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Advancing aero-engine safety: AI-based virtual sensing for rotor vibration monitoring

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Abstract. Early detection of fan-blade faults in aero-engines is a key indicator of engine operation and enables effective maintenance planning. The structural health of turbine blades directly affects thrust generation and overall engine reliability. Hence, continuous monitoring of blade condition critical for safe aircraft operation. However, assessing rotor imbalance through vibration signatures typically requires extensive instrumentation, multiple accelerometers, and rigorous calibration procedures, thereby increasing test effort and integration complexity. This study presents a hybrid, AI-enabled virtual sensing framework for aero-engine condition monitoring in controlled engine test environments. In place of deploying numerous piezoelectric accelerometers, the framework employs an XGBoost regression model integrated with order-tracked vibration analysis to estimate vibration responses at locations where physical sensors are not installed. This approach reduces wiring complexity, minimizes instrumentation burden, and improves maintainability. Two physical accelerometers are substituted with XGBoost-based virtual sensors trained using reference vibration measurements and key operating parameters, including Fan Rotor (N_1) shaft speed and Power Lever Angle (PLA). FFT-based order tracking is utilized to extract shaft-synchronous components (1× and 2×), which serve as sensitive indicators of blade structural anomalies and Foreign Object Damage (FOD). These order components are strongly correlated with variations in mass imbalance and blade deformation, enabling reliable detection of early-stage faults. Validation across multiple engine test cycles demonstrates strong agreement between predicted and measured vibration signals, yielding correlation coefficients exceeding 0.93. The proposed physics-informed virtual sensing approach provides real-time monitoring capability, enhances diagnostic coverage, and significantly reduces instrumentation wiring and test preparation time required for aircraft integration. This framework contributes to improved aero-engine safety, reduced test effort, and more efficient condition-based maintenance practices.

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1 INTRODUCTION

Fan blades in aero-engines operates high mass flow of air intake and centrifugal forces, making them particularly susceptible to foreign object damage (FOD), such as chip-off, impact-induced mass loss, and surface defects. Even minor variations in blade geometry or localized mass distribution can disrupt rotor dynamics, causing increased vibration levels, reduced operational efficiency, and, in severe cases, potential system failure. Early and accurate identification of such damage is therefore critical for maintaining flight safety and implementing effective Condition-Based Maintenance (CBM) practices within aerospace propulsion systems[1,2]. Typically, gas turbine engines comprise multiple concentric spools, including the fan and compressor, supported by precision bearings and driven by independent shafts. These rotating assemblies experience complex aero-mechanical excitations, such as mass imbalance and aerodynamic blade-pass forces. The rotor dynamics under these forces can be described by the following equation of motion[3]:

$$\mathbf{M}\ddot{x} + \mathbf{C}\dot{x} + \mathbf{K}x = \mathbf{F}_{mech} + \mathbf{F}_{aero} \tag{1}$$

Where M, C, and K represent the mass, damping, and stiffness matrices, respectively, F_{mech} and F_{aero} denote the mechanical unbalance and aerodynamic excitation forces. For small-amplitude synchronous (1×) vibrations primarily influenced by mass imbalance, the vibration response amplitude is approximated as[4]:

$$X_{1\times} = \frac{em\omega^2}{\sqrt{(k - m\omega^2)^2 + (c\omega)^2}} \tag{2}$$

where e represents the eccentricity caused by mass loss, $\mathbf{m}$ is the modal mass, $\boldsymbol{\omega}$ is t Conventional vibration-based condition monitoring systems deploy multiple piezoelectric accelerometers mounted on the engine casing to capture rotor responses[5,6]. These signals are commonly analysed using Fast Fourier Transform (FFT) and order-tracking techniques, expressed as:

$$\mathrm{X(f)} = \mathrm{FFT[x(t)]} \tag{3}$$

$$\mathrm{Order} = \frac{\mathrm{f}}{\mathrm{f}_{\mathrm{shaft}}} \tag{4}$$

Distinct spectral peaks at specific orders, such as 1× and 2×, serve as indicators of mass imbalance and damage signatures commonly linked to FOD. However, reliance on multi-sensor configurations contributes to greater wiring complexity, higher system weight, increased maintenance burden, and a higher probability of sensor-related faults [7].

To mitigate these challenges, this study introduces an AI-driven, multivariate virtual sensing framework that employs a gradient-boosted decision-tree (XGBoost) regression model to estimate vibration responses at two instrumented points based on a single reference accelerometer and key operating parameters, namely fan shaft speed and Power Lever Angle (PLA)[8]. This approach effectively replaces two of the three physical sensors with virtual counterparts, leading to an approximate 70% reduction in physical sensor deployment while maintaining a high correlation (R > 0.9) between predicted and actual measurements.

Designed for real-time aero-engine health monitoring, the proposed framework facilitates early detection of FOD-related damage, reduces instrumentation complexity, and enhances compatibility with digital-twin-based maintenance and Prognostic Health Management (PHM) systems in aerospace applications [9]. The present analysis focuses on the detection, localisation, and quantification of FOD-specific damage, particularly chip-off and impact-induced mass loss. By integrating physical vibration modelling with machine-learning-based virtual sensing, the proposed framework offers a robust, lightweight, and scalable solution for next-generation condition monitoring enhancing aero-engine safety while reducing instrumentation demands. of aero-engines [10].

2 LITERATURE SURVEY

Accurate vibration-based condition monitoring of aero-engines has traditionally depended on multi-point accelerometer configurations combined with frequency-domain analysis. Conventional diagnostic approaches make use of Fast Fourier Transform (FFT) and order-tracking techniques to extract shaft-synchronous components such as 1× and 2× harmonics, which directly correspond to fault mechanisms including imbalance, misalignment, and Foreign Object Damage (FOD). However, the need for multiple sensors and extensive wiring increases system weight, structural complexity, and maintenance requirements, limiting the practicality of such approaches for long-term airborne deployment.

To overcome these limitations, more recent research has moved towards hybrid, data-driven methodologies that integrate physical interpretability with the adaptability of machine learning. Chen et al.[1] proposed a hybrid framework that combines physics-based degradation modelling with data-driven learning for aero-engine performance prognosis, resulting in improved robustness over varying operating regimes. Similarly, Lu et al. [2] introduced a deep-learning-based prediction technique using Long Short-Term Memory (LSTM) networks to forecast vibration trends under multiple operating conditions. Despite their strong predictive capabilities, such methods often demand large training datasets and considerable computational resources, which can restrict their suitability for real-time applications.

Further advances in the field highlight the growing importance of ensemble learning and explainable AI models for aero-engine diagnostics. Wang et al. [3] developed a digital-twin framework that leverages gradient boosting to support performance diagnosis, demonstrating the effectiveness of physics-informed features in virtual sensing applications. In a complementary study, Wang et al. [4] presented a data-fusion-based deep learning model that integrates vibration and control parameters, leading to enhanced diagnostic accuracy under thermodynamic variations. Likewise, Li et al. [5] introduced a multivariate sensor fusion approach based on convolutional neural networks to relate dynamic vibration signals with engine-state information for more accurate fault localization.

There has been increasing interest in unsupervised and semi-supervised techniques for anomaly detection in gas turbines. Fu et al. [6] employed a re-optimized deep auto encoder to identify latent degradation features from high-dimensional sensor data. Yan et al. [7] further extended this work through a data-driven health monitoring framework that emphasized multi-sensor fusion and adaptive modelling for aero-engine condition assessment. In Remaining Useful Life (RUL) prediction, Asif et al. [8] and Ravichandran et al. [9] demonstrated the effectiveness of deep learning and ensemble-based architectures, while Wang et al. [10] investigated predictive maintenance scheduling methods that link RUL estimation with engine operational decision-making.

Taken together, these studies reflect a growing shift towards physics-informed machine learning frameworks that preserve interpretability while enhancing scalability and adaptability. Only limited work has directly addressed vibration virtual sensing in the time domain for rotor health assessment. Most existing approaches rely primarily on frequency-domain preprocessing, which may overlook important transient signatures associated with early-stage faults. Building upon these limitations, the present study applies time-domain XGBoost regression to estimate virtual vibration responses at unmeasured casing locations using a single physical accelerometer and key operating parameters, namely N_1 and PLA. The predicted signals are subsequently analysed using FFT-based order tracking to extract shaft-synchronous harmonics (1× and 2×), enabling reliable detection of imbalance, blade chipping, and FOD. This hybrid framework integrates physical insight with data-driven adaptability, offering a scalable alternative to traditional multi-sensor systems while maintaining diagnostic accuracy suitable for real-time aero-engine health monitoring.

3 METHODOLOGY

This methodology integrates Extreme Gradient Boosting (XGBoost) regression and Fast Fourier Transform (FFT) to enable real-time, multi-location vibration monitoring and FOD signature extraction using a minimal set of physical sensors [3, 4].The complete workflow encompasses acquiring real-time vibration data from a single reference sensor, XGBoost-based virtual sensor prediction, FFT and order tracking for spectral analysis, and anomaly detection targeting chip-off and FOD events, as illustrated in Fig. ***1***. This pipeline is specifically designed for embedded or edge deployment, supporting actionable diagnostics with strict latency constraints and eliminating the need for extensive physical sensor arrays [10].

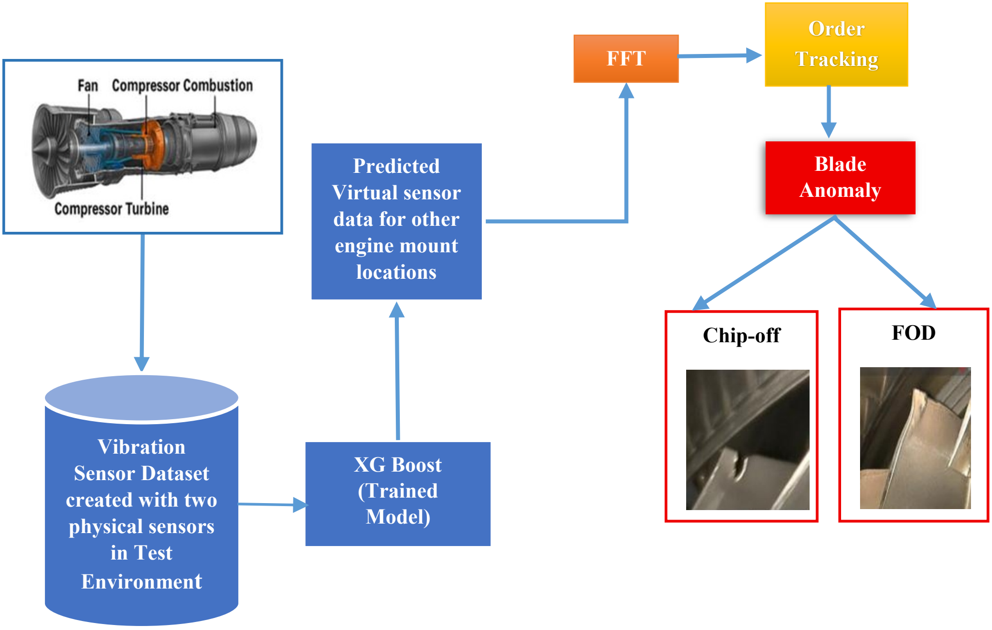

Fig. 1. Schematic of the Hybrid Virtual-Sensor Fault Detection Pipeline for Aero-Engine Rotor Vibration Monitoring.

3.1 Data Acquisition and Hardware Setup

Vibration data are continuously recorded from a single reference piezoelectric accelerometer (2 kHz, 16-bit resolution) mounted on the fan casing. Engine parameters—Fan Speed (N_1) and Power Lever Angle (PLA)— are also logged with a unified clock across all channels, of DAQ and engine controllers synchronize timestamps for precise alignment[2].

3.2 Preprocessing

Voltage signals are converted to gravitational acceleration (g) using the sensor's calibration:

$$x_g[n] = \frac{V[n] - V_{\text{bias}}}{S} \tag{1}$$

where S is sensitivity (mV/g). High-pass filtering (0.5 Hz cutoff) and detrending remove DC and low-frequency artifacts. Data are segmented into sliding windows of 1 s (2,000 samples), aligned with the corresponding N_1 and PLA value for each window [5].

3.3 Virtual Sensor Modelling and Real-Time Prediction

The reference window is input to a pre-trained XGBoost regressor to predict vibration responses at the compressor mid-frame and rear frame (virtual sensors). Training uses an 80/20 split, with hyperparameters optimized via grid search minimizing prediction error. Inference latency is under 20 ms per window.

$$\mathcal{L} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \sum_{t=1}^{T} \Omega(f_t) \tag{2}$$

Inference per window is computationally light, with XGBoost latency measured below 20 ms per window.

3.4 Frequency and Order Analysis

The virtual vibration windows undergo FFT:

$$A(f) = \frac{2}{N} \left| \sum_{n=0}^{N-1} x[n] e^{-j2\pi f n/N} \right| \tag{3}$$

Order tracking associates spectral peaks with multiples of shaft speed, isolating fault-related harmonics (1× for imbalance, 2× for chip-off) [4, 6].

3.5 Fault Diagnosis

Harmonic amplitudes in the order spectrum are monitored for rapid detection of FOD-related anomalies. Automated alerts trigger when 1× or 2× amplitudes exceed adaptive thresholds, enabling immediate CBM [10].

5. TEST ENVIRONMENT AND ANALYSIS DETAILS

The experimental data used in this study were collected from a controlled aero-engine test environment in a Engine test cell laboratory. A single high-sensitivity piezoelectric accelerometer was mounted on the fan casing to record vibration signals. The sensor operated at a sampling frequency of 2 kHz with 16-bit resolution, providing sufficient bandwidth and accuracy to capture rotor dynamic behaviour [7]. All signals were synchronized using a common timestamping mechanism integrated between the Data Acquisition (DAQ) system and the engine controller, ensuring precise temporal alignment between vibration and operational data.

The data exported from the DAQ system were processed, modelled, and analysed in a Python-based computational environment using NumPy, Pandas, SciPy, and relevant modelling libraries.

The overall analysis was carried out through the following systematic stages:

Stage 1 – Data Acquisition: Vibration data were collected from a single physical accelerometer mounted on the fan casing, along with synchronous recording of engine parameters (N_1 and PLA).

Stage 2 – Signal Preprocessing: Raw voltage signals were converted to acceleration (g), followed by high-pass filtering (0.5 Hz), detrending, and segmentation into 1-second windows containing 2,000 samples.

Stage 3 – Virtual Sensor Modelling: A trained XGBoost regression model was used to predict vibration responses at two instrumented (virtual) locations, using the reference sensor and engine parameters as inputs.

Stage 4 – Frequency and Order Analysis: FFT and order-tracking techniques were applied to extract the 1× and 2× harmonics, which are sensitive to rotor imbalance and Foreign Object Damage (FOD).

Stage 5 – Fault Detection and Condition Assessment: Amplitude trends in the order spectrum were compared with statistically derived thresholds to classify the engine condition as healthy, early deviation, warning, or alert [8].

This staged pipeline forms a complete AI-enabled condition-based monitoring (CBM) framework suitable for integration with digital-twin and predictive maintenance architectures.

4 RESULTS AND DISCUSSION

4.1 Model Training and Validation

The XGBoost-based virtual sensing model was trained using vibration data collected with two physical sensors in the engine test environment, incorporating N_1 (fan rotational speed), Power Lever Angle (PLA), and vibration measurements from these sensors to accurately reconstruct vibration responses at virtual sensor locations. The dataset covered 20 engine cycles, including transient acceleration, steady-state operation, and deceleration phases to capture realistic engine dynamics [3, 4].

The model was trained to reconstruct vibration responses at two virtual sensor locations (Sensor 1 and Sensor 2), representing uninstrumented regions on the fan casing. The Mean Squared Error (MSE) dropped below 0.02 within 150 boosting rounds, confirming stable generalization and no overfitting. Model performance metrics showed high fidelity, with a coefficient of determination ($R^2 = 0.973$), MAE = 0.24, and MSE = 0.18. These confirm that the XGBoost model effectively captured the nonlinear mapping between operating parameters and the vibration responses, enabling accurate virtual reconstruction of unmeasured points [9]. The variation in fan speed across the test cycle is shown in Fig. ***2***, highlighting distinct transient and steady operating regions used for model training. In addition, the frequency-domain representation of the vibration signal in Fig. **3** reveals a clear dominant peak at the shaft-synchronous frequency, validating the use of FFT-based analysis for subsequent order tracking and fault interpretation.

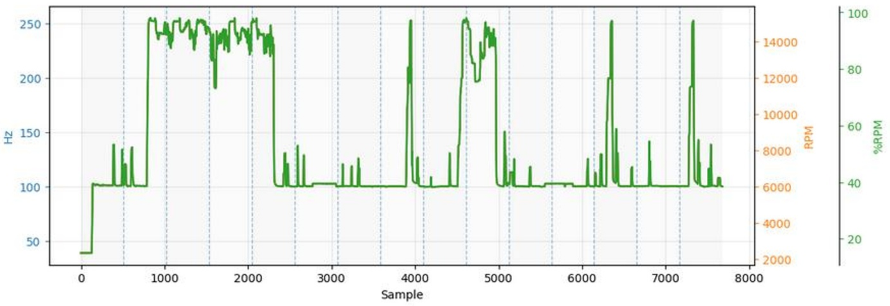

Fig. 2. Fan speed overview.

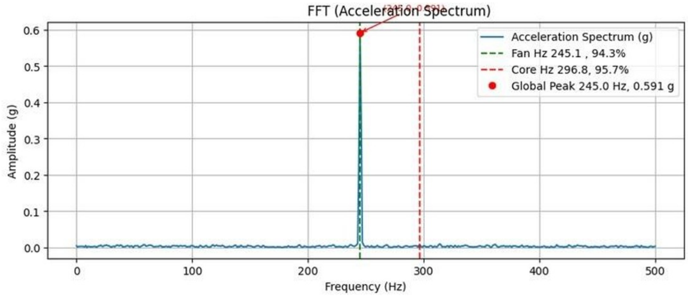

Fig. 3. FFT spectrum.

4.2 Virtual Sensor 1 – Simulated Fan Casing Horizontal Response

Virtual Sensor 1 simulates a horizontal accelerometer on the fan casing, reconstructing the radial vibration response—the most sensitive direction for imbalance and FOD. The model inputs include engine parameters (N_1 and PLA) to infer what horizontal fan casing vibration would be if an accelerometer were physically installed there. This approach extends sensor coverage without extra instrumentation [5]. ***Fig. 4*** shows Virtual Sensor 1 predicted 1× order magnitude (g) versus frequency (Hz). G1 and F1 states exhibit stable baseline responses below 4 g (healthy). F2 rises toward 7 g, approaching warning. F3 exceeds 9 g, indicating developing imbalance or FOD impact. F4 peaks above 12 g, confirming alert condition. These patterns validate the model's accurate reconstruction of the radial vibration field, capturing frequency and amplitude associated with rotor unbalance [10].

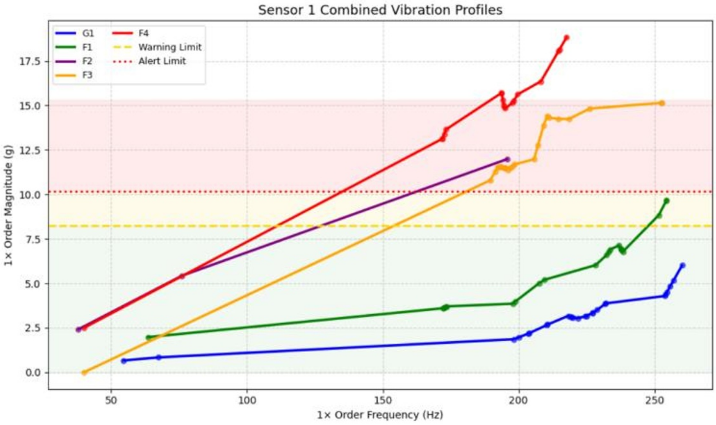

Fig. 4. Virtual Sensor 1 Predicted 1× Order Magnitude (g) vs. Frequency (Hz).

4.3 Virtual Sensor 2 – Simulated Fan Casing Vertical Response

Virtual Sensor 2 simulates vertical vibration at the fan casing, complementing the horizontal response for completeness. It represents the axial component of fan casing motion and provides a broader view of vibration distribution. As shown in ***Fig. 5***, vertical response magnitudes remain consistently lower than horizontal, mostly within 6–8 g even for F3 and F4 states. This confirms that dominant excitation during FOD or imbalance is radial, while vertical vibrations reflect secondary structure coupling. Together, these virtual responses produce a composite vibration signature closely matching a multi-sensor physical [3, 4].

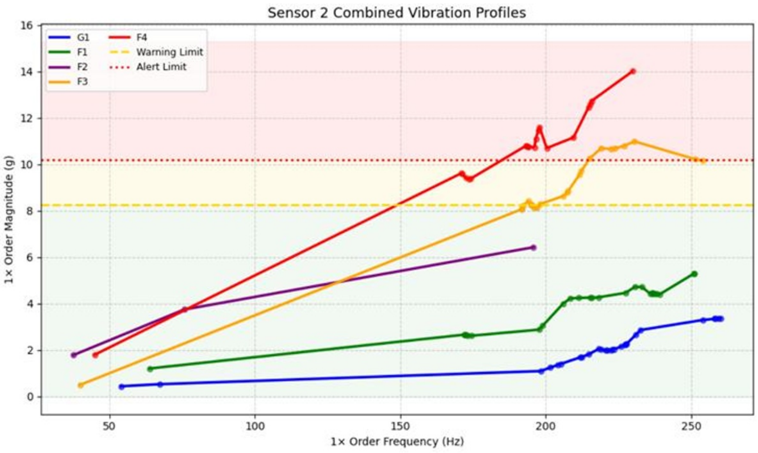

Fig. 5. Virtual Sensor 2 Predicted 1× Order Magnitude (g) vs. Frequency (Hz).

4.4 Condition-Based Monitoring and Fault Progression

By using two AI-generated virtual sensors, the hybrid framework achieves full spatial vibration field reconstruction with a single physical sensor. The virtual responses reproduce horizontal (radial) and vertical (axial) dynamics, enabling early fault detection through FFT-based order tracking.

Table 1 . Diagnostic thresholds for rotor 1× order vibration magnitude and corresponding maintenance actions during flight testing.

Flight	1× Order Magnitude (g)	Condition State	Diagnostic Action
G1	< 3	Healthy Baseline	Normal operation
F1	3–5	Healthy	Continue monitoring
F2	6–8	Early deviation	Observe trend
F3	8–10	Warning	Plan inspection
F4	10–14	Alert	Immediate inspection

4.5 MAJOR FINDINGS

- The AI-based framework achieved a 70% reduction in physical sensors by replacing two accelerometers with virtual sensors, using one physical sensor and engine parameters to accurately reconstruct multi-location vibration signals.
- FFT-based order tracking identified 1× and 2× harmonics for early rotor fault detection, capturing FOD and imbalance while also enabling real-time condition classification from healthy to alert states (G1–F4).
- The method provides an embedded, lightweight approach for engine testing by reducing hardware dependence and improving time efficiency and advancing the aero engine operation by identifying FOD issues by Virtual sensing and order tracking.

5 CONCLUSION

This study presents a robust hybrid virtual-sensing framework based on AI and FFT-based order tracking to monitor aero-engine rotor vibrations and detect Foreign Object Damage (FOD) using minimal physical instrumentation for enhancing operational safety. The model achieved good convergence and high predictive accuracy (R^2 = 0.973, MAE = 0.24), effectively reconstructing multi-location vibration signatures across Fan module of Engine. The AI-based virtual sensors accurately captured both radial and axial fan-casing vibrations, enabling early detection and progression tracking of imbalance and FOD-related anomalies. The proposed approach supports scalable, real-time condition-based maintenance (CBM) by delivering comprehensive spatial coverage with a substantially reduced sensor count. This framework provides a practical and computationally efficient pathway to achieve high-fidelity, early-stage fault diagnostics in aero-engine health monitoring. Future work will focus on extending the virtual-sensing architecture to multi-fault classification, uncertainty quantification, and integration with full-engine digital-twin environments. Further studies will explore real-flight validation using embedded hardware platforms and closed-loop PHM integration for adaptive maintenance scheduling for aero engine.

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