An Integrated Analytical Framework for Fault Detection and Predictive Maintenance of the Boeing 787 GEnx-1B Engine

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Abstract: The Boeing 787 Dreamliner is powered by the GEnx-1B turbofan engine, a highly efficient propulsion system that relies on advanced digital control and diagnostic technologies to ensure safe and reliable operation. Traditional maintenance strategies based on reactive or scheduled interventions are increasingly being replaced by predictive and condition-based approaches. This study proposes an integrated analytical framework for sustainable fault detection and predictive maintenance of the GEnx-1B engine, combining the Full Authority Digital Engine Control (FADEC), Engine Electronic Controller (EEC), Engine Monitoring Unit (EMU), and Common Data Network (CDN). The paper analyzes the data acquisition and communication architecture of these subsystems and examines how condition-based maintenance (CBM) and reliability-centered maintenance (RCM) principles can be enhanced using machine learning approaches such as multilayer perceptrons (MLP), long short-term memory (LSTM) networks, and adaptive neuro-fuzzy inference systems (ANFIS). A literature-grounded analytical comparison of diagnostic workflows and predictive maintenance strategies illustrates the expected benefits of integrating onboard systems with AI-driven analytics, including earlier anomaly detection and improved maintenance planning. The proposed framework supports the transition from reactive to predictive maintenance in modern aviation and provides a conceptual foundation for future data-validated implementations on next-generation aircraft engines.

1 INTRODUCTION

The increasing digitalization of aircraft systems has significantly enhanced engine monitoring, fault detection, and maintenance processes. The GEnx-1B turbofan engine, used on the Boeing 787 Dreamliner, incorporates an integrated electronic architecture that enables continuous acquisition and analysis of operational data throughout the engine lifecycle. Key elements of this architecture include the Full Authority Digital Engine Control (FADEC) system, the Electronic Engine Controller (EEC), and the Engine Monitoring Unit (EMU), which together support real-time control, diagnostic functions, and data exchange via the Common Data Network (CDN).

Conventional maintenance strategies based on fixed intervals or reactive fault response are limited in their ability to reflect actual engine condition and operational variability. Recent advances in sensor technology, avionics data networks, and artificial intelligence (AI) have enabled the adoption of condition-based and predictive maintenance approaches, improving fault anticipation and maintenance efficiency [1].

However, existing research on turbofan fault detection largely focuses on standalone data-driven methods, with limited integration of diagnostic analytics into onboard control and monitoring systems. In particular, the coordinated application of predictive algorithms within the FADEC-EEC-EMU framework of the GEnx-1B engine remains insufficiently investigated [2].

This study addresses this gap by proposing an integrated framework for fault detection and predictive maintenance that combines onboard engine control and monitoring systems with intelligent diagnostic analytics, supporting early anomaly detection and reliability-centered maintenance. This study presents a system-level analytical framework rather than an experimentally trained predictive model. Quantitative performance values reported in later sections represent typical ranges derived from published studies and industrial reports cited accordingly. The purpose of the evaluation is to demonstrate expected operational impact and architectural feasibility rather than to claim experimentally validated performance.

2 RELATED WORK

The development of advanced diagnostic and predictive maintenance systems for aircraft engines has been an active field of research over the past two decades. Traditional fault detection approaches relied primarily on threshold-based monitoring of key parameters such as exhaust gas temperature (EGT), rotor speeds, and oil pressure. While these methods were sufficient for early-generation turbofan engines, they lacked the capability to predict failures in advance or adapt to dynamic operating conditions. The emergence of digital control architectures such as Full Authority Digital Engine Control (FADEC), together with increased availability of high-resolution sensor data, enabled the transition toward condition-based maintenance (CBM) and predictive maintenance (PdM) strategies focused on real-time anomaly detection and prognostics [3], [4].

One of the foundational studies in this domain was conducted by Gharoun et al. [5], who proposed an integrated turbofan fault detection approach based on data-mining techniques. Their method used EGT residuals - the difference between predicted and measured values - as features for machine learning models including multilayer perceptrons (MLP), radial basis function networks, and adaptive neuro-fuzzy inference systems (ANFIS). The study demonstrated that data-driven models could identify abnormal engine behavior without explicit knowledge of internal engine dynamics. However, the approach operated primarily as a standalone anomaly detector and did not address integration with onboard diagnostic subsystems such as FADEC or Engine Electronic Controllers (EEC).

Subsequent research has increasingly incorporated artificial intelligence (AI) and machine learning (ML) into aero-engine diagnostics and maintenance decision-making. Survey studies highlight the growing role of predictive analytics and digital-twin concepts in aviation maintenance optimization [4]. Deep-learning-based predictive maintenance approaches, including long short-term memory (LSTM) models, have demonstrated improved capability for modeling temporal degradation behavior compared with traditional regression methods [6]. Additional research has explored transfer-learning strategies for adapting prognostic models across engine platforms while reducing labeled data requirements [7].

The role of condition-based maintenance (CBM) and reliability-centered maintenance (RCM) in aviation maintenance planning has also been widely discussed. Recent studies emphasize integrating sensor monitoring, reliability analysis, and AI-assisted decision support to reduce unscheduled maintenance events and improve lifecycle management [8]. Nevertheless, many works remain focused on maintenance policy optimization rather than tight coupling with onboard diagnostic subsystems such as the Engine Monitoring Unit (EMU) or aircraft data communication backbones like the Common Data Network (CDN).

Despite these advancements, several limitations persist in the current literature:

Integration gap. Many diagnostic models are implemented as standalone analytical tools without detailed interaction with onboard control and monitoring architectures (FADEC, EEC, EMU) [5], [7].

System-level perspective: few studies analyze the complete data flow from onboard sensing to ground-based predictive maintenance within a unified architectural framework.

Analytical validation context: comparative evaluations are often algorithm-centric and rarely framed within realistic operational maintenance workflows [4].

Platform specificity: limited analysis exists addressing how machine learning diagnostics can be operationalized within GEnx-1B-specific avionics and data architectures.

To address these gaps, this study proposes an integrated system-level framework for fault detection and predictive maintenance explicitly incorporating interactions among FADEC, EEC, EMU, and CDN subsystems. The framework further examines how MLP, LSTM, and ANFIS models can be embedded within this architecture to support anomaly detection, prognostics, and maintenance scheduling for the Boeing 787 GEnx-1B engine.

2.1 Methodology

This study proposes an integrated framework for sustainable fault detection and predictive maintenance of the GEnx-1B engine installed on Boeing 787 aircraft. The methodology adopts a system-level analytical approach, combining onboard diagnostic and control subsystems - including the Full Authority Digital Engine Control (FADEC), Engine Electronic Controller (EEC), Engine Monitoring Unit (EMU), and Common Data Network (CDN) - with data-driven analytics concepts and representative machine-learning models to support real-time anomaly detection and predictive maintenance decision processes.

Rather than developing or training a specific predictive model, the methodology focuses on architectural integration and functional interaction between onboard avionics systems and AI-based diagnostic analytics. The framework therefore evaluates how predictive algorithms can be operationally embedded within existing aircraft maintenance ecosystems, emphasizing data flow, decision logic, and maintenance feedback mechanisms.

The proposed framework is structured into three primary layers:

1) Data Acquisition and Control;
2) Data Communication and Processing;
3) Predictive Analytics and Maintenance Decision-Making [4], [7].

Together, these layers form a closed feedback loop that continuously monitors engine condition, enables analytical fault assessment, and supports condition-based maintenance planning consistent with modern predictive maintenance architectures.

2.2 Data Acquisition and Control Layer

At the core of the GEnx-1B digital control architecture is the Full Authority Digital Engine Control (FADEC) system (see Fig. 1), which governs engine operation through automated thrust regulation, fuel-flow control, and operational parameter management. The FADEC incorporates the Engine Electronic Controller (EEC), a dual-channel digital computing unit (channels A and B) designed to provide redundant and fault-tolerant control functionality.

The EEC receives continuous real-time sensor inputs distributed across the engine, including exhaust gas temperature (EGT), compressor and turbine pressures, low- and high-pressure rotor speeds (N1 and N2), vibration measurements, and fuel-flow and actuator position signals. These measurements are processed to generate control commands for actuators, valves, and fuel-metering components, enabling adaptive regulation of engine performance within certified operational limits.

In addition to control functions, the EEC performs onboard diagnostic monitoring by validating sensor consistency, detecting abnormal parameter deviations, and executing embedded fault-detection logic commonly described in aero-engine health-monitoring literature [5], [6]. When monitored parameters exceed predefined operational thresholds - for example abnormal temperature gradients or rotor-speed imbalance - diagnostic fault messages are generated and transmitted to higher-level monitoring subsystems for further analysis.

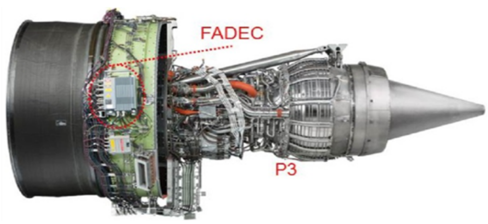

Figure 1: Location of the Full Authority Digital Engine Control (FADEC) within the GEnx-1B engine architecture.

Figure 1 illustrates the representative placement of the FADEC unit within the engine control loop. The FADEC functions as the central interface between sensor acquisition, control computation, and diagnostic monitoring. This centralized position enables continuous parameter acquisition and rapid response to abnormal operating conditions, forming the operational basis for integrating onboard diagnostics with predictive maintenance analytics proposed in this study.

2.3 Data Communication and Processing Layer

The Engine Monitoring Unit (EMU) serves as the primary data acquisition and logging interface within the aircraft health-management system (see Fig. 2). Its principal functions include:

- Recording long-term operational parameters such as vibration levels, temperature measurements, and rotor-speed characteristics.
- Logging diagnostic trouble codes (DTCs) generated by the Engine Electronic Controller (EEC) and associated subsystems.
- Transferring post-flight operational data to onboard and ground-based maintenance systems, including the Quick Access Recorder (QAR) and Aircraft Condition Monitoring System (ACMS).

- Maintaining historical performance datasets used for trend analysis and predictive diagnostics.

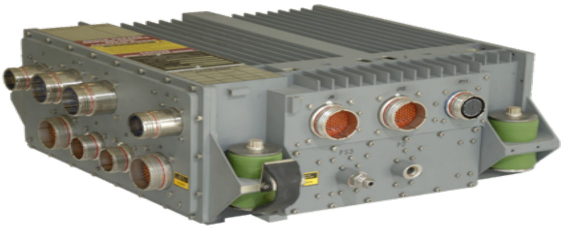

Figure 2: Engine Monitoring Unit (EMU) used for onboard data acquisition and health monitoring.

Figure 2 illustrates a representative Engine Monitoring Unit employed as the central interface for data collection and long-term engine health monitoring. The EMU aggregates diagnostic outputs produced by the EEC and other avionics subsystems and stores operational parameters for post-flight evaluation. By preserving historical performance records, the EMU enables trend analysis and anomaly identification, forming the data foundation required for condition-based and predictive maintenance workflows.

All data exchange between onboard subsystems is coordinated through the Common Data Network (CDN), a deterministic aircraft communication backbone based on the ARINC 664 (AFDX) protocol [7]. The CDN provides synchronized and high-throughput data transfer between control, monitoring, and avionics systems, enabling continuous operational data availability across the aircraft information architecture.

During operation, sensor and diagnostic data are distributed to multiple storage and analysis endpoints:

- Flight Data Recorder (FDR). Stores safety-critical flight and engine parameters for regulatory compliance and incident investigation.
- Quick Access Recorder (QAR). Retains detailed operational datasets for engineering diagnostics and performance evaluation.
- On-Ground Maintenance Server (OGMS). Receives transmitted datasets for fault analysis, predictive modeling, and maintenance planning.

Following landing, accumulated flight data may be transmitted to ground infrastructure via Ethernet, SATCOM, or ACARS communication channels. This near-real-time data availability enables maintenance personnel to initiate diagnostic assessment prior to aircraft arrival at the gate, reducing turnaround time and improving operational efficiency.

2.4 Predictive Analytics and Maintenance Decision Layer

The final layer of the proposed framework integrates machine-learning-based predictive analytics with condition-based maintenance (CBM) and reliability-centered maintenance (RCM) principles to support proactive maintenance decision-making. Historical performance records together with real-time sensor measurements are used to enable early anomaly detection, remaining useful life (RUL) estimation, and optimized maintenance scheduling.

This study presents an analytical integration framework rather than an experimentally trained predictive system. The performance characteristics discussed in this section are derived from published studies and representative operational scenarios reported in the literature.

Time-series features extracted from monitored engine parameters-such as exhaust gas temperature (EGT) residuals, rotor-speed variations, vibration signatures, and fuel-flow trends-are used as indicators of early mechanical degradation and abnormal operational behavior [6]. Within the proposed architecture, several machine-learning paradigms are considered conceptually to illustrate predictive capabilities. Multilayer perceptron (MLP) models enable nonlinear classification of engine operating states, long short-term memory (LSTM) networks support modeling of temporal degradation patterns in sequential flight data, and adaptive neuro-fuzzy inference systems (ANFIS) combine neural learning with fuzzy reasoning to improve interpretability of diagnostic decisions [4], [7]. These models are referenced as representative approaches reported in prior research rather than implementations trained within this study.

Model suitability is analyzed conceptually using commonly reported diagnostic indicators, including detection latency, false-positive rate, prediction horizon, and interpretability. Predictive outputs are assumed to be integrated into ground-based maintenance platforms such as the On-Ground Maintenance Server (OGMS) and Central Maintenance Computing Function (CMCF), where maintenance engineers can evaluate fault probabilities and RUL estimates to support CBM and RCM decision workflows.

2.5 System Workflow

Figure 3 illustrates the operational workflow of the proposed integrated diagnostic framework. The process begins with continuous sensor data acquisition and real-time engine control performed by the FADEC and EEC subsystems. Operational measurements are aggregated by the Engine Monitoring Unit (EMU) and transmitted through the Common Data Network (CDN) to onboard recording units and ground-based maintenance platforms. Predictive analytics modules conceptually analyze the transmitted data to identify potential anomalies, estimate degradation trends, and support maintenance planning decisions. The resulting diagnostic information is communicated to maintenance personnel via systems such as the On-Ground Maintenance Server (OGMS) and Central Maintenance Computing Function (CMCF), forming a closed feedback loop between onboard monitoring and ground-based analysis.

The workflow represents an architectural integration model demonstrating how sensing, communication, and predictive analytics components can operate within a unified maintenance ecosystem. The objective is to illustrate system interaction and data flow rather than to present experimentally validated performance outcomes.

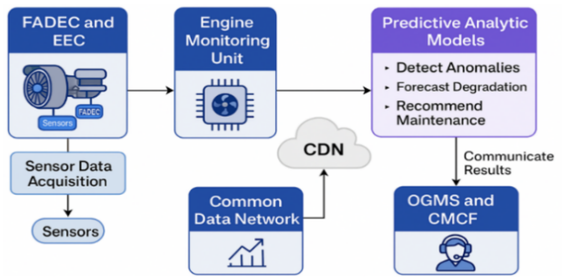

Figure 3: Workflow of the proposed integrated diagnostic framework showing data flow from onboard sensing and control (FADEC/EEC) through EMU and CDN communication to predictive analytics and ground-based maintenance decision systems.

2.6 Evaluation Protocol and Validation Assumptions

Since proprietary Boeing 787 operational datasets are not publicly accessible, validation is performed using a literature-grounded analytical evaluation protocol. Performance ranges are derived from published turbofan prognostics studies and publicly available benchmark environments, including the NASA CMAPSS dataset [9].

The evaluation follows a conceptual workflow commonly adopted in predictive maintenance research. Representative input variables include exhaust gas temperature (EGT), rotor speeds (N1/N2), vibration levels, fuel flow, and pressure measurements typically monitored by FADEC and engine health-management systems. Dataset characteristics correspond to publicly reported studies involving thousands of simulated flight cycles and degradation trajectories.

The analytical assessment considers widely used diagnostic metrics, including detection latency, false-positive rate, classification accuracy, and maintenance response time. Performance comparisons are interpreted relative to conventional threshold-based diagnostics, which serve as a baseline for evaluating AI-assisted predictive analytics approaches described in the literature.

The numerical ranges presented in subsequent sections therefore represent consolidated values reported across referenced studies rather than outcomes of a newly trained predictive model. The purpose of this evaluation is to assess the expected operational impact and architectural feasibility of integrating predictive analytics within the FADEC-EEC-EMU-CDN ecosystem.

The analysis focuses on three main aspects: diagnostic effectiveness of the integrated architecture, comparative suitability of predictive algorithms, and the operational impact of predictive maintenance strategies.

2.6.1 Diagnostic Workflow Analysis

The proposed diagnostic workflow, illustrated conceptually in Figure 3, consists of five sequential stages. First, continuous sensor measurements such as exhaust gas temperature (EGT), pressure, rotor speed, and vibration are collected by onboard sensors. Second, the Engine Electronic Controller (EEC) performs real-time control and threshold-based fault detection to maintain engine operation within safe limits. Third, operational data are logged by the Engine Monitoring Unit (EMU) and transmitted through the Common Data Network (CDN) to onboard recorders and ground maintenance systems, including the On-Ground Maintenance Server (OGMS). Fourth, predictive analytics models analyze historical and real-time data to identify degradation patterns and estimate potential failures. Finally, condition-based maintenance (CBM) and reliability-centered maintenance (RCM) frameworks interpret diagnostic outputs and support maintenance decision-making [7].

Literature studies indicate that predictive maintenance workflows generally reduce diagnostic latency and improve fault isolation compared with conventional threshold-based maintenance approaches [7], [10].

Table 1 presents representative performance ranges reported in prior research comparing conventional maintenance strategies with AI-assisted predictive maintenance frameworks.

Table 1 summarizes typical performance ranges reported in the literature comparing conventional maintenance and AI-assisted predictive maintenance frameworks.

These improvements demonstrate the value of integrating predictive analytics with onboard diagnostic systems [7], [8]. Early detection and higher accuracy directly contribute to reduced maintenance time, improved fleet availability, and lower operational costs.

2.6.2 Comparative Analysis of Machine Learning Models

A key component of the proposed framework is the use of machine learning methods for predictive diagnostics. This subsection presents a comparative analytical assessment of three representative algorithms - Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), and Adaptive Neuro-Fuzzy Inference System (ANFIS) - based on performance characteristics commonly reported in turbofan prognostics literature and operational studies. Table 2 summarizes typical analytical properties of these models with respect to diagnostic requirements in aircraft engine health monitoring.

Table 2 presents representative performance ranges consolidated from previously published studies rather than results obtained from model training within this work. The comparison indicates that LSTM networks are particularly effective for modeling temporal degradation processes due to their ability to capture long-term dependencies in sequential flight data. In contrast, ANFIS models provide improved interpretability, which is beneficial for maintenance decision support and engineering transparency.

MLP models remain suitable for rapid nonlinear classification tasks where computational efficiency and implementation simplicity are required. Existing literature suggests that LSTM-based approaches generally achieve improved early fault prediction capability, while ANFIS contributes explainable diagnostic reasoning useful in safety-critical environments [7], [10].

The complementary characteristics of these algorithms motivate a hybrid analytical perspective in which temporal prediction capability and interpretability are jointly considered. Such combinations have been discussed in predictive maintenance research as a practical trade-off between accuracy, explainability, and operational feasibility [4].

The trends summarized in Table 2 are consistent with reported developments in AI-assisted aircraft engine maintenance systems. Although the present study does not implement or train predictive models, the analysis illustrates how integrating machine-learning prognostics with onboard diagnostic subsystems (EEC and EMU) can support earlier fault awareness and improved maintenance planning within the proposed architecture.

Table 1: Diagnostic performance comparison between conventional and integrated predictive maintenance approaches.

Metric	Conventional maintenance	Proposed integrated framework	Typical improvement (reported ranges)
Fault detection latency	8-12 flight hours (after threshold breach)	1-2 flight hours (predictive detection).	~80% faster
False-positive rate	15-20% (manual review required)	5-8% (automated filtering and model-based validation)	~60% reduction
Fault isolation accuracy	75-82% (based on manual diagnostics)	90-95% (AI-enhanced analysis)	+10-15%
Mean time to repair (MTTR)	6-10 hours	3-6 hours	~40% reduction

Table 2: Comparative analytical performance of predictive models for turbofan diagnostics.

Criterion	MLP	LSTM	ANFIS
Temporal dependency modeling	Limited	Excellent	Moderate
Fault classification accuracy	87-90%	92-95%	89-92%
Prediction horizon (early detection)	Moderate (~4-6 hours)	High (~8-12 hours)	Moderate (~6-8 hours)
Adaptability to new fault types	Medium	High	Medium
Interpretability	Low	Low	High
Computational complexity	Low	Medium	High

3 CONCLUSIONS

This paper presented an analytical framework for sustainable fault detection and predictive maintenance of the GEnx-1B engine installed on Boeing 787 aircraft. The proposed approach integrates onboard control and diagnostic subsystems - including the Full Authority Digital Engine Control (FADEC), Engine Electronic Controller (EEC), Engine Monitoring Unit (EMU), and Common Data Network (CDN) - with machine-learning-based analytical concepts to form a closed-loop maintenance architecture addressing limitations of traditional reactive and scheduled maintenance strategies. Rather than introducing a newly trained predictive model, the study provides a system-level analysis illustrating how predictive analytics can be embedded within existing avionics and maintenance infrastructures. Literature evidence indicates that predictive maintenance architectures are capable of reducing diagnostic latency and false-alarm rates compared with conventional threshold-based approaches - for example, Table 1 summarizes reported ranges corresponding to an approximately 80% reduction in fault detection latency and an approximately 60% reduction in false-positive rate - while supporting improved operational planning and maintenance efficiency.

The comparative analytical assessment of representative machine learning approaches suggests that Long Short-Term Memory (LSTM) networks are well suited for modeling temporal degradation processes, whereas Adaptive Neuro-Fuzzy Inference Systems (ANFIS) offer improved interpretability required for safety-critical engineering decisions. A hybrid diagnostic perspective combining temporal prediction capability with interpretable reasoning appears particularly promising for future aviation maintenance applications.

The main contribution of this work lies in addressing a system-integration gap between onboard diagnostic subsystems and predictive analytics workflows. By outlining how FADEC, EEC, EMU, and CDN components can operate within a unified analytical framework, the study demonstrates the architectural feasibility of supporting condition-based maintenance (CBM) and reliability-centered maintenance (RCM) in modern aircraft operations.

Future research will focus on validating the proposed framework using publicly available benchmarks and real operational datasets, as well as extending the architecture toward digital-twin-supported simulation environments. Additional investigation into explainable artificial intelligence, certification-aligned machine learning pipelines, and privacy-preserving approaches such as federated learning will be necessary to enable practical deployment of predictive diagnostic systems in safety-critical aviation environments.

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