^{N_r} H_{ik}(\omega) G_{kn}(\omega) H_{pn}^*(\omega)}{\sum_{n=1}^{N_r} \sum_{k=1}^{N_r} H_{jk}(\omega) G_{kn}(\omega) H_{pn}^*(\omega)} \quad (4)$$

where H_{ik} is the frequency response function (FRF) representing the input-output relationship between Points i and k , G_{kn} is the load cross-spectrum applied to degrees of freedom k and n , the superscript $*$ indicates the complex conjugate of the matrix, and N_r is the excitation constant.

As the Laplace variable s approaches the r -th system pole λ_r , the limit of the individual term $t_{kn}(\omega)$ satisfies:

$$\lim_{s \rightarrow \lambda_r} (t_{kn}(\omega)) = \lim_{s \rightarrow \lambda_r} \left(\frac{H_{ik}(\omega) G_{kn}(\omega) H_{pn}^*(\omega)}{H_{jk}(\omega) G_{kn}(\omega) H_{pn}^*(\omega)} \right) = \lim_{s \rightarrow \lambda_r} \frac{H_{ik}(\omega)}{H_{jk}(\omega)} = \frac{\varphi_{ir}}{\varphi_{jr}} \quad (5)$$

where φ_{ir} and φ_{jr} denote the r -th mode shapes corresponding to the degrees of freedom i and j , respectively.

According to the limit theorem for proportional functions in Equation (6), it can be proven that for terms $t_{kn}(\omega)$ with identical subscripts in the numerator and denominator, the limit ratios are equal. Consequently:

$$\lim_{s \rightarrow \lambda_r} \left(T_{ij}^p(\omega) \right) = \frac{\varphi_{ir}}{\varphi_{jr}} \quad (6)$$

Similarly, the PSDT function $T_{ij}^q(\omega)$ for reference point q also satisfies:

$$\lim_{s \rightarrow \lambda_r} \left(T_{ij}^q(\omega) \right) = \frac{\varphi_{ir}}{\varphi_{jr}} = \lim_{s \rightarrow \lambda_r} \left(\frac{\sum_{n=1}^{N_r} \sum_{k=1}^{N_r} H_{ik}(\omega) G_{kn}(\omega) H_{qn}^*(\omega)}{\sum_{n=1}^{N_r} \sum_{k=1}^{N_r} H_{jk}(\omega) G_{kn}(\omega) H_{qn}^*(\omega)} \right) \quad (7)$$

Under identical operating conditions, subtracting the PSDT functions of two different reference points yields:

$$\lim_{s \rightarrow \lambda_r} \left(\Delta T_{ij}^{pq}(\omega) \right) = \lim_{s \rightarrow \lambda_r} \left(T_{ij}^p(\omega) - T_{ij}^q(\omega) \right) = \frac{\varphi_{ir}}{\varphi_{jr}} - \frac{\varphi_{ir}}{\varphi_{jr}} = 0 \quad (8)$$

Thus, the system poles are the zeros of $\Delta T_{ij}^{pq}(\omega)$. The system poles (and the resulting peaks) can be identified by the reciprocal of the magnitude of $\Delta T_{ij}^{pq}(\omega)$:

$$\lim_{s \rightarrow \lambda_r} \left| \Delta T_{ij}^{pq}(\omega) \right|^{-1} = +\infty \quad (9)$$

The reference outputs p and q in the PSDT formulation are not necessarily additional measurement points independent of the response points. In practical applications, they can be selected from the available measured output channels according to the sensor configuration. For a multi-channel measurement system, different output channels can be used as reference outputs to construct the PSDT difference function. For a two-channel measurement system, the two measured responses can be alternately used as reference outputs, thereby forming a mutual-reference PSDT implementation. This treatment preserves the general PSDT framework while allowing the method to be applied to engineering cases with a limited number of sensors.

It should be emphasized that PSDT is not used in this study as a tool that exclusively identifies structural natural frequencies, nor is it assumed to completely remove the influence of external excitation. The theoretical excitation-independence of PSDT is mainly valid near system poles and under specific excitation conditions. In a hydro-generator, however, the stator vibration response is governed by multiple excitation sources, including electromagnetic force, mechanical rotation, hydraulic fluctuation, and local structural transmission paths. Therefore, PSDT is used here as a transmissibility-based screening indicator to identify frequency components with relatively stable inter-sensor transmission characteristics. When structural modes are sufficiently excited, these components may correspond to natural frequencies. Under stable periodic electromagnetic excitation, however, they may also correspond to forced vibration response frequencies. The electromagnetic relevance of the identified components is therefore further interpreted by considering the generator rotational speed, pole-pair number, electrical fundamental frequency, harmonic relationships, and load-dependent response behavior.

2.3. Integrated CWT–PSDT Frequency Identification

Based on the above considerations, this study combines CWT and PSDT to identify electromagnetically induced stator vibration frequency components in a hydro-generator under normal operating conditions. The proposed strategy is designed to address the

limitation of FFT-based spectrum analysis, in which multiple spectral peaks can be observed but their structural relevance is often difficult to determine directly.

In this framework, the final frequency interpretation is not determined by PSDT alone. CWT provides candidate energy-concentrated frequency bands, PSDT screens the components with stable inter-sensor transmissibility, and the physical attribution is further made according to the generator rotational speed, pole-pair number, electrical fundamental frequency, harmonic relationship, and load-dependent behavior. CWT is employed to extract localized time-frequency energy distributions from non-stationary vibration signals, thereby identifying potential frequency components of interest. PSDT, in turn, is utilized to analyze the transmissibility consistency across different measurement points at each candidate frequency, so as to determine whether the frequency component exhibits relatively stable inter-sensor transmission characteristics. It should be emphasized that PSDT is not employed to directly separate or classify excitation sources. Rather, it functions as a supplementary screening indicator, aimed at determining whether the identified frequency component exhibits stable structural transmission characteristics.

The integrated procedure consists of three main steps. First, CWT is applied to the measured stator vibration signal to obtain its time-frequency representation and to identify the dominant energy bands. This step provides preliminary information on the frequency regions that carry the strongest vibration response under different operating conditions. Second, PSDT is calculated between the measured output responses to evaluate the transmission characteristics of the frequency components identified by CWT. In this process, the reference outputs are selected from the available measurement channels. For the experimental system used in this study, the two vibration channels are alternately used as reference outputs to construct a mutual-reference PSDT result. Frequency components that appear as persistent energy bands in the CWT scalogram and simultaneously exhibit stable peaks in the PSDT result are considered to have stronger inter-sensor transmission consistency and are therefore selected as key vibration response features for further physical interpretation. In contrast, components that are strong in the CWT result but weak or unstable in the PSDT result are regarded as more likely to be excitation-dominated or local response components.

In this framework, CWT answers the question of where the dominant vibration energy is concentrated, while PSDT answers the question of which of these components are more closely related to structural transmission characteristics. The combination of the two methods therefore provides a more reliable basis for identifying stator-core-related spectral features than either time-frequency energy analysis or transmissibility analysis alone.

According to the vibration characteristics observed in this study, the final identification of relevant frequency components follows the following principles:

- (1) the component should appear as a dominant or persistent energy band in the CWT scalogram;
- (2) the component should exhibit relatively stable transmissibility characteristics in the PSDT curves;
- (3) the component should be physically interpretable in relation to the hydro-generator system, such as rotational frequency, electromagnetic fundamental frequency, or higher-order electromagnetic-related frequency components.

Using this integrated identification strategy, the proposed method can distinguish the mechanical rotational component from the electromagnetic-related forced response component and retain higher-order electromagnetic-related frequency features, thereby providing a physically interpretable basis for identifying stator-core-related frequency components in hydro-generator vibration signals. The algorithmic flowchart of the proposed method is shown in Figure 1.

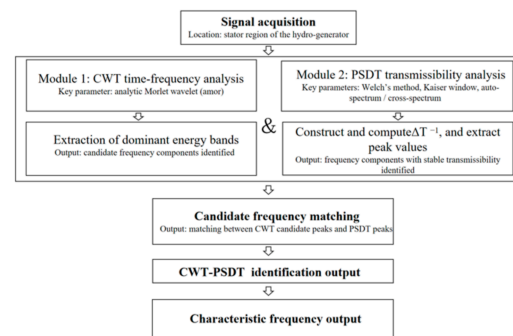


Figure 1. Algorithm principle diagram.

3. Validation

3.1. Numerical Model and Signal Generation

To verify the ability of the proposed CWT-PSDT method to identify structurally relevant frequency components under complex excitation, a clamped-clamped beam model was established for numerical simulation, as shown in Figure 2. The beam has a span of 5 m, a Young's modulus of $E = 43$ GPa, a density of $\rho = 2750$ kg/m³, and a Poisson's ratio of $\nu = 0.33$. The structure was discretized into eight planar beam elements with a total of nine nodes. Both ends of the beam were fixed, forming a classical clamped-clamped boundary condition.

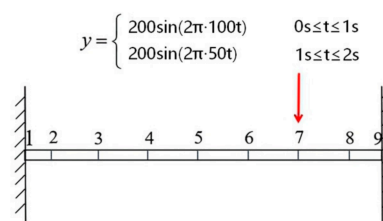


Figure 2. Clamped-clamped beam.

To simulate a complex response environment containing both intrinsic structural characteristics and transient excitation-dominated components, a mixed dynamic load was applied at measurement Point 7. The input consisted of broadband white noise superimposed with time-switched harmonic components: a 100 Hz sinusoidal force applied during the first half of the simulation (0–1 s), which abruptly switched to a 50 Hz sinusoidal force in the second half (1–2 s), both maintaining an peak value of 200 N. In this way, the numerical signal contained abrupt excitation-frequency changes together with the intrinsic dynamic characteristics of the structure, which is suitable for testing whether the proposed method can distinguish excitation-related components from structural modal frequencies. The acceleration responses at all measurement points were obtained by finite element analysis (FEA) with a sampling frequency of 1000 Hz and a sampling duration of 2 s. The first five theoretical natural frequencies obtained from the FEA model were 31.626 Hz, 32.681 Hz, 84.307 Hz, 88.586 Hz and 167.820 Hz, respectively. These frequencies were used as reference values for subsequent validation.

It should be acknowledged that the clamped-clamped beam model is not intended to equivalently simulate the complete multi-physics coupling behavior of a hydro-generator. The actual stator system features a ring-shaped geometry, spatially distributed support structures, and coupled electromagnetic-mechanical-hydraulic excitations. Nevertheless, the selection of this simplified model for numerical validation is intentional and reasonable, for the following reasons.

First, the purpose of this validation is to provide a controlled proof-of-concept platform in which the true structural natural frequencies are precisely known (obtained through finite element analysis as theoretical values). This allows for a purely quantitative evaluation of the CWT-PSDT method's identification capability under mixed conditions where both structural frequencies and excitation frequencies are known, free from the numerous uncertainties present in actual generator systems. Therefore, the simplified beam model provides a necessary preliminary benchmark for evaluating the basic frequency-identification capability of the method before applying it to a more complex hydro-generator system.

Meanwhile, the subsequent experimental validation is conducted on an actual Francis turbine-generator test rig, which fully incorporates coupled electromagnetic, mechanical, and hydraulic excitations. Thus, the numerical and experimental validations form a complementary validation chain: the numerical validation demonstrates the core identification capability of the method under controlled conditions, while the experimental validation confirms its engineering applicability under real multi-physics conditions.

This limitation is also explicitly discussed later in this paper, and it is noted that future work will establish a more representative ring-type or shell-element finite element model of the stator core system for more comprehensive validation.

3.2. CWT and PSDT Processing Results

The acceleration time histories extracted from measurement Points 2, 5, and 8 are shown in Figure 3a–c, and the corresponding CWT scalograms are presented in Figure 3d–f. In the CWT analysis, the analytic Morlet wavelet was selected as the mother wavelet in order to capture the dominant narrow-band response components. For the PSDT calculation, a Kaiser window was adopted with 2048 sampling points, a window length of 1024, a shape parameter of $\beta = 7$, and an overlap ratio of 50%.

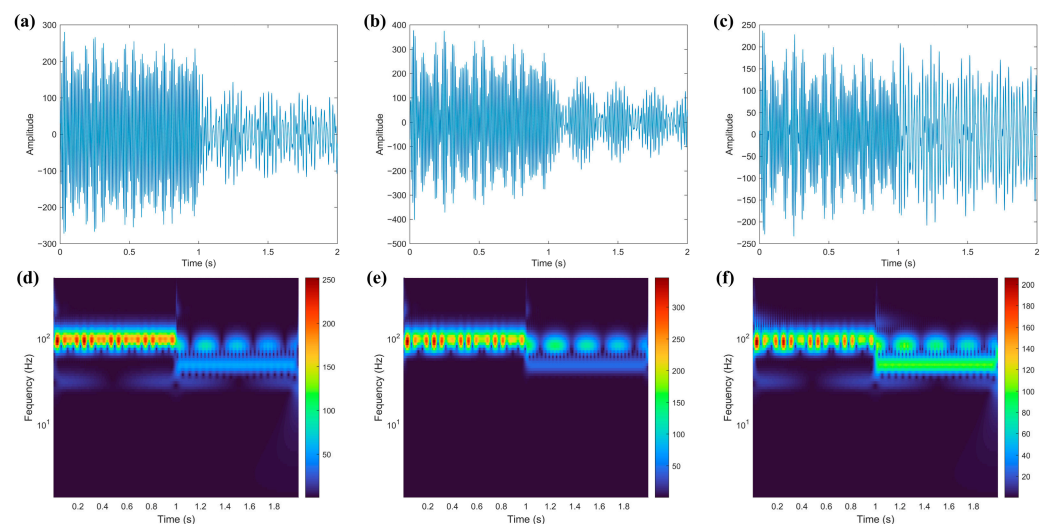


Figure 3. Time-domain vibration acceleration plots and corresponding CWT scalograms for three measurement points: (a–c) acceleration time-series for Points 2, 5, and 8; (d–f) corresponding CWT scalograms.

The CWT results show a clear energy transition at approximately $t = 1.0$ s, corresponding to the abrupt change in the sinusoidal excitation frequency. During the first half of the signal, the response energy is mainly concentrated near 100 Hz, whereas in the second half it shifts toward approximately 50 Hz. These results confirm that CWT can effectively localize the dominant energy bands and reflect the temporal evolution of the excitation-dominated components. However, the scalograms also exhibit noticeable vertical spreading and energy tailing along the frequency axis, especially near the excitation bands.

This indicates that although CWT provides strong time-frequency localization, it mainly reflects the energy distribution of the measured response and does not directly isolate the intrinsic structural frequencies from the excitation-related components.

The PSDT results for the selected measurement points are shown in Figure 4. Compared with the CWT scalograms, the PSDT curves exhibit much sharper frequency peaks and provide clearer identification of the structure-related characteristic frequencies. Five dominant peaks can be observed at 30.39 Hz, 34.06 Hz, 84.59 Hz, 88.33 Hz, and 166.64 Hz, respectively. These values correspond closely to the first five theoretical natural frequencies of the clamped-clamped beam. The results indicate that, although the raw response contains strong forced-vibration components at 50 Hz and 100 Hz, the PSDT analysis can still highlight the intrinsic structural frequencies of the system. This demonstrates the value of PSDT as a transmissibility-based screening tool under controlled excitation conditions.

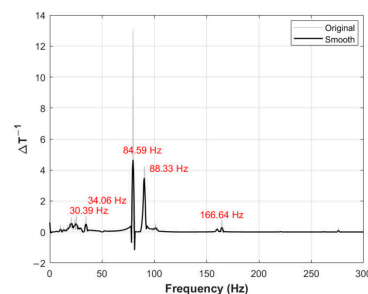


Figure 4. PSDT curves of the measurement points.

3.3. Validation of Frequency Identification Accuracy

Table 1 compares the characteristic frequencies identified by the proposed method with the theoretical modal frequencies obtained from the FEA model. The maximum relative error is 4.22% for the second mode, while the errors for the higher modes are all below 1%, and the errors for the fourth and fifth modes are below 0.70%. The relatively larger errors for the first two modes are mainly attributed to the close spacing of the low-order modal frequencies, limited frequency resolution under finite signal duration, and the influence of excitation switching in the simulated response. Nevertheless, the identified frequencies remain in good agreement with the theoretical modal values, confirming the effectiveness of the proposed method for structural frequency extraction under complex excitation.

Table 1. Comparison of frequency identification results.

Mode	Theoretical Value (Hz)	PSDT (Hz)	Error (%)
1	31.626	30.39	3.91
2	32.681	34.06	4.22
3	84.307	84.59	0.34
4	88.586	88.33	0.28
5	167.820	166.64	0.70

The validation results confirm two important points. First, CWT is effective in locating the dominant energy bands and in revealing the temporal switching behavior of excitation-related components. Second, in this simplified beam case, PSDT can reduce the ambiguity caused by forced-vibration energy concentration and highlight frequency components close to the intrinsic dynamic characteristics of the structure. Therefore, the numerical study verifies that the integrated CWT-PSDT strategy can reduce the ambiguity caused by excitation-dominated energy concentration and highlight modal-related components in this simplified beam case. This provides a methodological basis for applying PSDT as a transmissibility-based screening tool in the subsequent hydro-generator experiment.

4. Experiments

4.1. Experimental Data Acquisition

Experimental validation was conducted on a custom-developed Francis turbine-generator test rig at Kunming University of Science and Technology (KUST), as shown in Figure 5. The platform is part of the Hydro-Mechanical-Electrical Coupling Laboratory jointly established by KUST and the State Grid Electric Power Research Institute (SGEPRI), and it provides a prototype-scale environment for studying the dynamic responses of hydro-generator units under realistic operating conditions.



Figure 5. Francis turbine model test rig.

The turbine installed on the rig is an HLA551-LJ-43 Francis turbine (Yunnan Yuxi Hydropower Equipment Co., Ltd. Hongta Industrial Park, Yuxi City, China) with a design head of 10 m, a rated discharge of $0.7 \text{ m}^3/\text{s}$, and a rated output of 65 kW. The coupled generator is an SF55-10/740 synchronous generator (Yunnan Yuxi Hydropower Equipment Co., Ltd. Hongta Industrial Park, Yuxi City, China) with a rated capacity of 55 kW and a rated speed of 600 r/min. The detailed turbine parameters are listed in Table 2. Owing to the matched design of the turbine and generator, the test rig can reproduce stable hydro-mechanical-electrical operating conditions and is therefore suitable for experimental analysis of stator vibration responses. To facilitate multi-condition testing, the platform is integrated with a comprehensive control system, comprising a GYT-300 microcomputer (NARI Group Corporation, Jiangning Economic and Technological Development Zone, Nanjing, China) governor and supporting regulation modules such as DC power panels and outgoing switchgears. Through this integrated control system, the active power output of the generator can be precisely adjusted by inputting specific operational parameters, thereby enabling the reliable simulation of various load conditions.

Table 2. Basic parameters of the HLA551-LJ-43 Francis turbine.

Parameter	Value	Parameter	Value
Number of guide vanes	16	Guide vane height (m)	0.0134
Number of stay vanes	8	Runner diameter (m)	0.43
Number of runner blades	13	Rated head (m)	10
Runaway speed (rpm)	1095	Rated output (kW)	65
Rated discharge (m^3/s)	0.7	Rated speed (rpm)	600
Specific speed (n_s)	211.2	—	—

In the present study, five operating conditions were selected for vibration acquisition: no-load, 14 kW, 20 kW, 40 kW, and 55 kW. These conditions cover the main operating range

of the generator and provide the basis for investigating how the stator vibration frequency components evolve under different normal operating states.

Two MLS-9 low-frequency vibration sensors were installed on the stator core back-iron surface through the existing cooling-air windows of the generator casing. As shown in Figure 6, Sensor 1 and Sensor 2 were positioned at the same axial height with an angular separation of approximately 90° along the circumference. Both sensors were rigidly attached using magnetic bases, with their sensitive axes oriented radially toward the shaft center to measure the transverse vibration of the stator system.

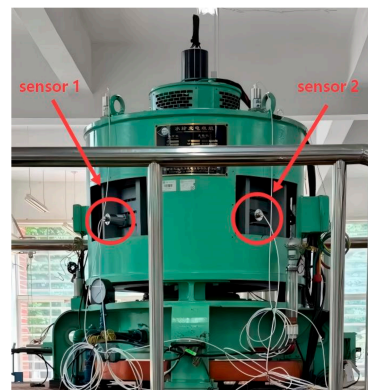


Figure 6. Layout of the sensor locations.

This configuration was selected based on two considerations. First, the 90° separation enables measurement of vibration response differences between two orthogonal directions, which is particularly sensitive to the stator core vibration modes and unbalanced magnetic pull (UMP) induced by air-gap non-uniformity. Second, the radial alignment ensures that the measured acceleration primarily reflects the transverse vibration, which is the dominant response direction under electromagnetic excitation. The selected measurement points also avoided local stiffening features such as casing ribs and support brackets, ensuring that the responses are representative of the overall stator core dynamic behavior.

The selection of only two orthogonal points was constrained by the limited accessibility through the cooling-air windows. Nevertheless, this configuration provides valuable differential information: under ideal concentric conditions, the responses at the two points should be equal in magnitude; any asymmetry would indicate non-uniform air-gap distribution or UMP. This configuration therefore offers a practical balance between engineering accessibility and diagnostic informativeness for online monitoring purposes.

The measured signals were used to analyze the stator vibration response from the perspective of both time-frequency energy concentration and structural transmission characteristics. Under each operating condition, vibration acceleration signals were recorded at a sampling frequency of 1000 Hz for 3 min. To maintain consistency in signal processing and comparison, a representative segment containing 16,384 data points was selected from each condition for further analysis. The corresponding time-domain vibration signals are shown in Figure 7.

4.2. Identification of Stator Vibration Frequency Components

To further verify the effectiveness of the proposed CWT-PSDT method in identifying features from measured vibration signals, FFT analysis was first performed on the vibration data collected under operating conditions from no-load to 55 kW, as shown in Figure 8. FFT provides an overall view of the frequency-domain energy distribution and can be used to identify dominant frequency components and their harmonics, making it a suitable baseline for conventional spectral analysis.

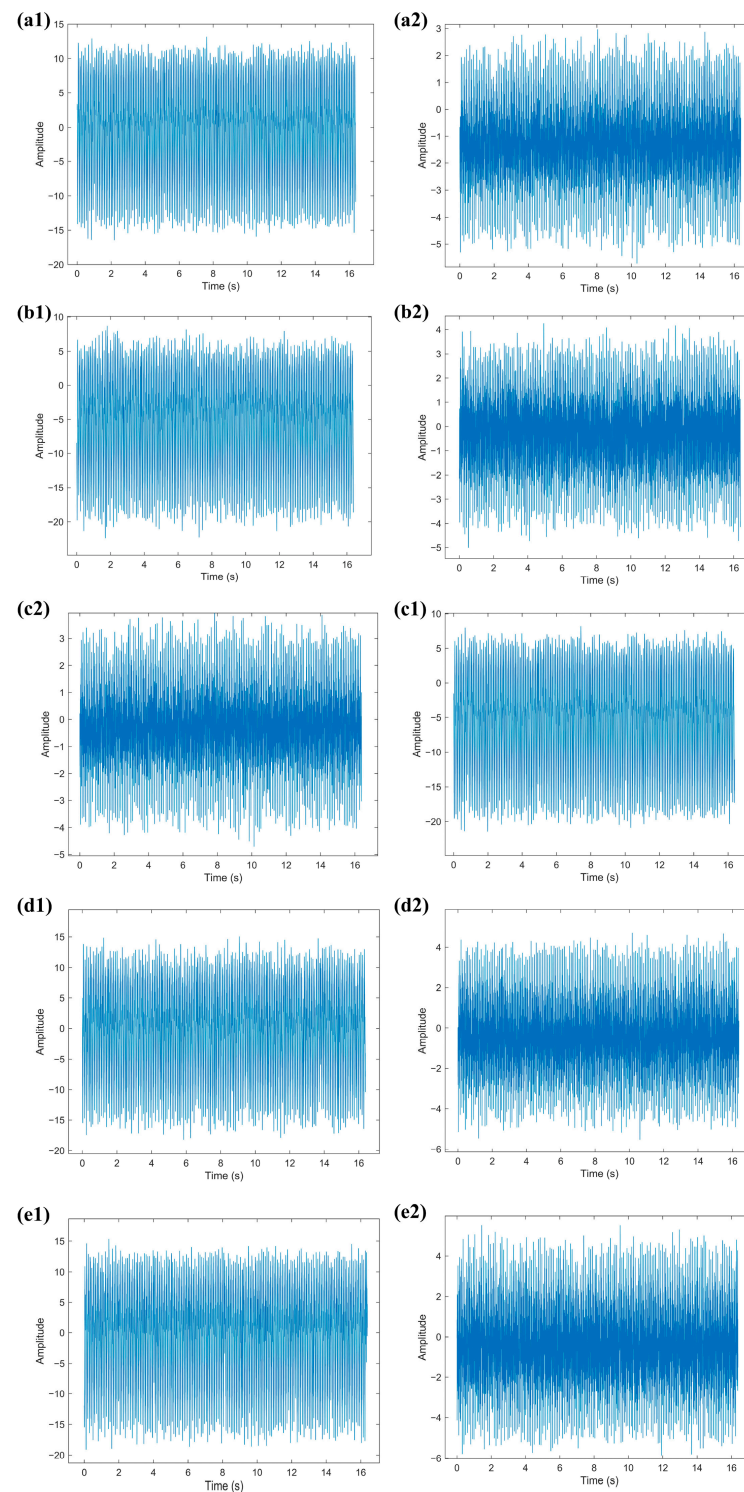


Figure 7. Time-domain stator vibration acceleration signals under different operating conditions: (a) No-load; (b) 14 kW; (c) 20 kW; (d) 40 kW; (e) 55 kW. (where (a1–e1) correspond to Sensor 1 and (a2–e2) correspond to Sensor 2).

The FFT results show that, under the five operating conditions of no-load, 14 kW, 20 kW, 40 kW, and 55 kW, the vibration signals measured at both sensor locations contain several prominent frequency components, with the spectral energy mainly concentrated in the low-frequency range. Clear peaks can be observed around 10 Hz and 50 Hz, together with their corresponding harmonic components. These frequency components remain generally stable across operating conditions, although their peak indices vary noticeably

with load. At this stage, the FFT results only indicate the existence of these frequency components, while their physical origins require further identification through time-frequency and transmissibility-based analysis.

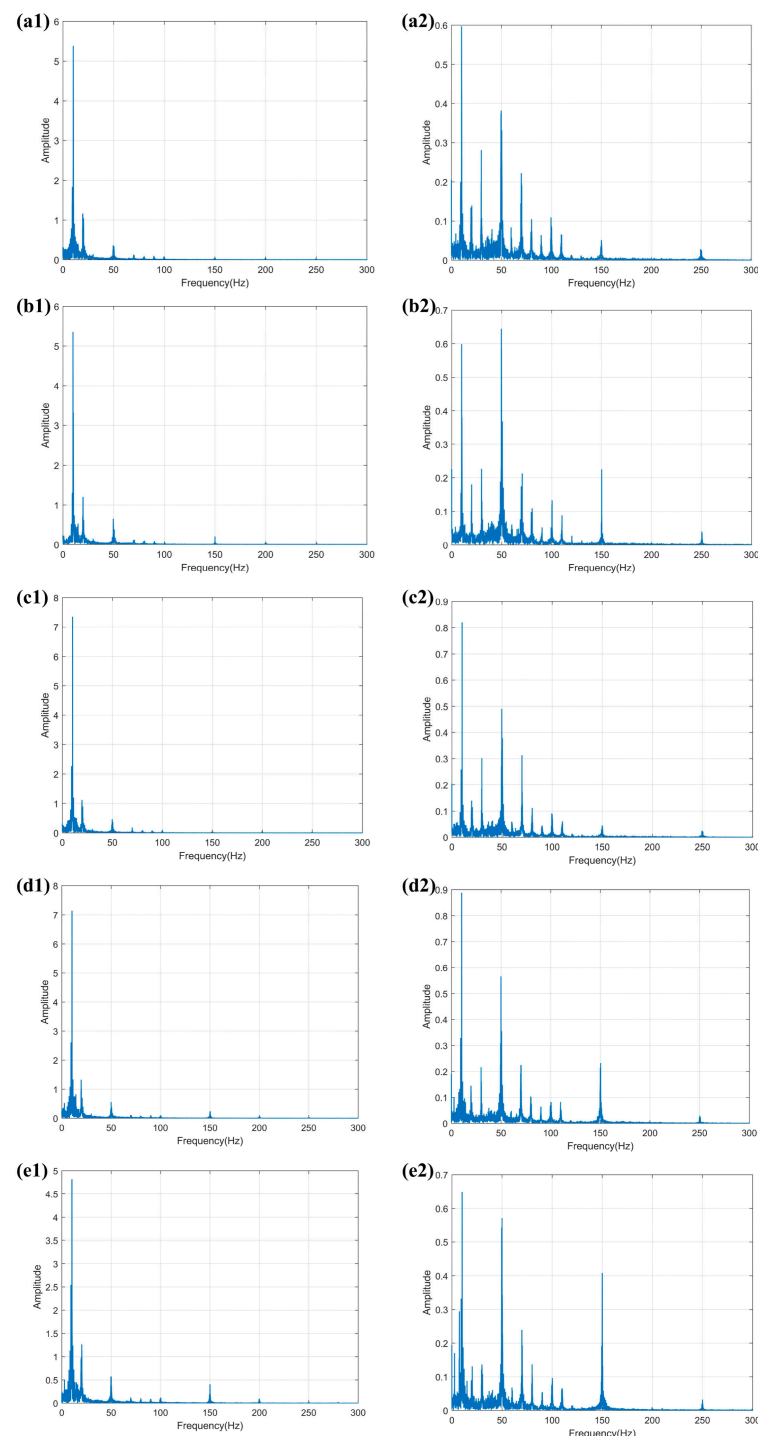


Figure 8. FFT results under different operating conditions: (a) No-load; (b) 14 kW; (c) 20 kW; (d) 40 kW; (e) 55 kW. (where (a1–e1) correspond to Sensor 1 and (a2–e2) correspond to Sensor 2).

In addition, the spectral distributions at the two sensor locations differ significantly under the same operating condition. Some frequency components are more pronounced at one measurement point but become much weaker at the other, indicating evident sensor-location dependence and local response characteristics in the vibration propagation.

Overall, FFT alone is insufficient to fully characterize the time-frequency evolution and inter-sensor propagation characteristics of the vibration signals.

To address this limitation, the proposed CWT-PSDT method combines CWT-based time-frequency localization with PSDT-based transmissibility enhancement. Specifically, CWT is used to extract the dominant energy bands in the time-frequency representation, while PSDT is used to identify frequency components with stable transmissibility between measurement points. The candidate frequencies obtained from the two analyses are then matched to satisfy both time-frequency energy concentration and transmissibility stability, thereby effectively suppressing irrelevant interference components, highlighting physically meaningful characteristic frequencies, and improving the reliability of frequency identification.

To ensure consistency in the identification process, the same signal-processing parameters were applied to all five operating conditions. In the CWT analysis, the analytic Morlet wavelet was adopted as the mother wavelet because of its good frequency concentration and suitability for identifying narrow-band harmonic-like components in stator vibration signals. In the PSDT analysis, the two measured vibration responses were processed using the mutual-reference strategy described in Section 2.2. Specifically, each vibration channel was alternately used as the reference output, and the corresponding PSDT difference was used to highlight frequency components with relatively stable transmission characteristics between the two measurement points. A data length of 16,384 points was used together with a Kaiser window of length 8192, a shape parameter of $\beta = 9$, and an overlap ratio of 50%. The corresponding CWT scalograms are shown in Figure 9.

CWT provides time-frequency energy localization, allowing the identification of candidate frequency bands that contain dominant vibration energy. Figure 9 shows that the dominant energy bands identified by CWT are concentrated around approximately 50 Hz, 150 Hz, and 250 Hz. These regions constitute candidate frequency bands for the vibration response, but their physical origins remain to be determined.

Next, PSDT was calculated between the two measurement points to assess the transmission characteristics of the candidate frequencies identified by CWT. The combined CWT-PSDT results are presented in Figure 10.

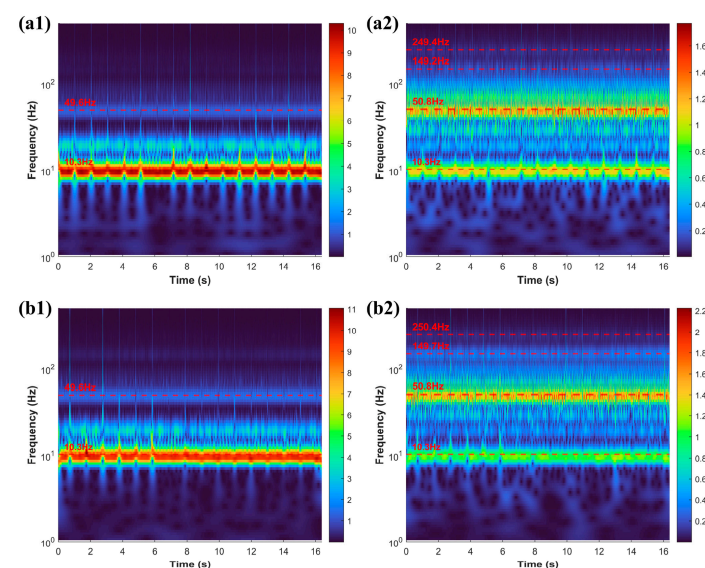


Figure 9. Cont.

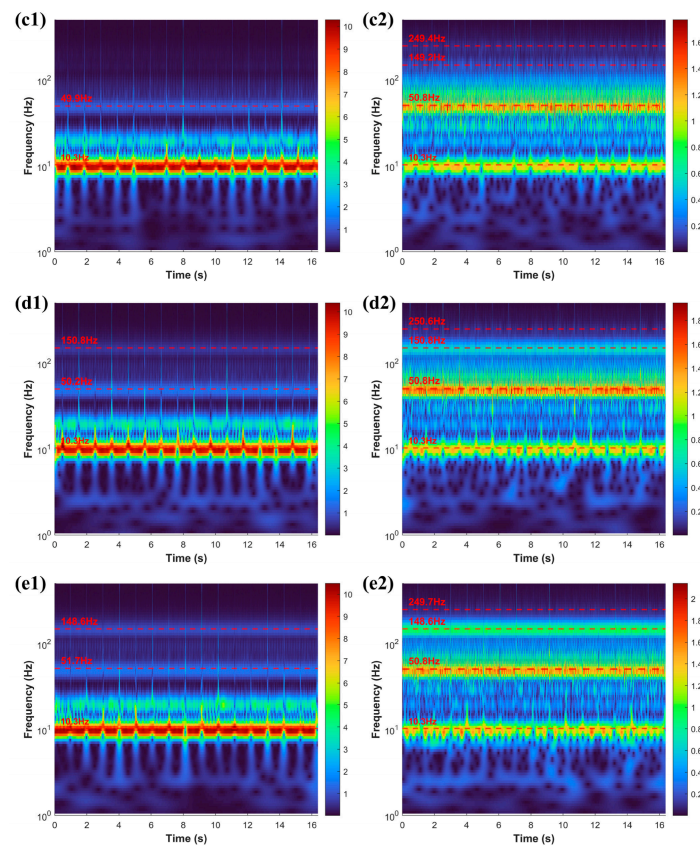


Figure 9. Combined CWT results under different loads: (a) No-load; (b) 14 kW; (c) 20 kW; (d) 40 kW; (e) 55 kW. (where (a1–e1) correspond to Sensor 1 and (a2–e2) correspond to Sensor 2).

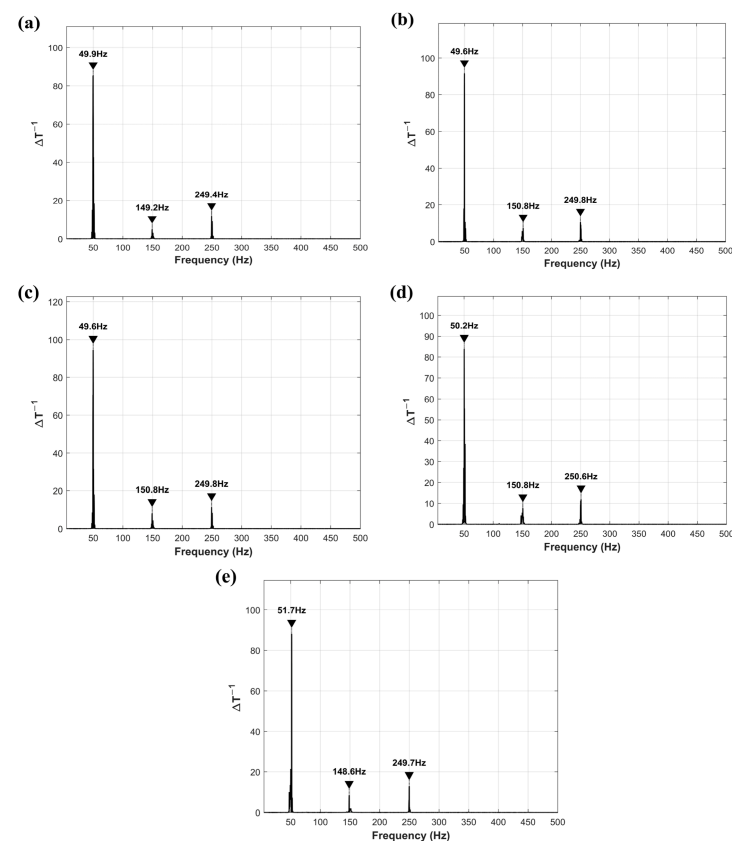


Figure 10. CWT-PSDT joint identification results: (a) No-load; (b) 14 kW; (c) 20 kW; (d) 40 kW; (e) 55 kW.

It should be noted that the peaks shown in Figure 10 represent the characteristic frequencies enhanced by the mutual-reference PSDT analysis rather than the original vibration amplitude spectrum. Based on the CWT-PSDT results under different operating conditions, a dominant frequency component consistently appears near 50.8 Hz. The rated rotational speed of the generator is 600 r/min and the mechanical rotational frequency is approximately 10 Hz. For a 10-pole synchronous generator, the corresponding electrical fundamental frequency can be estimated by $f_e = pn/60$, where p is the number of pole pairs and n is the rotational speed in r/min. In the present case, $p = 5$ and $n = 600$, which gives $f_e = 50$ Hz. Therefore, the component near 50.8 Hz can be reasonably identified as the dominant electromagnetic-related vibration component associated with the electrical fundamental frequency of the generator. Meanwhile, the stable low-frequency component near 10.3 Hz corresponds well to the mechanical rotational frequency of the shaft system and is therefore interpreted as a mechanical rotational feature rather than a dominant electromagnetic-related stator vibration feature. In addition, the components observed around 150 Hz and 250 Hz approximately correspond to the third- and fifth-order multiples of the electrical fundamental frequency, and are therefore likely associated with higher-order electromagnetic effects related to air-gap field distribution and electromagnetic force harmonics [52]. It should be noted that the components near 50 Hz, 150 Hz, and 250 Hz are not interpreted as natural frequencies of the stator core. Instead, they are regarded as electromagnetic-related forced vibration response frequencies with stable inter-sensor transmissibility.

4.3. Adaptability Analysis Under Different Operating Conditions FFT Spectrum

To analyze the sensitivity of different frequency components to load variations, the peak indices of key frequency components were extracted from the FFT spectra at Sensor 1 and Sensor 2. Table 3 summarizes the peak indices and relative changes of these components under no-load and 55 kW rated conditions at Sensor 1, and Table 4 presents the corresponding results at Sensor 2.

Table 3. FFT peak indices of key frequency components at Sensor 1.

Frequency Components	Physical Origin	No-Load	55 kW	Absolute Change	Relative Change
10.193 Hz	Mechanical rotational frequency	5.387	4.758	−0.629	−11.68%
49.866 Hz	Electromagnetic fundamental frequency	0.362	0.567	+0.205	+56.60%
150.024 Hz	3rd-order electromagnetic harmonic	0.054	0.405	+0.351	+654.06%
250.061 Hz	5th-order electromagnetic harmonic	0.011	0.030	+0.019	+170.58%

Table 4. FFT peak indices of key frequency components at Sensor 2.

Frequency Components	Physical Origin	No-Load	55 kW	Absolute Change	Relative Change
10.193 Hz	Mechanical rotational frequency.	0.597	0.649	+0.052	+8.67%
49.866 Hz	Electromagnetic fundamental frequency.	0.382	0.571	+0.189	+49.65%
150.024 Hz	3rd-order electromagnetic harmonic.	0.051	0.408	+0.357	+693.50%
250.061 Hz	5th-order electromagnetic harmonics.	0.024	0.032	+0.008	+33.33%

The results reveal two distinct patterns. First, Load-insensitivity of the mechanical rotational component (~10 Hz). The variation directions at the two sensors are inconsistent (a decrease of 11.68% at Sensor 1 versus an increase of 8.67% at Sensor 2), and the magnitudes of change are relatively small. This lack of systematic fluctuation indicates

that the 10 Hz component does not exhibit deterministic variation with load, which is consistent with the physical mechanism that mechanical unbalanced force primarily depends on rotational speed and is decoupled from electrical load. Second, Load-sensitivity of electromagnetic-related components (50 Hz, 150 Hz, 250 Hz). All three frequency components show consistent increasing trends at both sensors. The 50 Hz component increases by approximately 50–57%, the 250 Hz component by approximately 33–171%, and the 150 Hz component exhibits the most dramatic growth of approximately 6.5–7 times. This systematic, unidirectional significant growth is fully consistent with the physical law that electromagnetic force increases with stator current. The exceptionally high growth of the 150 Hz component can be attributed to the intensification of air-gap field harmonic distortion and the nonlinear amplification caused by magnetic saturation effects under heavy load. According to the Lorentz force law and Maxwell’s stress tensor theory, the current circulating in the stator windings generates a magnetic field, and the interaction between this magnetic field and the current gives rise to electromagnetic forces. The magnitude of the radial electromagnetic force acting in the air gap is proportional to the square of the magnetic flux density, which in turn increases with the armature current as the electrical load rises. This fundamental relationship explains why the FFT peak indices, which directly reflect the absolute vibration energy of the stator structure, exhibit systematic growth with increasing load.

The above analysis indicates that FFT peak indices reflect the load-response characteristics of each frequency component—the mechanical rotational component remains essentially stable, while the electromagnetic-related components grow significantly with load, which is consistent with their respective physical origins. To further verify whether the CWT-PSDT method extracts structural transmission characteristics rather than excitation-dependent response energy, the peak indices of the three characteristic frequencies in the PSDT-enhanced spectra were extracted under all five load conditions, as summarized in Table 5.

Table 5. Stability of PSDT peak indices of frequency components identified by CWT-PSDT.

Frequency Components	No-Load	14 kW	20 kW	40 kW	55 kW	Fluctuation Range
50 Hz	85.406	90.159	90.193	83.907	88.077	83.907~90.193
150 Hz	6.972	6.281	7.978	8.298	7.536	6.281~8.298
250 Hz	11.781	10.512	11.105	11.838	11.861	10.512~11.861

As shown in Table 5, the 50 Hz component maintains PSDT peak indices between 83.907 and 90.193 across all five conditions, with a maximum deviation of -1.75% to $+5.60\%$ relative to no-load. The 250 Hz component remains stable between 10.512 and 11.861, with a maximum deviation of -10.77% to $+0.68\%$. Both frequency components exhibit good peak index stability under different loads, indicating that they possess stable structural transmission characteristics. The 150 Hz component fluctuates between 6.281 and 8.298, with a maximum deviation of -9.91% to $+19.02\%$ relative to no-load. Its relatively larger fluctuation may be attributed to the fact that higher-order electromagnetic force harmonics are more sensitive to air-gap field distribution variations and magnetic saturation effects. Nevertheless, all three frequency components are consistently identified by the CWT-PSDT method across all operating conditions, without frequency shift or loss.

Combining the FFT peak value variations (Tables 3 and 4), the following conclusions can be drawn. The three electromagnetic-related frequency components (50 Hz, 150 Hz, 250 Hz) identified by the CWT-PSDT method exhibit excellent frequency stability under different operating conditions, and their PSDT peak indices do not show systematic increasing or decreasing trends with load variation. This suggests that the CWT-PSDT result is less

sensitive to excitation-peak variation than the direct FFT spectrum and is more reflective of stable inter-sensor transmissibility characteristics. In contrast, the FFT peak indices of the same frequency components show systematic growth with load, reflecting the physical fact that electromagnetic excitation intensifies with increasing load. These two perspectives corroborate each other, supporting the effectiveness and preliminary robustness of the CWT-PSDT method under the tested normal operating conditions.

To provide a systematic comparison, Table 6 summarizes the analytical functions, strengths, and limitations of typical methods for stator vibration frequency identification, including conventional Fourier-based techniques, adaptive decomposition methods, data-driven deep learning approaches, and the proposed CWT-PSDT framework.

Table 6. Comparison of typical methods for stator vibration frequency identification.

Method	Main Capability	Main Limitation for This Study	Comparison with the Present Work
FFT	Identifies global spectral peaks such as rotational and electromagnetic harmonic components	Cannot determine whether a peak is local, excitation-dominated, or transmissibility-stable	FFT reveals 10 Hz, 50 Hz, 150 Hz, and 250 Hz, while CWT-PSDT further screens components with stable inter-sensor transmissibility
STFT/CWT	Localizes time-varying energy bands of non-stationary vibration signals	Provides energy localization but no independent inter-sensor transmission judgment	CWT is used as the front-end step to locate candidate energy-concentrated frequency bands
EMD/VMD	Decomposes nonlinear and non-stationary signals into modal components	May suffer from mode mixing, endpoint effects, or parameter sensitivity	CWT-PSDT avoids presetting mode numbers and emphasizes electromechanical interpretability
Deep learning	Learns diagnostic features automatically from vibration data	Requires large labeled datasets and has limited physical interpretability	The proposed framework is suitable for normal-condition baseline extraction with limited labeled data
Electromagnetic vibration studies of electrical machines	Explain electrical fundamental and harmonic vibration components	Usually focus on electromagnetic mechanism or fault classification rather than transmissibility-based feature screening	The identified 50 Hz, 150 Hz, and 250 Hz components are consistent with electrical fundamental and harmonic relationships, and are further shown to have stable inter-sensor transmissibility
CWT-PSDT	Combines CWT energy localization and PSDT transmissibility screening	Requires multi-channel response data and physical interpretation	Identifies electromagnetic-related forced vibration response features with both persistent energy concentration and stable inter-sensor transmissibility

As summarized in Table 6, conventional FFT analysis can reveal the coexistence of rotational and electromagnetic-related frequency components, but it cannot determine whether these components exhibit stable transmission characteristics between stator measurement points. Time-frequency methods such as STFT and CWT provide energy localization, whereas adaptive decomposition methods such as EMD and VMD may suffer from mode mixing or parameter sensitivity. Deep-learning-based methods are powerful for fault classification, but they usually require large labeled datasets and provide limited physical interpretability. In comparison, the proposed CWT-PSDT framework combines CWT-based energy localization with PSDT-based inter-sensor transmissibility screening. The identified components near 50 Hz, 150 Hz, and 250 Hz are consistent with

the electrical fundamental frequency and higher-order harmonic relationships of the tested generator, and they are further shown to have stable inter-sensor transmissibility under different normal operating conditions. Therefore, the proposed method provides a physically interpretable strategy for selecting stable electromagnetic-related stator vibration response features for online monitoring.

5. Limitations and Future Work

Although the proposed CWT-PSDT method achieves satisfactory performance in identifying electromagnetically induced frequency components in hydro-generator stator vibrations under normal operating conditions, certain limitations should be acknowledged. First, the present investigation is confined to steady-state or quasi-steady operating regimes; transient processes such as start-up, shutdown, or large-disturbance events have not been considered. Second, only two accelerometers were installed in the experimental setup, which restricts the spatial resolution of the measured vibrational field. Third, the numerical model adopts a simplified beam-type structure, which is intended primarily for methodological validation rather than for fully capturing the complex multiphysics interactions present in an actual generator unit. In addition, the electromagnetic attribution of the 50 Hz, 150 Hz, and 250 Hz components is mainly based on their frequency relationships with the electrical fundamental frequency and their load-dependent FFT peak trends. Direct validation using synchronized electrical quantities, air-gap flux density measurements, or electromagnetic-force simulations has not yet been included.

To address these shortcomings, future work will focus on the following aspects: (i) expanding the measurement array with additional sensors and optimizing their placement to enhance the spatial representativeness of the data; (ii) developing a more realistic coupled numerical model that better reproduces the structural–electromagnetic–thermal coupling behavior of a full-scale hydro-generator; and (iii) incorporating a wider range of off-design and abnormal operating conditions, including rotor eccentricity and inter-turn short circuits, so as to further verify the robustness and diagnostic applicability of the proposed method for online condition monitoring and fault identification.

6. Conclusions

This study proposed a coupled continuous wavelet transform and power spectral density transmissibility (CWT-PSDT) method for identifying electromagnetic-related stator vibration response frequency components in a hydro-generator under normal operating conditions. Based on the theoretical formulation, numerical validation, and experimental analysis, the following conclusions can be drawn.

1. CWT provides effective time-frequency localization of dominant vibration components. The CWT results clearly reveal the major energy bands of the stator vibration signal and their distribution in the time-frequency domain. In the experiments, the dominant component near 50.8 Hz and the rotational component near 10.3 Hz can both be identified effectively.
2. PSDT enhances the screening of frequency components with stable inter-sensor transmissibility. In the numerical beam case, the identified PSDT peaks correspond well to the first five natural frequencies, with a maximum relative error of 4.22%. In the hydro-generator experiments, the PSDT-based screening result does not significantly enhance the rotational component near 10.3 Hz, whereas the electromagnetic-related forced response components near 50 Hz, 150 Hz, and 250 Hz are consistently retained.
3. The integrated CWT-PSDT framework is effective under different normal operating conditions. The experimental results show that the proposed method can distinguish the mechanical rotational component from electromagnetic-related forced vibration

response components over the tested load range. Compared with direct FFT-based analysis, it provides a more physically interpretable way to identify stator-core-related vibration frequency features.

4. This study is restricted to quasi-steady normal operations, a simplified beam model, and only two sensor locations. Subsequent research will incorporate transient and off-design cases, develop a more comprehensive coupled model, and optimize sensor placement to support fault diagnosis and online monitoring.

In summary, the proposed CWT-PSDT framework provides a physically interpretable and data-efficient approach for identifying electromagnetically induced stator vibration frequency components in hydro-generators under normal operating conditions, thereby establishing a solid baseline for spectrum-based condition monitoring. Nevertheless, the limitations discussed above highlight the need for further validation under off-design and faulty states. The planned future investigations—particularly those targeting fault-specific feature extraction, adaptive parameter tuning, and hybrid physical-data-driven models—are expected to significantly extend the practical value and diagnostic generality of this methodology for real-world hydropower applications.

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References

1. Gielen, D.; Boshell, F.; Saygin, D.; Bazilian, M.D.; Wagner, N.; Gorini, R. The role of renewable energy in the global energy transformation. *Energy Strategy Rev.* **2019**, *24*, 38–50. [\[CrossRef\]](#)
2. Child, M.; Breyer, C. Transition and transformation: A review of the concept of change in the progress towards future sustainable energy systems. *Energy Policy* **2017**, *107*, 11–26. [\[CrossRef\]](#)
3. Berga, L. The role of hydropower in climate change mitigation and adaptation: A review. *Engineering* **2016**, *2*, 313–318. [\[CrossRef\]](#)
4. Zarfl, C.; Lumsdon, A.E.; Berlekamp, J.; Tydecks, L.; Tockner, K. A global boom in hydropower dam construction. *Aquat. Sci.* **2015**, *77*, 161–170.
5. Nautiyal, H.; Goel, V. Sustainability assessment of hydropower projects. *J. Clean. Prod.* **2020**, *265*, 121661. [\[CrossRef\]](#)
6. Gatta, F.M.; Geri, A.; Lauria, S.; Maccioni, M.; Nati, L. The Path Towards Decarbonization: The Role of Hydropower in the Generation Mix. *Energies* **2025**, *18*, 5248. [\[CrossRef\]](#)
7. Mohanta, R.K.; Chelliah, T.R.; Allamsetty, S.; Akula, A.; Ghosh, R. Sources of vibration and their treatment in hydro power stations—A review. *Eng. Sci. Technol. Int. J.* **2017**, *20*, 637–648. [\[CrossRef\]](#)
8. Betti, A.; Crisostomi, E.; Paolinelli, G.; Piazzzi, A.; Ruffini, F.; Tucci, M. Condition monitoring and predictive maintenance methodologies for hydropower plants equipment. *Renew. Energy* **2021**, *171*, 246–253. [\[CrossRef\]](#)
9. Basak, D.; Tiwari, A.; Das, S. Fault diagnosis and condition monitoring of electrical machines-A Review. In Proceedings of the 2006 IEEE International Conference on Industrial Technology, Mumbai, India, 15–17 December 2006; pp. 3061–3066.

10. Wang, L.; Cheung, R.W.; Ma, Z.; Ruan, J.; Peng, Y. Finite-element analysis of unbalanced magnetic pull in a large hydro-generator under practical operations. *IEEE Trans. Magn.* **2008**, *44*, 1558–1561. [\[CrossRef\]](#)
11. Qi, P.; Li, Y.; Ma, M.; Wu, Y.; Lu, W. Research on the vibration characteristics of pumped storage unit stator core based on fiber optic sensing. *IEEE Trans. Energy Convers.* **2023**, *38*, 2179–2190. [\[CrossRef\]](#)
12. Brito Junior, G.C.; Machado, R.D.; Chaves Neto, A.; Martini, M.F. Experimental Aspects in the Vibration-Based Condition Monitoring of Large Hydrogenerators. *Int. J. Rotating Mach.* **2017**, *2017*, 1805051. [\[CrossRef\]](#)
13. Yun, J.; Park, S.W.; Yang, C.; Lee, S.B.; Antonino-Daviu, J.A.; Sasic, M.; Stone, G.C. Airgap search coil-based detection of damper bar failures in salient pole synchronous motors. *IEEE Trans. Ind. Appl.* **2019**, *55*, 3640–3648. [\[CrossRef\]](#)
14. Antonino-Daviu, J.; Fuster-Roig, V.; Park, S.; Park, Y.; Choi, H.; Park, J.; Lee, S.B. Electrical monitoring of damper bar condition in salient-pole synchronous motors without motor disassembly. *IEEE Trans. Ind. Appl.* **2020**, *56*, 1423–1431. [\[CrossRef\]](#)
15. Tomar, A.S.; Jayaswal, P. Rolling element bearing fault investigation based on translation invariant wavelet means denoising and empirical mode decomposition (EMD). *J. Inst. Eng. (India) Ser. C* **2024**, *105*, 127–140. [\[CrossRef\]](#)
16. Guo, T.; Deng, Z. An improved EMD method based on the multi-objective optimization and its application to fault feature extraction of rolling bearing. *Appl. Acoust.* **2017**, *127*, 46–62. [\[CrossRef\]](#)
17. Lv, Y.; Li, Z.; Yuan, R.; Zhang, Q.; Wu, H. Variable-bandwidth self-convergent variational mode decomposition and its application to fault diagnosis of rolling bearing. *IEEE Trans. Instrum. Meas.* **2024**, *73*, 3511615. [\[CrossRef\]](#)
18. Liu, Y.; Yang, G.; Li, M.; Yin, H. Variational mode decomposition denoising combined the detrended fluctuation analysis. *Signal Process.* **2016**, *125*, 349–364. [\[CrossRef\]](#)
19. Li, H.; Liu, T.; Wu, X.; Chen, Q. An optimized VMD method and its applications in bearing fault diagnosis. *Measurement* **2020**, *166*, 108185. [\[CrossRef\]](#)
20. Chen, Y.; Zhang, R.; Gao, F. Multi-scale residual attention networks with spatio-temporal attention co-optimization for industrial fault diagnosis. *Comput. Chem. Eng.* **2025**, *205*, 109482.
21. Liu, D.; Cheng, X.; Jiang, Z.; Cui, L. Multi-attention collaborative temporal-spatial hypergraph attention network for machinery fault diagnosis. *ISA Trans.* **2026**, *175*, 164–183. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Li, Y.; Gu, X.; Wei, Y. A deep learning-based method for bearing fault diagnosis with few-shot learning. *Sensors* **2024**, *24*, 7516. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Cheng, J.; Ran, R.; Fang, B.; Li, B. Symmetric Positive Definite manifold deep metric learning for bearing fault diagnosis. *Eng. Appl. Artif. Intell.* **2026**, *167*, 113821. [\[CrossRef\]](#)
24. Wang, W.; Pavesi, G.; Pei, J.; Yuan, S. Transient simulation on closure of wicket gates in a high-head Francis-type reversible turbine operating in pump mode. *Renew. Energy* **2020**, *145*, 1817–1830. [\[CrossRef\]](#)
25. Newland, D.E. Wavelet analysis of vibration: Part 1—Theory. *J. Vib. Acoust.* **1994**, *116*, 409–416. [\[CrossRef\]](#)
26. Newland, D. Wavelet analysis of vibration: Part 2—Wavelet maps. *ASME J. Vib. Acoust.* **1994**, *116*, 417–425. [\[CrossRef\]](#)
27. Newland, D.E. Some properties of discrete wavelet maps. *Probabilistic Eng. Mech.* **1994**, *9*, 59–69. [\[CrossRef\]](#)
28. Wang, W.Q.; Ismail, F.; Golnaraghi, M.F. Assessment of gear damage monitoring techniques using vibration measurements. *Mech. Syst. Signal Process.* **2001**, *15*, 905–922. [\[CrossRef\]](#)
29. Wang, Y.; Sun, T.; Huang, T.; Sun, D. Isolated singularity points recognition of hydroelectric generators fault signals based on CWT. In Proceedings of the 2004 7th International Conference on Signal Processing (ICSP'04), Beijing, China, 31 August–4 September 2004; pp. 2530–2532.
30. Zhang, L.; Gao, R.X.; Lee, K.B. Spindle health diagnosis based on analytic wavelet enveloping. *IEEE Trans. Instrum. Meas.* **2006**, *55*, 1850–1858. [\[CrossRef\]](#)
31. He, W.; Jiang, Z.-N.; Feng, K. Bearing fault detection based on optimal wavelet filter and sparse code shrinkage. *Measurement* **2009**, *42*, 1092–1102. [\[CrossRef\]](#)
32. Li, P.; He, Q.; Kong, F. An approach for fault diagnosis of bearings using wavelet-based fractal analysis. In Proceedings of the 2010 IEEE International Conference on Information and Automation, Harbin, China, 20–23 June 2010; pp. 2338–2343.
33. Gu, J.; Peng, Y.; Lu, H.; Chang, X.; Chen, G. A novel fault diagnosis method of rotating machinery via VMD, CWT and improved CNN. *Measurement* **2022**, *200*, 111635. [\[CrossRef\]](#)
34. Tang, T.; Wang, J.; Yang, T.; Qiu, C.; Zhao, J.; Chen, M.; Wang, L. An improved prototypical network with L2 prototype correction for few-shot cross-domain fault diagnosis. *Measurement* **2023**, *217*, 113065. [\[CrossRef\]](#)
35. Chen, J. Fault diagnosis of large-scale electric pumping and irrigation electromechanical equipment by integrating CWT and swin transformer. *Front. Mech. Eng.* **2025**, *11*, 1708745. [\[CrossRef\]](#)
36. Liu, T.; Jing, X.; Liu, P.; Hao, F. A bearing fault diagnosis method based on continuous wavelet transform and an SPDSwin Transformer. *Trans. Can. Soc. Mech. Eng.* **2026**, *50*, 1–15. [\[CrossRef\]](#)
37. Jardine, A.K.; Lin, D.; Banjevic, D. A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mech. Syst. Signal Process.* **2006**, *20*, 1483–1510. [\[CrossRef\]](#)

38. Ding, G.; Li, M.; Gao, X.; Wang, Z.; Lei, Z.; Zhou, N. Propeller's operational modal parameters identification based on Fiber Bragg Grating sensing. *Ocean Eng.* **2022**, *266*, 112737. [[CrossRef](#)]
39. Brincker, R.; Ventura, C.E.; Andersen, P. Damping estimation by frequency domain decomposition. In Proceedings of the 19th International Modal Analysis Conference, Orlando, FL, USA, 5–8 February 2001; pp. 698–703.
40. Devriendt, C.; Guillaume, P. Identification of modal parameters from transmissibility measurements. *J. Sound Vib.* **2008**, *314*, 343–356. [[CrossRef](#)]
41. Devriendt, C.; De Sitter, G.; Vanlanduit, S.; Guillaume, P. Operational modal analysis in the presence of harmonic excitations by the use of transmissibility measurements. *Mech. Syst. Signal Process.* **2009**, *23*, 621–635. [[CrossRef](#)]
42. Devriendt, C.; De Sitter, G.; Guillaume, P. An operational modal analysis approach based on parametrically identified multivariable transmissibilities. *Mech. Syst. Signal Process.* **2010**, *24*, 1250–1259. [[CrossRef](#)]
43. Yan, W.J.; Ren, W.X. Operational modal parameter identification from power spectrum density transmissibility. *Comput.-Aided Civ. Infrastruct. Eng.* **2012**, *27*, 202–217. [[CrossRef](#)]
44. Araújo, I.G.; Laier, J.E. Operational modal analysis using SVD of power spectral density transmissibility matrices. *Mech. Syst. Signal Process.* **2014**, *46*, 129–145. [[CrossRef](#)]
45. ter Meulen, D.W.B.; Cabboi, A.; Antonini, A. Hybrid operational modal analysis of an operative two-bladed offshore wind turbine. *Mech. Syst. Signal Process.* **2025**, *223*, 111822. [[CrossRef](#)]
46. Wan, T.; Zhang, M.; Wang, G.; Liu, C.; Ding, Y.; Peng, Z.; Du, Y. Harmonic extraction method with continuous wavelet transform based on the prior knowledge of wavelength modulation spectroscopy and shift strategy. *IEEE Trans. Instrum. Meas.* **2025**, *74*, 7006712. [[CrossRef](#)]
47. Chen, J.; Rostami, J.; Peter, W.T.; Wan, X. The design of a novel mother wavelet that is tailor-made for continuous wavelet transform in extracting defect-related features from reflected guided wave signals. *Measurement* **2017**, *110*, 176–191. [[CrossRef](#)]
48. Kulkarni, P.; Sahasrabudhe, A. Investigations on mother wavelet selection for health assessment of lathe bearings. *Int. J. Adv. Manuf. Technol.* **2017**, *90*, 3317–3331.
49. Peng, Z.K.; Chu, F. Application of the wavelet transform in machine condition monitoring and fault diagnostics: A review with bibliography. *Mech. Syst. Signal Process.* **2004**, *18*, 199–221. [[CrossRef](#)]
50. Su, W.; Wang, F.; Zhu, H.; Zhang, Z.; Guo, Z. Rolling element bearing faults diagnosis based on optimal Morlet wavelet filter and autocorrelation enhancement. *Mech. Syst. Signal Process.* **2010**, *24*, 1458–1472. [[CrossRef](#)]
51. Sun, Q.; Yan, W.-J.; Ren, W.-X. Analytical investigation into error propagation of power spectral density transmissibility (PSDT) based on coherence function. *J. Sound Vib.* **2021**, *514*, 116429. [[CrossRef](#)]
52. Yang, C.; Wang, Y.; Qiu, H.; Chen, S.; Lian, Z. Electromagnetic Vibration of High-Voltage Line-Start Permanent Magnet Synchronous Motor with Demagnetization Fault. *J. Electr. Eng. Technol.* **2024**, *19*, 4143–4158. [[CrossRef](#)]

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