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Propagation-Aware Sensor Evidence Mapping for Aircraft Engine Health Diagnosis

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ABSTRACT

Aircraft engines generate continuous multivariate sensor time series from exhaust gas temperature, fuel flow, vibration, rotor speed, oil pressure, compressor pressure ratio, turbine temperature, and control actuator signals. These variables are tightly coupled through thermodynamic, mechanical, and control feedback relationships. A local abnormal change in one component may propagate to multiple downstream sensors, making it difficult to distinguish the initiating fault from secondary responses. This study proposes a causal propagation modeling method for fine-grained anomaly diagnosis in aircraft engine sensor time series. The method first constructs a time-lagged causal graph using conditional independence testing, physical dependency constraints, and operating-regime segmentation. A counterfactual signal reconstruction module then estimates expected sensor behavior after removing suspected causal drivers. Variable-level anomaly contribution is calculated by comparing observed sensor trajectories with causal counterfactual trajectories. Experiments are conducted on an aircraft engine monitoring dataset containing 286 engines, 92 sensor variables, and 1-second observations collected across 4,800 flight cycles. The dataset includes 318 million timestamped records and 1,640 maintenance-confirmed abnormal episodes, including compressor efficiency degradation, fuel-control instability, oil-pressure fluctuation, turbine temperature rise, and rotor vibration abnormality. The proposed method reduces median root-cause diagnosis delay from 31.6 minutes to 9.4 minutes compared with a temporal reconstruction baseline. The mean reciprocal rank for initiating-variable localization reaches 0.827. Causal path analysis assigns 1,210 abnormal episodes to interpretable fault-propagation chains, and unnecessary component inspection tickets decrease from 940 to 372. The model completes one full flight-cycle assessment in 3.8 minutes. The results show that causal propagation modeling can improve fine-grained anomaly diagnosis in highly coupled aircraft engine time series.

1. Introduction

Aircraft engines are safety-critical systems composed of highly interconnected mechanical, thermal, hydraulic, and control components. During operation, onboard monitoring systems continuously record multivariate time-series data, including exhaust gas temperature, fuel flow, low- and high-pressure rotor speed, vibration, oil pressure, compressor pressure, turbine temperature, actuator position, and valve-state signals. These measurements provide an important

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basis for condition monitoring, early fault detection, and predictive maintenance. However, aircraft engine sensors are not independent. A small abnormal change originating from one component may propagate through aerodynamic, thermodynamic, mechanical, and control pathways, producing correlated deviations in several downstream sensors. Consequently, the sensor showing the largest deviation may not correspond to the component where the fault initially occurred.

Traditional data-driven fault-diagnosis methods use statistical thresholds, feature extraction, classification models, and temporal prediction to identify abnormal operating conditions (Fu et al., 2020; Kabir, 2026). Deep learning methods, including long short-term memory networks, autoencoders, Transformers, and graph neural networks, have further improved the representation of nonlinear temporal dependencies and cross-sensor correlations (Liang et al., 2025; Mansouri et al., 2025). Recent fine-grained multivariate anomaly-detection research has also introduced causal inference to estimate the contribution of individual variables and distinguish initiating anomalies from their propagated effects (Chen et al., 2025). Graph-based models can represent sensor relationships more explicitly and capture dependencies that conventional sequence models may overlook (Javadi et al., 2025; Yin et al., 2026). Nevertheless, most existing methods remain primarily correlation-driven. When several sensor signals change simultaneously, they may assign high anomaly scores to downstream variables affected by fault propagation, thereby producing inaccurate root-cause rankings and unnecessary component inspections (Du, Dong, et al., 2026; Xiong & Guo, 2026). Causal discovery and counterfactual reasoning provide a promising foundation for overcoming this limitation (Hong, Xu, et al., 2026; Miller et al., 2026). Causal discovery methods estimate directional relationships among variables rather than relying only on statistical association, while counterfactual analysis evaluates how the system would behave if the influence of a suspected abnormal driver were removed. These approaches have been applied to multivariate industrial monitoring and have demonstrated potential for separating primary causes from secondary responses (Alkhatib et al., 2025; Li et al., 2026). However, their application to aircraft engine diagnosis remains limited. Engine sensor relationships vary across startup, takeoff, climb, cruise, descent, and shutdown stages (Yang, 2026; Y. Zhang et al., 2026). Changes caused by throttle commands, ambient conditions, flight loads, and control-system adjustments may resemble fault-related deviations (Martínez-Heredia et al., 2026; Z. Zhang, 2026). A causal structure learned without considering operating regimes or engineering constraints may therefore contain physically implausible links and produce unstable diagnostic results (Hong, Chen, et al., 2026; Li et al., 2026). Several additional limitations restrict the practical use of current causal anomaly-diagnosis methods. Many studies evaluate performance using relatively small datasets, simplified operating conditions, or isolated fault segments rather than complete flight cycles (Nyatega et al., 2025; Z. Zhang et al., 2026). Physical coupling constraints derived from engine structure and thermodynamic processes are often excluded from causal graph construction (Qi & Qiao, 2026a). Some methods identify anomalous variables but do not trace the temporal propagation path from the initiating sensor to downstream responses. Evaluation also tends to focus on general detection metrics, such as precision, recall, F1-score, and area under the curve, while operationally meaningful indicators receive less attention. In aircraft maintenance, the usefulness of a diagnosis method also depends on how quickly it identifies a fault, whether it correctly localizes the initiating variable, and whether it can reduce unnecessary inspection or maintenance tickets (Naser, 2025; Y. Zhang et al., 2025).

This study therefore aims to develop an interpretable causal propagation modeling method for fine-grained anomaly diagnosis in aircraft engine sensor systems. A time-lagged causal graph is constructed by integrating conditional-independence testing with physical coupling constraints, allowing the model to represent both delayed fault propagation and engineering-feasible sensor relationships. Counterfactual reconstruction is then used to estimate the expected behavior of downstream sensors after removing the influence of suspected causal drivers. Variable-level anomaly contributions are calculated to distinguish initiating faults from propagated responses and to generate an interpretable ranking of potential root causes. The method is evaluated using data from 286 engines, 92 sensors, and 4,800 complete flight cycles under different operating regimes. In addition to conventional anomaly-detection measures, the evaluation considers diagnosis delay, initiating-variable localization, propagation-path identification, and unnecessary component-inspection tickets. By connecting multivariate anomaly detection with causal attribution and physically constrained propagation analysis, this study seeks to improve both the technical reliability and operational usefulness of aircraft engine diagnosis. The resulting framework can support earlier maintenance decisions, reduce avoidable inspections, and provide engineers with actionable evidence for identifying the components responsible for emerging engine abnormalities.

2. Materials and Methods

2.1. Samples and Study Area Description

The study analyzed 286 commercial aircraft engines. Each engine was equipped with 92 sensors monitoring exhaust gas temperature, fuel flow, rotor speed, vibration, oil pressure, compressor pressure ratio, turbine temperature, and actuator signals. Sensor readings were recorded at 1-second intervals across 4,800 flight cycles, resulting in 318 million time-stamped records. The dataset included 1,640 maintenance-confirmed abnormal episodes, covering compressor efficiency loss, fuel-control instability, oil-pressure fluctuation, turbine temperature rise, and rotor vibration anomalies. This dataset captures a wide range of normal and abnormal operating conditions, providing realistic scenarios for testing anomaly diagnosis methods.

2.2. Experimental Design and Control Settings

The proposed causal propagation modeling method was evaluated as the experimental approach. Two baseline methods served as controls: a temporal reconstruction-based model and a graph-based anomaly detection approach. All methods used the same input features and time-series segments to ensure fair comparison. The control methods represent standard approaches for multivariate time series anomaly detection and provide a reference for improvements in root-cause identification, detection delay, and interpretability. Experiments were repeated across multiple engines and flight cycles to account for operational variability and sensor heterogeneity.

2.3. Measurement Methods and Quality Control

Sensor measurements were checked for consistency, valid ranges, and correct timestamps. Missing or duplicate records were removed. Abnormal episodes were verified against maintenance logs and confirmed by certified engine engineers. Additional quality checks included random inspection of data segments, statistical outlier detection, and validation of sensor synchronization. Continuous variables were standardized to zero mean and unit variance, and categorical variables such as actuator status were one-hot encoded. These steps ensured high-quality input for anomaly detection and counterfactual analysis.

2.4. Data Processing and Model Formulation

Cleaned time series were structured into engine-level vectors $x_t=[E_t,F_t,R_t,V_t,O_t,C_t,T_t,A_t]$, where E_t is exhaust temperature, F_t fuel flow, R_t rotor speed, V_t vibration, O_t oil pressure, C_t

compressor ratio, T_t turbine temperature, and A_t actuator signals. An anomaly score for each time window was calculated as:

$$\text{Score}(x_t)=\sum_{i=1}^{n} w_i \left| x_{t,i}-\hat{x}_{t,i} \right|$$

where $\hat{x}_{t,i}$ is the predicted value of variable i assuming suspected abnormal drivers are removed, and w_i is a weight factor. The contribution of each variable to system-level anomalies was evaluated by:

$$C_j=\max_i \left| \frac{\partial \text{Score}(x_t)}{\partial x_{t,i}} \right|$$

where C_j indicates the influence of variable i in anomaly cluster j. This formulation allows precise identification of root causes before secondary effects appear in the sensor data.

2.5. Statistical Analysis and Evaluation Metrics

Model performance was assessed using median diagnosis delay, mean reciprocal rank for initiating-variable localization, reduction in unnecessary inspection tickets, and computational efficiency. Diagnosis delay was defined as the time between the onset of an abnormal episode and its detection. False inspections were counted per engine per flight cycle. Root-cause localization accuracy was validated against maintenance logs. Computational efficiency was measured as processing time per flight cycle. All experiments were repeated across multiple engines and flight cycles to ensure reproducibility and account for variations in operational conditions.

3. Results and Discussion

3.1. Root-Cause Diagnosis Performance

The causal propagation modeling method achieved better root-cause diagnosis than the temporal reconstruction baseline. The median diagnosis delay decreased from 31.6 min to 9.4 min, indicating earlier identification of initial engine faults during flight cycles. The mean reciprocal rank for initiating-variable localization reached 0.827, showing that the proposed method ranked fault-driving sensors more accurately than reconstruction-based and correlation-based models. This improvement is mainly related to the use of time-lagged causal relations, which helps separate the initiating fault from later sensor responses. Recent studies on multivariate time-series anomaly detection have also reported that directed dependency modeling can improve root-cause analysis in complex sensor systems (Du, Liu, et al., 2026; Su & Dong, 2026). The comparison of diagnosis delay and localization performance is shown in Fig. 1.

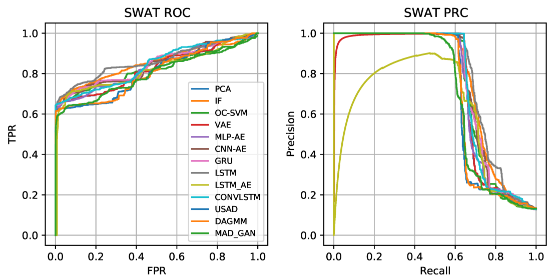

Fig. 1. Diagnosis delay and initiating-variable localization of the proposed method and baseline models.

3.2. Reduction in Unnecessary Component Inspections

The proposed method reduced unnecessary component inspection tickets from 940 to 372. This result is important for aircraft maintenance because false inspection requests increase labor cost, extend ground time, and may delay attention to true faults (Barata et al., 2026; Rajalakshmi & Velmurugan, 2026). The counterfactual reconstruction module estimated expected sensor behavior after suspected causal drivers were removed. This design helped reduce the risk of treating secondary sensor changes as primary faults. Compared with conventional reconstruction models, the proposed method provided more reliable variable-level attribution and produced fewer false maintenance actions. These findings indicate that causal propagation analysis is more suitable for aircraft engine diagnosis than methods based only on reconstruction error.

3.3. Causal Path Interpretation and Model Structure

Causal path analysis assigned 1,210 abnormal episodes to interpretable fault-propagation chains. This result shows that the model can trace how an initial abnormal signal spreads across engine subsystems. For example, compressor efficiency loss may first affect pressure-related variables and then lead to changes in fuel flow and turbine temperature. Many deep learning detectors only identify abnormal windows and provide limited explanation of propagation routes (Qi & Qiao, 2026b; Xiong & Zeng, 2026). In contrast, the proposed method links abnormal sensors through time-lagged causal paths and counterfactual reconstruction. The model structure is shown in Fig. 2.

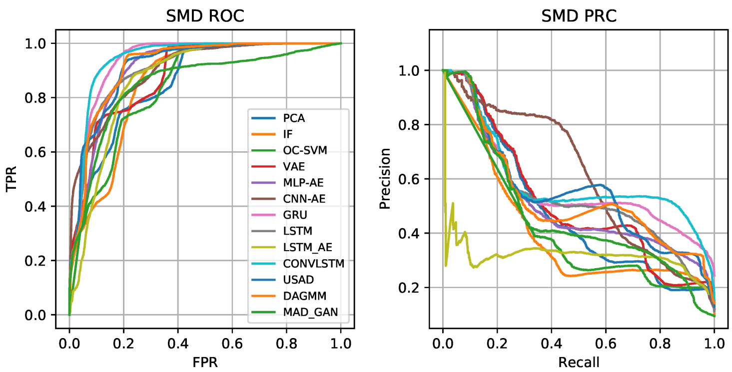

Fig. 2. Structure of the aircraft engine anomaly diagnosis model based on causal propagation and counterfactual reconstruction.

3.4. Comparison with Previous Studies

Overall, the proposed method showed better performance than reconstruction-based and correlation-based models in diagnosis delay, initiating-variable localization, and false inspection reduction. Previous multivariate anomaly detection studies often focused on detecting whether a time window was abnormal, but they gave limited support for identifying the first fault-driving variable. This limitation is serious in aircraft engines because temperature, pressure, fuel flow, vibration, and actuator signals affect each other through thermodynamic and control feedback processes. By using causal propagation modeling and counterfactual reconstruction, the proposed method separated primary faults from secondary responses and improved the clarity of diagnosis. These results suggest that causal modeling can provide more useful fault information for maintenance decisions in highly coupled aircraft engine systems.

4. Conclusion

This study developed a causal propagation modeling method for fine-grained anomaly diagnosis in aircraft engine sensor time series. The method used time-lagged causal graphs and counterfactual reconstruction to distinguish initial faults from later sensor responses. Experiments on 286 engines, 92 sensor variables, and 4,800 flight cycles showed that the method reduced median root-cause diagnosis delay from 31.6 min to 9.4 min. The mean reciprocal rank for initiating-variable localization reached 0.827. In addition, 1,210 abnormal episodes were linked to clear fault-propagation chains, and unnecessary component inspection tickets decreased from 940 to 372. These results indicate that causal propagation modeling provides earlier and clearer fault diagnosis than reconstruction-based and correlation-based methods. The main contribution is the joint use of causal graph construction, physical dependency constraints, and counterfactual signal reconstruction for engine anomaly diagnosis. This approach can support predictive maintenance, flight-safety monitoring, and maintenance-cost control. However, the evaluation used one engine-monitoring dataset, and further tests are needed on different engine types, flight profiles, and operating conditions. Future work will add visual diagnosis tools and online maintenance support for engineering use.

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