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ORDER TRACKING TEMPORAL–FREQUENCY HYPERGRAPH FOR MULTI SENSOR FAULT DIAGNOSIS OF OFFSHORE WIND TURBINE MAIN BEARINGS

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Abstract

To address the issues that the main bearings in the drive train of offshore wind turbines operate long-term under variable speed, variable load, strong noise, and environmental disturbances, with vibration energy showing intermittent and sparse distribution, cross-sensor signals suffering from asynchrony and nonlinear coupling, and limited on-site labeling, this paper proposes an order-aligned time-frequency hypergraph multi-sensor modeling framework (OT-TFH). The method first performs order tracking and multi-resolution time-frequency transformation on multi-source signals such as vibration, current, and temperature, then constructs hyperedges through co-activation events in the same time slice and fuses amplitude coherence with mutual information to obtain a weighted time-frequency hypergraph, extracts high-order co-occurrence relationships across sensors via attention-based hypergraph convolution, and simultaneously introduces a lightweight 1D-CNN to capture short-term dynamics and an operating condition gate to achieve adaptive fusion, which has been integrated into an online prototype system to meet real-time diagnostic requirements. Experiments based on CWRU bearing data and self-built wind turbine drive train data demonstrate that the proposed method achieves higher accuracy and stability than graph modeling and temporal fusion baselines under complex operating conditions, and the generalization performance of CWRU single-sensor data is improved through data augmentation techniques such as multi-speed and noise disturbance. This study verifies the effectiveness and engineering applicability of the order-aligned time-frequency hypergraph in characterizing high-order coupling across multiple sensors.

Key Words

Hypergraph; Time-frequency Hypergraph; Order Alignment; Multi-sensor Fusion; Main Bearing of Wind Turbine; Fault Diagnosis.

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1. Introduction

Offshore wind power is a core field of global clean energy, and the main bearing of its drive train is a key component—it bears over 90% of the radial load of the main shaft [1]. A fault in this bearing will cause the unit to shut down, resulting in a daily power generation loss of more than 20,000 kWh per unit and a maintenance cost of 500,000 RMB per repair (China Wind Power Operation and Maintenance White Paper 2023).

However, the main bearings of offshore wind turbines have long been subjected to operating conditions characterized by "variable speed, variable load, harsh environment, and few labeled samples", leading to three core challenges in fault diagnosis:

Feature drift caused by variable speed and load: Fluctuations in wind speed cause the main shaft speed to change dynamically within the range of 10-20 rpm, leading to a drift of up to 40% in fault characteristic frequencies (e.g., outer ring fault frequency). The traditional Fourier transform fails due to its "stable speed" assumption, resulting in an early fault miss rate of over 65% [2] [3].

Reduced data quality due to harsh environment: Interferences from salt spray and ocean waves reduce the signal-to-noise ratio (SNR) of sensor signals to as low as 5 dB. A single vibration sensor is prone to distortion caused by electromagnetic interference, leading to a false alarm rate of 32.7% (ASME, 2022) [4].

Constraints from cross-sensor coupling and few samples: Sensors for vibration, temperature, and current exhibit signal asynchrony due to differences in installation positions. Moreover, on-site fault samples account for only 3% of all samples, with high labeling costs, making traditional multi-sensor methods difficult to adapt.

Current mainstream bearing fault diagnosis methods struggle to address the above challenges: Single-sensor methods (e.g., vibration time-domain analysis) only capture local information and cannot identify hidden faults such as insufficient lubrication under low SNR conditions. Multi-sensor temporal fusion methods (e.g., LSTM-

DenseNet) improve robustness through feature concatenation, but fail to handle frequency drift caused by variable speed—their accuracy decreases by 18.5% under variable-speed conditions of wind turbines (IEEE Trans.Ind.Inf., 2023) [5]. Static graph methods (e.g., STGCN) can model spatial correlations, but rely on fixed adjacency matrices and cannot adapt to changes in sensor correlations caused by variable loads—their accuracy drops to 78% under variable-load conditions (J.Manuf.Syst., 2023). Existing hypergraph methods mostly focus on the spatial dimension and do not integrate time-frequency features, making it difficult to capture the dynamic coupling relationships of offshore wind turbine main bearings [6].

To address the above challenges, this paper proposes an order-aligned time-frequency hypergraph multi-sensor modeling method, which achieves high-precision fault diagnosis through time-space-time-frequency cross-domain fusion: In the time dimension, order tracking is used to map dynamic rotational speed to a stable order domain, and 1D-CNN is integrated to extract temporal features, thereby solving the problem of frequency drift. In the spatial dimension, an autoencoder is applied to reduce the dimensionality of multi-sensor data, and a hypergraph with "time-frequency atoms-sensors" as nodes is constructed. Hyperedges are used to characterize cross-sensor co-activation relationships (e.g., synchronization between vibration impact and sudden temperature rise), breaking the limitation of "pairwise correlation" in traditional graphs. In the fusion dimension, a gating mechanism is designed to dynamically balance the weights of spatiotemporal features, enabling adaptation to variable-load conditions [7] [8]. Additionally, the method supports dual-mode tasks of "supervised classification-weakly supervised anomaly detection" to adapt to few-sample scenarios.

The main contributions of this paper are as follows: Innovation in scenario-specific modeling: To address the challenges of "variable speed, low SNR, and few samples" for main bearings of offshore wind turbines, an order-time-frequency-hypergraph fusion framework is proposed, filling the gap in the adaptability of existing methods to offshore wind power scenarios. Optimization of technical pathway: A core module of "order tracking + time-frequency hypergraph" is designed. The hyperedge weight integrates amplitude coherence and mutual information, which enhances the ability to capture dynamic coupling features. Compared with traditional static graph models, its accuracy increases by more than 15% under variable operating conditions [9]. Verification of engineering application: A digital twin monitoring system integrated with this method is developed, with an inference delay of <100 ms. The system has been pilot-applied in an offshore wind farm, providing a practical diagnostic solution for real industrial scenarios.

The subsequent chapter arrangement of this paper is as follows: Chapter 2 reviews the research related to multi-sensor fault diagnosis and time-frequency hypergraph. Chapter 3 elaborates on the overall framework of the proposed method. Chapters 4-6 respectively introduce the construction of time-frequency hypergraph, spatiotemporal feature fusion, and dual-mode diagnosis logic in detail. Chapter 7 verifies the effectiveness of the method using the CWRU dataset (processed with multi-speed/noise augmentation) and the self-built offshore wind turbine main bearing dataset, and demonstrates the application effect of the digital twin system. Chapter 8 summarizes the full paper and prospects future research directions.

2. Related Works

2.1 Scenario Characteristics and Modeling Challenges of Wind Turbine Main Bearing Fault Diagnosis

2.1.1 Non-stationary Signal Characteristics and Feature Drift

Wind turbine main bearings operate long-term under dynamic speed fluctuations of 10-20 rpm. The fault characteristic frequencies (e.g., outer ring fault frequency) can drift by up to 40% with rotational speed [10] [12]. The traditional Fourier Transform (FFT) completely fails due to its "stable speed" assumption, resulting in an early fault miss rate of over 65% [13].

Meanwhile, salt spray corrosion and ocean wave vibration interference reduce the signal-to-noise ratio (SNR) of sensor signals to as low as 5 dB. A single vibration signal can attenuate by up to 60% in the drive train (ASME, 2022), which further increases the difficulty of feature extraction [14].

2.1.2 High-Order Coupling and Asynchrony Across Sensors

Typically, multiple types of sensors (e.g., vibration, current, and temperature) are deployed on-site. However, differences in installation positions lead to signal asynchrony (with a time delay of up to 10-50 ms). Fault evolution is often accompanied by a multi-physical field coupling effect of "vibration impact + sudden temperature rise + current fluctuation" [15].

Traditional multi-sensor methods mostly focus on "pairwise signal correlation" and cannot characterize such "many-to-many" high-order co-occurrence relationships, resulting in a false alarm rate as high as 32.7%.

2.1.3 Dilemma of Few Samples and Domain Shift

On-site fault samples account for only 3% of the total samples, with extremely high labeling costs. Moreover, wind speed and load vary significantly across different wind farms, leading to a sharp decline in the model's generalization performance during cross-condition transfer (when training data is reduced by 50%, the accuracy of traditional methods decreases by 27%).

2.2 Research on Time-Frequency Analysis and Order Alignment Techniques for Non-Stationary Signals

Time-frequency analysis is a core method for processing non-stationary signals [16]. Its application in wind turbine main bearing diagnosis has undergone three rounds of technological iteration, yet there remains a gap in scenario adaptability.

2.2.1 Limitations of Traditional Time-Frequency Analysis Methods

Early studies used Short-Time Fourier Transform (STFT) or Continuous Wavelet Transform (CWT) to extract frequency-domain features. However, the fixed time-frequency resolution of STFT cannot simultaneously capture "low-frequency features at low speeds" and "high-frequency impacts at high speeds" [17]. Although CWT can adjust resolution adaptively, frequency band features still exhibit blurred drift under continuous speed fluctuations, reducing fault feature discriminability by over 30% (Mechanical Systems and Signal Processing, 2022) [1].

2.2.2 Breakthroughs and Limitations of Order Tracking Technology

Order tracking synchronizes with rotational speed signals to map the "time-frequency" domain to the "time-order" domain, which effectively offsets the impact of speed drift and has become a key technology for non-stationary signal processing in wind power systems [18].

Existing order tracking methods can be divided into hardware synchronization (e.g., encoder speed measurement) and software synchronization (e.g., instantaneous frequency estimation) [2]. Among them, software synchronization is more favored in industry due to its flexible deployment (IEEE Transactions on Industrial Electronics, 2023) [19].

However, current research mostly applies order tracking to single-sensor signal processing and does not integrate it with multi-sensor fusion modeling, making it impossible to use cross-sensor information to enhance feature robustness [20] [21].

2.3 Evolution of Graph and Hypergraph Modeling for Multi-Sensor Fusion

The core of multi-sensor fusion is to characterize the correlation between sensors. Graph and hypergraph modeling provide effective paradigms for this problem, yet they still need to break through the adaptability bottleneck in wind power scenarios [22].

2.3.1 Limitations of Traditional Multi-Sensor Fusion Methods

Early fusion methods can be divided into feature-level concatenation (e.g., LSTM-DenseNet cascades vibration and acoustic emission features, achieving an accuracy of 89.3%) and decision-level voting (e.g., multi-classifier integration). However, both ignore the spatial topology and dynamic correlations between sensors, leading to an 18.5% accuracy decrease under variable-load conditions of wind turbines (IEEE Trans. Ind. Inf., 2023) [17].

Single-sensor methods (e.g., time-domain analysis of vibration signals), on the other hand, suffer from information limitations, resulting in a miss rate of over 67% for hidden faults such as insufficient lubrication.

2.3.2 Application and Defects of Graph Modeling in Multi-Sensor Fusion

Graph Neural Networks (GNNs) explicitly model spatial correlations between sensors through adjacency matrices, significantly enhancing fusion robustness. For example, Spatiotemporal Graph Convolutional Networks (STGCN) capture dynamic features via spatiotemporal convolution but use fixed adjacency matrices, failing to adapt to changes in sensor correlations caused by variable wind turbine loads, with accuracy dropping to 78% under variable loads (J. Manuf. Syst., 2023). Methods like Dynamic Graph Convolutional Recurrent Networks (DCRNN) cascade temporal and graph convolutions, which separate the spatiotemporal coupled propagation characteristics of fault shock waves, further undermining performance.

2.3.3 Advantages of Hypergraph Modeling and Gaps in Wind Power Scenarios.

Hypergraphs connect multiple nodes through "hyperedges", which naturally adapts to the "many-to-many" high-order coupling relationships among multiple sensors and has gradually become a research hotspot in recent years. However, existing hypergraph methods have two major limitations:

(1) Simplified spatial dimension: They only focus on the correlations between sensor entities and do not integrate time-frequency features, making it impossible to capture the three-dimensional coupling of "time-order-sensor".

(2) Simplified weight design: Most methods use a single mutual information to calculate hyperedge weights, which are vulnerable to noise interference in wind power scenarios with low SNR, leading to distortion in correlation characterization.

To address the few-sample challenge in offshore wind turbine main bearing diagnosis, this study integrates weakly supervised anomaly detection based on the isolation forest, with supplementary theoretical explanations to clarify its rationality: Determination process of the 0.8 anomaly threshold. The anomaly threshold is determined through 5-fold cross-validation on the mixed dataset of healthy and fault samples (10,000 healthy samples + 1,000 fault samples from the self-built dataset) to balance detection accuracy and false alarm rate: Step 1: Split the mixed dataset into 5 equal subsets, with 4 subsets as the validation set (containing 8,000 healthy + 800 fault samples) and 1 subset as the test set (2,000 healthy + 200 fault samples), repeating 5 times. Step 2: For each validation set, train the isolation forest and calculate anomaly scores (range: 0–1) for all samples. Test thresholds in the interval [0.6, 0.9] with a step size of 0.05, recording true positive rate (TPR) and false positive rate (FPR) for each threshold. Step 3: Select the threshold that maximizes the F1-score (harmonic mean of TPR and 1-FPR). The results show that when the threshold is 0.8, the average F1-score reaches 0.94 (TPR = 0.93, FPR = 0.02), which is higher than other thresholds (e.g., 0.75: F1 = 0.91, FPR = 0.04; 0.85: F1 = 0.92, TPR = 0.89). Step 4: Verify on the independent test set (3,000 samples from 2 new offshore wind farms). The threshold of 0.8 maintains a TPR of 0.92 and FPR of 0.03, meeting the industrial requirement of "FPR < 0.05", thus confirming its generalizability.

3. Methodological Framework

3.1 Overview of the Framework

To address the core pain points of offshore wind turbine main bearings—feature drift caused by variable speed and load, cross-sensor high-order coupling, low signal-to-noise ratio (SNR), and few annotations—this paper proposes an Order-Tracking-based Time-Frequency Hypergraph Multi-Sensor Modeling Framework (OTTFH) [2].

Centered on the principles of "time-frequency atoms as the foundation, hypergraph modeling as the core, and working condition fusion as the adaptation," the framework enables end-to-end diagnosis covering the entire process of "stable feature extraction from non-stationary signals → high-order correlation modeling → dynamic fusion for accuracy improvement → online diagnosis implementation." [19] The overall architecture follows a cross-domain fusion pipeline and comprises five core modules: non-stationary signal order alignment, time-frequency atom generation, cross-sensor time-frequency construction, dual-branch feature enhancement, and condition-adaptive gated fusion for dual-mode fault diagnosis. The pipeline enables end-to-end processing from raw multi-sensor data to final diagnostic results [23].

3.2 Order Alignment of Non-Stationary Signals and Extraction of Time-Frequency Atoms

3.2.1 Multi-Source Signal Preprocessing

In the spatial dimension, the raw data from each sensor is mapped to a low-dimensional embedding vector via an Autoencoder (AE), which serves as the feature representation of sensor nodes while preserving the core differential features of the data [18].

By calculating the cosine similarity of sensor embedding vectors, a multi-sensor spatial feature graph $g_s = (v_s, \varepsilon_s)$, that reflects the spatial correlations between sensors is constructed [24]. Here, v_s represents sensor entities (as nodes), and ε_s denotes the spatial dependencies between sensors (e.g., physical location correlations, signal coupling relationships, etc.) [22].

A Graph Neural Network (GNN) is then used to perform convolution operations on the spatial feature graph, aggregating information from neighboring nodes to extract the spatial structural features of the sensor network and capture the collaborative variation patterns among multiple sensors [17].

3.2.2 Frequency Stabilization via Order Tracking

For rotational speed fluctuations of 10–20 rpm, software-based order tracking is used to eliminate characteristic frequency drift. Step 1: Instantaneous rotational speed $n(t)$ is estimated based on the envelope spectrum peak extraction of the vibration signal [25]. Step 2: Equal-angle resampling transforms the non-stationary "time–amplitude" signal into a stationary "angle–amplitude" signal. The mathematical principle of equal-angle resampling is supplemented as follows: Given the original signal sampling time sequence $\mathrm{t} = [t_1, t_2, ..., t_N]$ with corresponding instantaneous rotational speed $n\left(t\right)$, the equal-angle resampling interval is calculated by $t_k = \frac{60}{n(t_k) \times F_s \times O}$, where F_s denotes the sampling frequency and O represents the target order. The angle-aligned signal is obtained via linear interpolation: $x\left(\theta_k\right) = x\left(t_k\right) + \left(x\left(t_{k+1}\right) - x\left(t_k\right)\right) \times \frac{\theta_k - \theta(t_k)}{\theta(t_{k+1}) - \theta(t_k)}$, in which $\theta(t) = 2\pi \int_0^t \frac{n(\tau)}{60} d\tau$ stands for the cumulative rotation angle. Step 3: The order is defined as $O = \frac{f}{f_r}$ (where f is the actual signal frequency and f_r is the rotational frequency), mapping the frequency domain into a stable order domain [12] [13].

3.2.3 Multi-Resolution Time-Frequency Atom Generation

The order-aligned signals are subjected to a Wavelet Packet Transform (WPT) to achieve refined extraction of time–frequency features. The decomposition depth is set to five levels, covering the 0–5000 Hz range (including the 0–2000 Hz band where the main-bearing fault characteristics are concentrated). The "time–frequency energy" of each decomposition node is taken as the feature value to form a time–frequency atom composed of three elements—time slice t, order band f_0, and sensor s—expressed as $a_{t,f_0,s} = [E_{t,f_0,s}, \mu_{t,f_0,s}, \sigma_{t,f_0,s}]$ where $E_{t,f_0,s}$ is denotes the time–frequency energy, and $\mu_{t,f_n,s}$ and $\sigma_{t,f_n,x}$ represent the mean and standard deviation of the atom, respectively, jointly characterizing the time–frequency distribution characteristics of the signal [17].

3.3 Construction of Cross-Sensor Time-Frequency Hypergraph

Taking time–frequency atoms as nodes, a weighted time–frequency hypergraph H = (V, E, W) is constructed to explicitly model high-order coupling relationships across sensors.

3.3.1 Definition of Hypergraph Nodes

The time–frequency atoms generated in Section 3.2.3 are directly used as hypergraph nodes V, that is, V = $\{a_{t,f_0,s} \mid t = 1, \ldots, T; f_0 = 1, \ldots, F; s = 1, S\}$, where T denotes the number of time slices, F the number of order bands, and S the number of sensors (in this study, S = 3, corresponding to vibration, current, and temperature). The feature vectors of nodes retain the energy, mean, and standard deviation of the time–frequency atoms to ensure completeness of information [6].

3.3.2 Construction of Hyperedges and Weight Calculation

Based on the "cross-domain co-occurrence of fault features," hyperedges e ∈ E are designed as follows: for any time slice t, if at least two different sensors s1 and s2 generate time–frequency atoms $a_{t,f,1,51}$ and $a_{t,f_v,2,s2}$ that satisfy "similar order bands ($\mid f_{o1} - f_{o2} \mid \leq 0.5$) and energy above threshold (E $\geq 1.5 \times \bar{\text{E}}$, where $\bar{E}$ denotes the average energy in the healthy state)," then a hyperedge e is used to connect these atoms, representing "cross-sensor, same-time, near-frequency" co-activation events (e.g., simultaneous occurrence of mid–high-frequency vibration and rapid temperature rise during main bearing outer race failure). The hyperedge weight we combines amplitude coherence (Coh) and mutual information (MI) to account for both linear and nonlinear coupling relationships, expressed as $w_s = \alpha \cdot \operatorname{Coh}(a_i, a_j) + (1-\alpha) \cdot MI(a_i, a_j)$, where $\alpha = 0.4($ optimized $\times$ experimentally $) \operatorname{Coh}(a_i, a_j)$ calculates the frequency-domain linear coherence between atoms, and $MI(a_i, a_j)$ measures their information entropy correlation, both normalized to the range [0,1] [26]. A higher weight indicates a stronger fault-related correlation between the connected atoms.

3.4 Dual-Branch Spatiotemporal Feature Enhancement

A dual-branch feature enhancement module combining "hypergraph convolution + 1D-CNN" is designed to capture high-order spatial correlations and short-term temporal dynamics.

3.4.1 Hypergraph Attention Convolution Branch

An attention-based hypergraph convolution (HyperGAT) is employed to extract high-order cross-sensor correlation features, with a load-adaptive mechanism integrated to address variable-load scenarios (0.8P to 1.2P) as required. First, a load-energy threshold mapping rule is established: the co-activation energy threshold E_{thres} or hyperedge construction is dynamically adjusted with real-time load P, following the formula $E_{thres}(P) = E_{thres,base} \times [1 + 0.3 \times (P/P_{rated} - 1)]$. Here, $E_{thres,base} = 1.2 \times E_{healthy}\,(energythresholdforratedloadP_{rated})$, 0.3 is the load sensitivity coefficient (calibrated via 5-fold cross-validation on the self-built dataset), ensuring the co-activation criteria adapt to load fluctuations—for low load (0.8P), E_{thres} decreases to $1.04 \times E_{healthy}$ to capture weak fault signals, while for high load (1.2P), it increases to $1.36 \times E_{healthy}$ to avoid false correlations caused by load-induced noise.

3.4.2 1D-CNN Short-Term Dynamic Branch

To capture the "impact-type temporal characteristics" of main bearing faults, a lightweight 1D-CNN is designed for temporal dynamic extraction. The time–frequency atoms of the same sensor are sorted by time slices to form sequential data, which are then processed through three 1D convolutional layers (kernel sizes 3, 5, and 3) and max pooling to capture transient variations between adjacent time slices. Global average pooling is subsequently used to generate temporal dynamic features $F_t, R^{N \times D_1}$, where D_t denotes the temporal feature dimension.

3.5 Working-Condition-Adaptive Gated Fusion and Diagnosis

3.5.1 Working-Condition Gating Fusion Mechanism

To adapt to the "variable-speed/variable-load" operating conditions of wind turbines, a gated fusion module based on real-time condition parameters is designed. Real-time rotational speed n and load P from the wind turbine SCADA system are input into a two-layer fully connected network to generate gating weights $\beta(\mathrm{n}, \mathrm{P})\dot{o}[0,1]$. The dual-branch features are fused according to the formula $F_{\text{flsion}} = \beta(n, P) \cdot F_S + (1 - \beta(n, P)) \cdot F_t$, where at high rotational speed (n > 18 rpm), β decreases (enhancing temporal dynamic features), and under load fluctuations ($P > 1.2 \times \mathbf{P}_{\text{rated}}$), β increases (enhancing correlation features), thereby achieving adaptive adjustment across operating conditions [5].

3.5.2 Dual-Mode Output for Fault Diagnosis and Anomaly Detection

For scenarios with few annotations, a dual-mode diagnostic logic is designed. Supervised classification: for labeled samples (fault types including inner race, outer race, and rolling element faults), F_{flasion} is input into a fully connected classifier optimized via cross-entropy loss. Weakly supervised anomaly detection: for unlabeled samples, an isolation forest model is used to learn the feature distribution of healthy samples and output an anomaly score (classified as abnormal when >0.8) [27].

For supervised classification (labeled fault samples), the hypergraph's hyperedges—constructed via "cross-sensor co-activation events" (formulated as $\mathrm{e} = \{v_{\mathrm{i}1}, \mathrm{v}_{\mathrm{i}2}, \ldots \mathrm{v}_{\mathrm{ik}}\} \mid k \geq 2$, nodes from vibration/current/temperature sensors)—can aggregate multi-source fault features (e.g., vibration 2× order impact + current fluctuation + temperature rise). This avoids the "local information limitation" of traditional graph pairwise correlation (modeling error >30%), enabling more accurate classification of fault types (inner race, outer race, rolling element faults) [21].

For weakly supervised anomaly detection (unlabeled samples), the hypergraph's weighted correlation calculation ($\omega_e = \alpha\ \mathrm{Coh}(v_{i1}, \ldots \mathrm{v_{ik}}) + (1-\alpha)\ \mathrm{MI}(v_{i1}, \ldots \mathrm{v_{ik}})$, $\alpha = 0.6$) can characterize the "normal coupling pattern" of healthy samples. When anomalies occur (e.g., bearing crack), hyperedge weights of fault-related nodes will deviate significantly from the healthy range(e.g ω_e drops from 0.7–0.8 to 0.3–0.4) providing distinguishable features for the isolation forest model [27].

3.6 Online Diagnostic System Integration

The OTTFH model is integrated into the digital-twin monitoring system of the wind turbine main bearing to enable engineering implementation. Model lightweighting: depthwise separable convolution replaces standard convolution, reducing parameters by 60%. Real-time optimization: time–frequency atom extraction and hypergraph construction are performed in parallel, achieving inference latency $\leq$80 ms to meet online diagnostic requirements. Visualization output: the twin interface displays sensor data, time–frequency hypergraph topology, fault type, and confidence in real time, supporting rapid decision-making by maintenance personnel.

3.7 Core Advantages of the Framework

Scenario adaptability: order tracking resolves speed drift, multi-source alignment and denoising adapt to low-SNR conditions, and working-condition gating addresses load fluctuations. Accurate correlation modeling: the time–frequency hypergraph surpasses conventional pairwise graph limitations and captures multi-sensor "many-to-many" high-order couplings. Strong generalization: dual-branch feature enhancement and dual-mode diagnosis adapt to few-label and cross-condition transfer scenarios. Engineering feasibility: lightweight design and real-time optimization allow deployment at wind-power edge computing nodes.

4. Time-Domain Modeling of the Order-Aligned Time–Frequency Hypergraph

The time-domain modeling of offshore wind turbine main bearings needs to address three key challenges: "feature instability caused by rotational speed drift, difficulty in describing correlations under strong noise interference, and asynchronous distortion across sensors." [28] This paper adopts the technical route of "order alignment for stable features, time–frequency atoms as nodes, dynamic hyperedges for correlation modeling, and dual-branch fusion for feature enhancement" to realize accurate time-domain modeling under non-stationary conditions, providing high-quality temporal input for subsequent spatial modeling and cross-domain fusion [29].

4.1 Multi-Source Signal Preprocessing of Wind Turbine Main Bearings: Order Alignment and Denoising

The preprocessing aims to "eliminate non-stationary interference and improve signal quality," encompassing three steps: order alignment, denoising, and synchronization.

4.1.1 Order Alignment: Counteracting Speed Drift

For dynamic speed fluctuations of 10–20 rpm, software-based order tracking maps non-stationary signals into a stable order domain. Instantaneous speed estimation: the vibration signal is analyzed by envelope spectrum, and the peak frequency is extracted as the real-time rotational frequency $fr(t)$, from which the speed curve is fitted as $n(t) = 60 \times fr(t)$. Equal-angle resampling: with rotation angle $\theta = 2\pi fr(t)$ and time t as references, linear interpolation resampling is performed on vibration, current, and temperature signals to convert the "time–amplitude" sequence into an "angle–amplitude" sequence [22]. Order mapping: the order is defined as o = f / fr (where f is the signal frequency), converting the traditional frequency domain into the order domain. This process eliminates up to 40% of the frequency deviation caused by speed drift and ensures that fault-related orders remain stable (e.g., the outer race fault remains fixed at twice the rotational frequency) [16].

4.1.2 Denoising and Synchronization: Enhancing Signal Quality

Wavelet threshold denoising: a db4 wavelet is used for five-level decomposition of the resampled signal, and high-frequency coefficients are processed with a hard threshold ($\lambda = \sqrt{2\ln L}$, where L is the sampling length). This suppresses low-frequency noise caused by salt spray and ocean waves, improving the signal SNR from 5 dB to above 15 dB. Cross-sensor synchronization: using the trigger signal from the rotational pulse sensor as the time reference, the timestamps of vibration (accelerometer), current (inverter sampling), and temperature (thermocouple) signals are aligned, reducing asynchronous delay from 50 ms to less than 5 ms, ensuring the authenticity of cross-sensor temporal correlations [18].

4.2 Construction of Time–Frequency Atom Nodes: Three-Dimensional Representation of Time, Order, and Sensor

Nodes serve as the foundation for hypergraph modeling. This paper defines each node as a three-dimensional time–frequency atom ("time–order–sensor"), enabling refined representation of fault features.

4.2.1 Multi-Resolution Time–Frequency Transformation

Wavelet Packet Transform (WPT) is performed on preprocessed signals for hierarchical extraction of time–frequency features. Parameters: db4 wavelet is selected as the basis function (reason: its compact support and orthogonal properties match the intermittent impact characteristics of main bearing faults [17]), with five decomposition levels—this generates 32 frequency bands covering 0–5000 Hz, among which the 0–2000 Hz order band is focused (as it concentrates over 90% of main bearing fault characteristic frequencies, e.g., outer ring fault frequency at 2× rotational frequency, inner race fault frequency at 3.5× rotational frequency [12]).

Time–frequency parameter extraction: For each frequency band, the signal is segmented into T non-overlapping time slices (window length: 2048 samples; selection basis: matching the 25.6 kHz sampling rate of the self-built dataset, ensuring each time slice covers 0.08 s—long enough to capture at least 1 full rotation of the main shaft (10–20 rpm) and avoid missing transient fault impacts [25]).

4.2.2 Definition of Time–Frequency Atom Nodes

The combination of "time slice t, order band o, and sensor s" forms a time–frequency atom node $v_{t,0,x}$, expressed as $v_{t,0,s} = [E_{t,0,s}, \mu_{t,0,s}, \sigma_{t,0,s}] \in \mathrm{R}^3$, where $t \in [1,T]$ (T is the total number of time slices), $o \in [1,F]$ (F = 32, number of order bands), and $s \in [1,S]$ (S = 3, number of sensors). All nodes constitute the hypergraph node set $V = \{v_{t,0,s} \mid t = 1.1, T, o = 1.F, s = 1.S\}$. Each node contains complete semantic information of "when (t), which feature (o), and which sensor (s)," overcoming the "single-dimensional" limitation of conventional time-domain nodes [7].

4.3 Construction of Dynamic Temporal Correlation Hyperedges: Coupling Correlation and Condition Adaptation

4.3.1 Hyperedge Construction Rules

Fault evolution often exhibits "cross-sensor, same-time, near-order" co-activation (e.g., outer-race faults cause simultaneous energy surges in the vibration 2× rotational frequency band and low-frequency temperature band). Accordingly, hyperedge e ∈ E is defined as follows: for any time slice t, if at least two different sensors s1 and s2 have nodes $v_{t\rho 1,s1}$ and $v_{t,02,s2}$ that satisfy

$$\begin{cases} |01 - o2| \leq 0.1(\text{ similar order }), \\ E_{t,o1,s1} \geq 1.5\bar{E}_{\text{hadialy, } 01,51}(\text{ energyabnormal }), \\ E_{t,o2,52} \geq 1.5\bar{E}_{\text{healthy },02,52} \end{cases}$$

then a hyperedge e connects these nodes, where $\bar{E}_{\text{heality, } 0,5}$ is the average energy of that order–sensor under healthy conditions. This rule ensures that hyperedges only capture fault-related temporal correlations while avoiding noise interference.

4.3.2 Hyperedge Weight Calculation: Robust Correlation Measurement

Traditional Pearson correlation poorly adapts to nonlinear coupling and strong noise in wind power environments. This paper combines amplitude coherence (Coh) and mutual information (MI) to compute hyperedge weights, balancing linear and nonlinear relationships: $w_\varepsilon = \alpha \cdot \mathrm{Coh}\left(v_i, v_j\right) + (1-\alpha) \cdot MI\left(v_i, v_j\right)$, where $\alpha = 0.4$ (optimized via experiments on CWRU and in - house dattasetts) $\mathrm{Coh}\left(v_{\bar{i}}, v_j\right)$ measures linear frequency-domain correlation: $\mathrm{Coh} = \left|P_{\bar{i}}(f)\right|^2 / [P_{ii}(f) P_{ii}(f)]$, where $P_{\ddot{i}\dot{i}}(f)$ is the cross-power spectral density. $MI\left(v_i, v_j\right)$ measures entropy-based dependency: $\mathrm{MI} = \sum_{\mathrm{v}_i, \mathrm{v}_j} \mathrm{p}\left(v_i, v_j\right) \log \left[\mathrm{p}\left(v_i, v_j\right) / \left(\mathrm{p}\left(v_i\right) \mathrm{p}\left(v_j\right)\right)\right]$, where p is the probability density function. All weights are normalized to [0,1]; higher values indicate stronger fault-related temporal correlations between nodes [15].

4.3.3 Dynamic Threshold Adaptation: Responding to Operating Conditions

Energy and correlation thresholds for hyperedge construction are dynamically adjusted according to operating conditions. Energy threshold: under high load ($\mathrm{P} > 1.2 \times \mathbf{P}_{\text{rated}}$), it decreases to $1.3 \times \overline{\mathrm{E}}_{\text{healthy}}$ to capture weak fault features. Correlation threshold: at high speed (n > 18 rpm), it decreases from 0.6 to 0.55 to accommodate multi-activation events caused by high rotational speed. Dynamic adjustment ensures accurate hyperedge construction under varying conditions, preventing false or missed correlations caused by fixed thresholds [20].

4.4 Temporal Feature Extraction and Multi-Sensor Fusion: Dual-Branch Enhancement and Attention Focusing

A "hypergraph convolution + 1D-CNN" dual-branch feature extraction and channel attention fusion mechanism is designed to capture both cross-sensor high-order correlations and single-sensor short-term dynamics.

4.4.1 Dual-Branch Feature Extraction

(1) Hypergraph convolution branch: extracts high-order temporal correlation features. An attention-based hypergraph convolution (HyperGAT) aggregates information from hyperedge-linked nodes. Node attention scoring: each node is assigned an importance score $a_{t,0,s} = \mathrm{softmax}\left(W_v v_{t,0,s} + b_v\right)$; energy-abnormal nodes $\left(E \geq 2\overline{\mathrm{E}}_{\text{halithy}}\right)$ are amplified by 1.5 ×. Hyperedge information aggregation: via hypergraph convolution operator, $h_{t,0,5} = \sigma\left(\frac{1}{\left|\mathrm{N}_{\left(v_{1,x,k}\right)}\right|} \sum_{v_j \in \mathrm{N}_{\left(h_{k,k,k}\right)}} w_g \cdot a_j \cdot W_h v_j + b_h\right)$, where $\mathbf{N}_{(v_{1,,\infty})}$ is the hyperedge neighborhood, W_h and b_n are learnable parameters, and σ is the ReLU activation. Layer normalization (LayerNorm)

yields cross-sensor high-order temporal features $F_h \in R^{N \times D_h}$, where N is the node count and D_h is the feature dimension.

(2) 1D-CNN branch: captures short-term dynamic impact features. Sequence construction: for each sensor s, the time–frequency atoms are ordered by time slices, forming $X_s = [v_{1,0,s}, v_{2,0,s}, \ldots, v_{T,0,s}]$ Convolutional extraction: three 1D convolution layers (kernel sizes 3, 5, 3; stride 1) with max pooling (pool size 2) progressively extract transient variations. Global pooling: global average pooling produces single-sensor short-term dynamic features $F_c^s \in R^{\mathrm{b}D_\varepsilon}$; three sensors yield $\left[F_c^v, F_c^{\bar{I}}, F_c^t\right]$ (v = vibration, i = current, t = temperature) [17].

4.4.2 Channel Attention Fusion

A channel attention mechanism dynamically assigns weights to multi-sensor and temporal features. Global feature aggregation: F_h and F_c undergo global average pooling to produce global feature vector Fg. Attention weight learning: two fully connected layers ($W_1 \in R^{(D_k+D_k)\{(D_k+D_k)/4}$, $W_2 \in R^{(D_k+D_k)/4x(D_k+D_k)}$) compute weights: $w_{\text{flusion}} = \text{sigmoid}\left(W_2 - RELU\left(W_1 F_g\right) + b_{\text{flusion}}\right)$. Weighted fusion: F_h and F_c are combined element-wise by $F_t = w_{\text{flsision}} \square [\mathrm{F_h}; \mathrm{F_c}]$, where [;] denotes feature concatenation and $\odot$ denotes element-wise multiplication. During fusion, vibration features are assigned higher weights than current or temperature (validated experimentally: vibration sensitivity improves by 20–30%), ensuring attention on critical information.

4.5 Scene Adaptability Advantages of Time-Domain Modeling

Compared with conventional time-series models (LSTM, TCN, or static graph CNN), the proposed time-domain modeling offers the following advantages: (1) Non-stationary adaptability: order alignment fundamentally solves speed drift; the order dimension of time–frequency atom nodes ensures fault feature stability, improving discriminability by 40% over time-domain nodes. (2) Robust correlation modeling: multi-node hyperedges and "coherence + mutual information" weighting achieve robust nonlinear coupling modeling under low-SNR (5 dB) conditions, with correlation modeling error <10%, significantly better than Pearson correlation (>30% error) [13]. (3) Comprehensive feature representation: dual-branch extraction captures both high-order correlations and short-term dynamics, while attention fusion enhances key sensor information, improving feature discrimination by 25% over single 1D-CNN. (4) Condition adaptability: dynamic threshold and weight adjustment ensure consistent features across varying speed/load conditions, improving cross-condition feature consistency by 30%. Through this modeling, the fused temporal feature Ft encodes both the temporal evolution of faults and cross-sensor high-order correlations, providing a solid foundation for subsequent spatial modeling and time–frequency cross-domain fusion.

5. Order-Aligned Time–Frequency Hypergraph Multi-Sensor Fusion Strategy and Diagnostic Implementation

To address the challenges of offshore wind turbine main bearings—feature drift caused by variable speed and load, low signal-to-noise ratio (SNR), and limited labeled samples—this paper proposes a full-chain fusion strategy of "preprocessing–intra-domain fusion–cross-domain fusion–diagnostic optimization." The core idea is to achieve high-order coupling feature extraction of multi-source signals through "order alignment for feature stabilization, scene-aware weighting for adaptive correlation, and physics-guided robust modeling." [1].

5.1 Pre-Fusion Preprocessing: Order Alignment and Data Augmentation

The goal of preprocessing is to eliminate non-stationary interference and enhance sample diversity, providing high-quality inputs for hypergraph fusion.

5.1.1 Order Alignment and Asynchrony Correction

Multi-source signal order tracking: for vibration (accelerometer), current (inverter), and temperature (thermocouple) signals, software-based order tracking is achieved via "instantaneous speed estimation and equal-angle resampling." (1) Extract the rotational speed curve n(t) (10–20 rpm) from the envelope spectrum of the vibration signal; (2) resample non-stationary signals into "angle–amplitude" sequences mapped to the "time–order" domain, eliminating approximately 40% of the frequency drift in fault features. Cross-sensor asynchrony alignment: using the rotational pulse signal as the time reference, linear interpolation correction is applied across different sensors, reducing asynchronous delay from 50 ms to less than 5 ms, ensuring the authenticity of cross-sensor correlations [8].

5.1.2 Data Augmentation for Few-Sample Scenarios

To address the imbalance where fault samples account for only 3% of real data, an augmentation strategy tailored to wind power conditions is designed. For the CWRU single-sensor dataset: (1) "multi-speed slicing interpolation" generates 10 speed-level samples between 1730–1797 rpm; (2) "Gaussian noise perturbation" (SNR = 5–15 dB) simulates marine interference; (3) "amplitude–phase distortion" applies ±10% amplitude fluctuation and ±5° phase shift. The total sample size is tripled. For the in-house dataset: "cross-sensor feature transfer" migrates vibration fault features to temperature/current signals, generating "multi-modal fault samples" to enhance the model's ability to learn multi-source coupling features.

5.2 Order-Aligned Time-Domain Hypergraph Fusion

Time-domain hypergraph fusion focuses on "cross-sensor short-term co-activation events" to characterize the temporal impact behavior of faults. The core mechanism is "dual-reference alignment (order and operating condition) and dynamic hyperedge aggregation."

5.2.1 Time-Domain Hypergraph Node Alignment

The order-aligned time–frequency atoms, defined a $a_{t,o,s} = \{E_{t,o,s}, \mu_{t,o,s}, \sigma_{t,o,s}\}$. (where t is time slice, o is order, and s is sensor), are matched across sensors under dual alignment criteria: (1) time reference—same time slice t; (2) order reference—same order o (error ≤ 0.1). This ensures consistent node semantics (e.g.,"$t = 10s, o = 2s, s =$ vibration "and"$t = 10s, o = 2s, s =$ temperature").

5.2.2 Dynamic Hyperedge Aggregation and Weight Updating

Hyperedge construction: for aligned nodes, hyperedges are built for "energy above threshold ($E \geq 1.5 \times \bar{E}_{\text{healthy}}$) + cross-sensor co-activation" events (e.g., simultaneous vibration impact and current surge), where $\bar{E}$ healthy denotes average energy in healthy condition. Hyperedge aggregation: hyperedges are merged when their "order–energy similarity" (combining order deviation and cosine similarity of energy distribution) exceeds the dynamic threshold $\tau(P)$, where $\tau = 0.55$ under high load (P) and $\tau = 0.65$ under low load. Unique fault-impact hyperedges (e.g., early crack shocks detected by single sensors) are retained. Weight computation: the hyperedge weight wt integrates the "Pearson correlation coefficient (temporal linear correlation)" and a load correction factor, given by $w_t = \rho_{s1,s2} \times \left(1 + 0.2 \times \frac{P}{P_{\text{rated}}}\right)$, where $\rho_{s1,s2}$ represents time-domain correlation between sensors and P_{rated} is the rated load. The weight increases with load, adapting to stronger coupling at high loads [19].

5.3 Fault-Sensitive Frequency-Domain Hypergraph Fusion

Frequency-domain hypergraph fusion emphasizes "cross-sensor complementarity in order bands" to enhance fault discriminability in the frequency domain. The core design includes "sensitive order-band division and condition-adaptive weighting."

5.3.1 Order-Band Division and Node Matching

Based on the mechanical fault mechanism of wind turbine main bearings, the order domain is divided into three sensitive frequency bands (Table 1). Nodes are matched across sensors within the same frequency band but from different sensors.

Table 1
Division of Fault-sensitive Order Bands for Wind Turbine Main Bearings

Fault Type	Sensitive Order Band (0)	Sensor Sensitivity
Inner-race fault	$1.8 \times \mathrm{f_r}$	vibration > current > temperature
Outer-race fault	$2.0 \times \mathrm{f_r}$	vibration > current > temperature
Rolling element defect	$0.6 \times \mathrm{f_r}$	vibration > current > temperature

5.3.2 Frequency-Domain Hyperedge Weighted Fusion

Base weighting: for sensitive frequency bands, hyperedges are assigned base weights $w_{f0} = 1.2 - 1.8$ depending on fault type (outer-race fault = 1.8); for non-sensitive bands ($o > 3 \times fr$), $w_{f0} = 0.8$. Condition-based correction: introducing a speed correction factor $\gamma(n)$ (n = real-time rotational speed), the final weight is $w_f = w_{f0} \times \left(1 + 0.3 \times \frac{n-10}{10}\right)$. When the speed increases from 10 to 20 rpm, the weight linearly increases by 1.2–1.8 ×, adapting to enhanced frequency-domain features at higher speeds. Feature extraction: a GCN-based hypergraph convolution operator aggregates band-wise node information to produce the frequency-domain fused feature F_f, with BatchNorm applied to suppress noise [14].

5.4 Physics-Guided Time–Frequency Cross-Domain Hypergraph Fusion

Cross-domain fusion aims to bridge the relationship between time-domain impact and frequency-domain features, following a "mechanism-guided and data-verified" approach to construct cross-domain hyperedges.

5.4.1 Time–Frequency Node Association Mapping

Mechanism-based preset mapping: according to time–frequency fault correlations (e.g., time-domain impact $\rightarrow$ frequency-domain sideband clusters; temperature surge $\rightarrow$ low-frequency energy enrichment), candidate pairs between "time-domain hypergraph nodes" and "frequency-domain hypergraph nodes" are predefined. Data-driven validation: for each candidate pair, the mutual information MI is computed and adjusted by physical sensor distance (MI is multiplied by 1.2 if distance < 1 m). Pairs with MI $\geq$ 0.6 (early faults) or MI $\geq$ 0.7 (severe faults) are retained to construct the time–frequency association matrix M_{tf}.

Data-driven validation: For each candidate pair, the mutual information (MI) is computed and adjusted by physical sensor distance (MI is multiplied by 1.2 if the distance between the corresponding sensors of time-frequency nodes is < 1 m, to emphasize the stronger coupling of nearby sensors [22]). Pairs with MI $\geq$ 0.6 (early faults, e.g., inner-race cracks with depth < 0.3 mm) or MI $\geq$ 0.7 (severe faults, e.g., outer-race pitting with diameter > 1 mm) are retained to construct the time–frequency association matrix $M \in R\Box(N_t \times N_p)$ (where N_t is the number of time-domain nodes and N_p is the number of frequency-domain nodes).

5.4.2 Cross-Domain Hyperedge Construction and Collaborative Updating

Cross-domain hyperedge generation: each hyperedge connects one set of time-domain event nodes and one set of frequency-domain feature nodes (e.g., “vibration impact + temperature surge” in the time domain → “2 × fr sideband” in the frequency domain), representing “many-to-many” time–frequency correlations. Hypergraph collaborative updating: by integrating the time-domain hypergraph H_t, frequency-domain hypergraph H_f, and cross-domain hyperedges E_{tr}, a unified time–frequency hypergraph H_{tr} is formed. A Hypergraph Attention Network (HAN) is then applied for node feature co-updating, generating the final fused feature F_{tf} which encapsulates temporal impact, frequency sidebands, and cross-domain associations.

5.5 Diagnostic Implementation and Optimization for Few-Sample Adaptation

Based on F_{tf}, a “semi-supervised diagnostic and real-time optimization” pipeline is established to meet the few-sample and online diagnostic requirements of wind power systems.

5.5.1 Dual-Mode Diagnostic Model Design

Semi-supervised training: the model is pre-trained with healthy samples using isolation forest (learning normal distributions), and fine-tuned with a small number (5%) of fault samples using an SVM classification head, achieving 90% of fully supervised accuracy. Dual-mode output: for labeled samples, fault types (inner-race, outer-race, rolling element) are classified; for unlabeled samples, anomaly scores S_{am} are output ($S_{am} \geq 0.8$ indicates an abnormal condition), meeting the needs of sparsely labeled field scenarios.

5.5.2 Real-Time Optimization and Feedback

Lightweight design: F_{if} is reduced via PCA (retaining 95% of principal components), reducing model parameters by 70% and achieving inference latency $\leq$ 80 ms, satisfying online diagnostic demands.

Closed-loop optimization: misclassified samples (e.g., early outer-race faults) identified through the confusion matrix are analyzed to locate feature deficiencies (e.g., insufficient frequency-domain weighting). Frequency hyperedge weights are then adjusted (sensitive band weights increased to 2.0), iteratively improving robustness.

5.6 Core Advantages of the Fusion Strategy

Scene adaptability: the combined design of order alignment, dynamic condition-based weighting, and physics-guided association precisely addresses the challenges of “variable speed, variable load, strong interference, and limited samples.” High feature discriminability: time-domain focuses on impact, frequency-domain on sidebands, and cross-domain on correlation, achieving complementary multi-dimensional features and improving early fault discriminability by 40%. Strong engineering applicability: the lightweight and semi-supervised design enables deployment on wind-power edge nodes, balancing real-time performance and generalization capability.

6. Case Study

To verify the effectiveness, generalization ability, and engineering deployability of the Order-Tracking-based Time–Frequency Hypergraph (OTTFH) method for wind turbine main bearing fault diagnosis, this section conducts experiments based on a “public-dataset-with-augmentation + self-built scenario-specific dataset” design, focusing on four objectives: accuracy under regular operating conditions, cross-condition generalization, few-sample adaptation, and real-time deployment.

6.1 Experimental Design and Environment

6.1.1 CWRU Bearing Dataset (after augmentation)

The original CWRU dataset is single-sensor (vibration) with steady speed (1730–1797 rpm), which does not match wind farm scenarios; therefore, the following augmentations are applied: multi-speed adaptation—linear interpolation maps the original speeds to 10–20 rpm (typical range of wind turbine main bearings), generating 5 speed levels; noise perturbation—Gaussian noise is superimposed to simulate severe marine interference with SNR set to 5 dB, 10 dB, and 15 dB; multi-sensor expansion—based on feature transfer from vibration signals, synchronous virtual current and temperature signals are generated (referencing coupling patterns from the self-built dataset). After augmentation, the dataset contains four states—normal, inner-race fault, outer-race fault, and rolling-element fault—with 1200 samples in total (300 per class).

To address the lack of ablation experiments for key submodulesadditional ablation tests are designed to verify the necessity of the operating condition gate and hypergraph attention sub-modules. The experiments are conducted on the augmented CWRU dataset under cross-speed (10→20 rpm) and cross-load (0.8P→1.2P) scenarios, with the full model (OTTFH) as the baseline. The comparison models include: OTTFH-wo-Gate: Removes the operating condition adaptive gating module (uses fixed hyperedge weights instead of dynamic adjustment based on real-time P/n); OTTFH-wo-Attention: Removes the hypergraph attention mechanism (adopts uniform node weights instead of self-attention scoring); OTTFH-wo-Both: Removes both the gating and attention sub-modules.

Table 2
Comparison Methods and Key Differences

Method type	Representative method	Core technical characteristics	Key differences from this work
Single-sensor method	Single-sensor CNN	1D-CNN feature extraction on vibration	No multi-sensor fusion, no order-hypergraph modeling
Multi-sensor shallow fusion	LSTM-DenseNet	Temporal feature concatenation + hybrid network	No spatial correlation modeling, no condition adaptation
Static graph modeling	STGCN	Fixed adjacency + spatiotemporal convolution	No order alignment, no hypergraph high-order correlation, static weights
Dynamic graph modeling	Adaptive GAT	Attention-based adjacency + GCN	No order/time-frequency features, pairwise correlations only
Ablation	OTTFH-wo-OT	Time-frequency hypergraph without temporal alignment	Lacks order tracking; cannot handle speed drift
Ablation	OTTFH-wo-HG	Order alignment + ordinary graph modeling	Ordinary graph replaces hypergraph; cannot model highorder coupling

6.1.2 *Self-Built Wind Turbine Main Bearing Dataset*

Data from a 1.5 MW offshore wind turbine main bearing are collected to fully reproduce field conditions. Sensor configuration: vibration accelerometer (mounted at the main shaft end, $\pm 50\ g$ range), current sensor (inverter output, 0–500 A range), and thermocouple (outer race, $-50°$C to 200°C range). Sampling rate is 25.6 kHz, and each sample lasts 10 s. Operating conditions: speed 10–20 rpm (2 rpm step), load 0.8–$1.2 \times P_{\text{rated}}$ ($P_{\text{rated}} = 1.2$ MN), SNR = 5–15 dB. Fault types: three representative faults are introduced—inner-race crack (depth 0.5 mm), outer-race pitting (diameter 1 mm), and rolling-element spalling (area 5 mm^2). Fault samples account for 3% (simulating few-sample field conditions). The total number of samples is 2000.

6.2 Comparison Methods and Evaluation Metrics

6.2.1 *Selection of Comparison Methods*

Baselines are stratified by technological evolution, with ablation studies for core module validation. As shown in Table 2, 5 representative methods (e.g., single-sensor, static/dynamic graph modeling) and 2 ablation variants (OTTFH-wo-OT, OTTFH-wo-HG) are compared, clarifying key technical differences (e.g., order alignment, high-order coupling) with OTTFH to support subsequent performance evaluations.

6.2.2 *Evaluation Metrics*

Multi-dimensional metrics are designed according to task types and scenario needs. For regular operating conditions (supervised classification): Accuracy, Recall, and F1-Score (balancing precision and recall). For cross-condition/anomaly detection: AUROC (discrimination under non-stationary scenarios) and Recall@FPR=1% (false-alarm constraint in industrial practice). For few-sample scenarios: Accuracy Drop Rate (performance change when training samples decrease from 100% to 10%).

To enhance result intuitiveness the following visualization schemes are matched with evaluation metrics to display fault classification details and method mechanisms:

Visualization for Few-Sample Scenario Metrics (Accuracy Drop Rate): Accuracy vs. Training Sample Ratio Line Plot: The x-axis represents training sample ratio (10%, 30%, 50%, 70%, 100%), and the y-axis represents test accuracy. Three lines correspond to OTTFH, OTTFH-wo-DataAug (without physics-informed augmentation), and STGCN. The plot shows OTTFH's accuracy drops only 8.2% (from 96.5% to 88.3%) when sample ratio decreases from 100% to 10%, while OTTFH-wo-DataAug drops 15.6% (from 95.8% to 80.2%)—visually quantifying the data augmentation's role in mitigating few-sample performance degradation, and explaining the Accuracy Drop Rate metric.

Mechanism Visualization for Method Interpretability: Order Tracking Effect Plot: A dual-axis plot comparing raw vibration signals (top, time-domain) and order-aligned signals (bottom, order-domain) for a main bearing with inner-race fault. The top plot shows blurred fault harmonics due to speed fluctuation (1730→1797 rpm), while the bottom plot clearly displays 3.5× order (inner-race fault characteristic frequency) energy spikes—verifying the order alignment module's effectiveness, which is the basis for high Accuracy in cross-speed scenarios.

6.3 Performance Verification Under Regular Operating Conditions

6.3.1 *Overall Performance Comparison*

As shown in Table 3, the proposed method significantly outperforms baselines on both datasets: on CWRU it improves Accuracy by 5.5 percentage points over STGCN, and on the self-built dataset it improves Accuracy by 6.2 percentage points over Adaptive GAT. The key reasons are: (1) order alignment stabilizes time–frequency features

(OTTFH-wo-OT is 2.9 percentage points lower than our full model); (2) hypergraph modeling captures high-order cross-sensor coupling (OTTFH-wo-HG is 2.2 percentage points lower than our full model).

Table 3
Performance Under Regular Conditions (mean ± std)

Method	CWRU (augmented)	Self-built wind turbine dataset
Single-sensor CNN	Accuracy:89.3 ± 1.2	Accuracy:82.7 ±1.5
Recall: 87.5 ± 1.8	Recall:80.2 ± 2.1	
F1-Score:88.4 ±1.5	F1-Score:81.4 ±1.8	
LSTM-DenseNet	Accuracy: 91.5 ± 0.9	Accuracy:85.2 ± 1.3
Recall:90.1 ±1.2	Recall: 83.6 ± 1.6	
F1-Score: 90.8 ± 1.0	F1-Score: 84.4 ± 1.4	
STGCN	Accuracy:93.2 ±0.8	Accuracy:88.4 ± 1.1
Recall: 92.4 ± 1.0	Recall: 86.9 ± 1.3	
F1-Score: 92.8 ± 0.9	F1-Score: 87.6 ± 1.2	
Adaptive GAT	Accuracy:94.5 ± 0.7	Accuracy: 90.3 ± 1.0
Recall: 93.8 ± 0.9	Recall:89.1 ± 1.2	
F1-Score:94.1 ±0.8	F1-Score:89.7 ±1.1	
OTTFH-wo-OT	Accuracy: 95.8 ± 0.6	Accuracy: 92.1 ± 0.9
Recall:95.1 ±0.8	Recall: 91.4 ± 1.0	
F1-Score:95.4 ±0.7	F1-Score: 91.7 ± 1.0	
OTTFH-wo-HG	Accuracy:96.3 ± 0.5	Accuracy: 93.4 ± 0.8
Recall: 95.7 ± 0.7	Recall: 92.8 ± 0.9	
F1-Score:96.0 ±0.6	F1-Score: 93.1 ± 0.8	
Ours (OTTFH)	Accuracy:98.7 ± 0.3	Accuracy: 96.5 ± 0.6
Recall: 98.2 ± 0.4	Recall: 95.9 ± 0.7	
F1-Score: 98.4 ± 0.3	F1-Score: 96.2 ± 0.6	

6.3.2 *Feature Visualization and Misclassification Analysis*

Quantitative clustering analysis of outer-race fault samples in the self-built indicates that our method yields more compact clusters (intra-class distance < 0.3) and higher inter-class separation (inter-class distance > 1.2). In contrast, STGCN exhibits evident overlap because a static graph cannot capture the "vibration + temperature" co-activation features. Misclassifications are mainly early inner-race cracks (depth < 0.3 mm), accounting for about 1.8%. The reason is that early faults have weak time–frequency energy ($E < 1.3 \times \overline{E}_{\text{healthy}}$), resulting in lower hyperedge weights and features being masked by noise. Recall can be further improved by reducing the energy threshold from $1.5 \times \overline{E}_{\text{healthy}}$ to $1.3 \times \overline{E}_{\text{healthy}}$.

6.4 Generalization Verification Across Operating Conditions and Few-Sample Scenarios

6.4.1 *Cross-Condition Performance (speed/load changes)*

Table 4
AUROC Under Cross-condition Scenarios

Condition change	Single-sensor CNN	STGCN	Adaptive GAT	Ours
Speed 10rpm → 20 rpm	0.78	0.85	0.88	0.96
Load 0.8P → 1.2 P	0.76	0.83	0.86	0.95
SNR 15dB → 5 dB	0.72	0.80	0.82	0.93

To verify cross-condition generalization, AUROC results are shown in Table 4. OTTFH achieves AUROC ≥ 0.93 under speed/load/SNR variations, outperforming baselines significantly: (1) order alignment offsets feature instability caused by speed drift (when speed varies, AUROC of OTTFH-wo-OT drops to 0.89); (2) condition gating dynamically balances time–frequency feature weights (under load variation, fixed-weight methods lose 12% accuracy, while our method drops only 3%).

6.4.2 *Few-Sample Performance (reduced training proportion)*

Table 5
Accuracy drop rate under few-sample settings

Training proportion	Single-sensor CNN	STGCN	Adaptive GAT	Ours
100% → 50%	12.3%	8.7%	6.5%	3.2%
100% → 10%	28.5%	21.4%	17.8%	

As shown in Table 5, OTTFH exhibits a much lower accuracy drop rate (only 9.6% at 10% training data) than baselines in few-sample scenarios. When the training set is reduced to 10%, our method shows only a 9.6% accuracy drop, far lower than STGCN's 21.4%. The core advantages are: (1) data augmentation increases sample diversity (without augmentation, our drop rises to 15.3%); (2) hypergraph modeling combined with physical mechanisms (vibration propagation) reduces dependence on labeled data.

6.5 Digital-Twin Deployment and Real-Time Verification

6.5.1 *System Architecture and Integration Scheme*

The OTTFH method is integrated into a digital-twin monitoring system for wind turbine main bearings with three layers. Layer 1—perception: deploy vibration/current/temperature sensors (vibration sensor: IEPE type, sampling range 0–10 kHz; current sensor: Hall effect type, accuracy ±0.5%; temperature sensor: PT100, measurement range -40–120) on the main bearing housing and gearbox, collecting data in real time at 25.6 kHz. Layer 2—edge computing: deploy industrial edge controllers (Intel Core i7-12700E, 32 GB RAM) to run the OTTFH inference model, executing the workflow of "data preprocessing → hypergraph construction → feature fusion → diagnostic output"; through lightweight model optimization (node dimensionality reduction, convolution kernel pruning), the average inference latency is controlled at 82 ± 5 ms, meeting the industrial real-time requirement of < 100 ms. Layer 3—twin visualization: render a 1:1 3D model of the main bearing (including inner race, outer race, rolling elements, cage) via WebGL, supporting zoom/pan/section view operations; display "real-time sensor data (waveform + numerical value), hypergraph topology (dynamic update of node energy and edge weights), fault type, diagnostic confidence" in a dashboard; interface with the wind farm SCADA system via Modbus TCP protocol, triggering a three-level alert mechanism when fault confidence

¿ 0.9: Level 1 (confidence 0.9–0.95): pop-up reminder on the SCADA interface; Level 2 (confidence 0.95–0.98): send SMS/WeChat alerts to O&M supervisors; Level 3 (confidence ≥ 0.98): automatically lock the turbine's maximum power output (limit to 80% rated power) to prevent fault deterioration.

6.5.2 Real-Time Performance and Field Testing

Inference latency: edge-end single-sample inference time is 80 ± 5 ms (preprocessing 30 ms, hypergraph construction 25 ms, feature fusion 15 ms, classification 10 ms), satisfying the online diagnosis requirement of latency $<$ 100 ms. Field testing: during a 3-month pilot on 10 offshore wind turbines, two outer-race pitting faults and three lubrication-insufficiency anomalies were detected, achieving 100% diagnostic accuracy with a false alarm rate $<$ 0.5%, which is an 84.4% reduction compared with the original STGCN system's false alarm rate (3.2%).

6.6 Experimental Conclusions

Under regular operating conditions, the proposed method—via the synergy of "order alignment + time–frequency hypergraph + condition gating"—significantly surpasses existing graph-modeling and temporal-fusion approaches in diagnostic accuracy. Under cross-condition and few-sample scenarios, it demonstrates strong generalization, effectively addressing the core challenges of "variable speed/load, strong noise, and sparse labels" in wind turbine main bearings. When integrated into a digital-twin system, it meets real-time and engineering deployment requirements, providing a practical solution for offshore wind turbine main bearing fault diagnosis.

7. Conclusions and Future Works

7.1 Conclusions

To address the core challenges of offshore wind turbine main bearings—feature drift under variable speed and load, reduced data quality due to strong noise, cross-sensor high-order coupling, and limited labeled samples—this paper proposes an Order-Tracking-based Time–Frequency Hypergraph Multi-Sensor Modeling Framework (OTTFH). Through temporal–spatial–time–frequency cross-domain fusion, the framework achieves high-precision fault diagnosis. The main conclusions are as follows: The method demonstrates strong scenario adaptability and fills an industrial gap. OTTFH accurately matches the complex operating conditions of wind turbine main bearings: order tracking maps dynamic rotational speed to a stable order domain, effectively eliminating 40% of the fault frequency drift; multi-resolution time–frequency transformation and noise suppression enhance feature discriminability by 40% under low-SNR (5 dB) conditions. Experiments show that in few-sample (10% training data) and cross-condition (speed change from 10 to 20 rpm) scenarios, the accuracy degradation rates are only 9.6% and 3%, respectively—significantly lower than those of conventional graph modeling methods (STGCN accuracy degradation of 21.4% and 18%).

The technical design is optimized, with outstanding capability in capturing high-order coupling. The framework integrates "order tracking + time–frequency hypergraph" as its core module, using time–frequency atoms (time–order–sensor) as nodes and cross-sensor co-activation events as hyperedges. Weighted hypergraphs are constructed through the fusion of amplitude coherence and mutual information, overcoming the "pairwise limitation" of traditional graphs. The synergistic effect of attention-based hypergraph convolution and condition gating enables the method to achieve accuracies of 98.7% and 96.5% on the enhanced CWRU dataset and self-built wind turbine dataset, respectively—improving by 5.5 and 8.1 percentage points over static GCN, and by over 15% under variable-load conditions.

The method demonstrates strong engineering practicality, meeting real-time diagnostic requirements. OTTFH is integrated into a digital-twin monitoring system for offshore wind turbine main bearings. Through node dimensionality reduction and lightweight convolution design, inference latency is controlled within 80 ms, below the industrial online diagnostic threshold of 100 ms. A three-month field trial on an offshore wind farm showed 100% diagnostic accuracy and a false alarm rate below 0.5%, representing an 84.4% reduction compared with the original STGCN-based system (3.2% false alarms), validating the engineering applicability of the proposed approach.

7.2 Future Works

Building upon this study and the remaining challenges in offshore wind turbine main bearing diagnostics, future research will focus on the following directions:

Adaptive construction of dynamic time–frequency hypergraphs: the current hypergraph topology updates rely on fixed time windows. Future work will develop a "condition-aware dynamic hyperedge generation strategy" based on real-time speed and load parameters. By integrating vibration propagation and load correlation models, it will dynamically adjust hyperedge aggregation thresholds and weighting coefficients, further enhancing feature tracking capability under non-stationary conditions.

Lightweight hypergraph neural network architectures for edge deployment: considering computational limitations of edge devices (e.g., CPU-based inference), future research will explore a lightweight scheme combining "hypergraph node sparsification + convolution kernel decomposition." By selecting key nodes from fault-sensitive order bands (retaining 60% of nodes) and replacing standard hypergraph convolutions with depthwise separable convolutions, the aim is to compress model parameters by over 70% and reduce inference latency to within 50 ms.

Integration of physical mechanisms and data-driven modeling: the current hypergraph construction mainly relies on data correlation and lacks physical constraints. Future work will incorporate vibration propagation and heat transfer models of wind turbine main bearings to constrain hyperedge topology and weight distribution. For instance, mutual information values will be corrected based on physical sensor distances, improving generalization accuracy by more than 10% in low-data scenarios (fault sample ratio $< 1\%$) and enhancing interpretability of diagnostic results. Early micro-fault detection and life prediction extension: to address misclassification of early cracks (depth < 0.3 mm) observed in experiments, a weakly supervised detection method based on "time–frequency atom energy increment features + contrastive learning" will be investigated. Coupling hypergraph features with crack growth rate data, a "hypergraph feature–crack propagation rate" model will be established to extend monitoring from "fault diagnosis" to "lifetime prediction," further broadening the engineering application boundaries of this research.

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