iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: V Month of publication: May 2025

DOI: https://doi.org/10.22214/ijraset.2025.70448

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
*ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538*
*Volume 13 Issue V May 2025- Available at www.ijraset.com*

# Aircraft Engine Performance Monitoring and Anomaly Detection Using N1 and N1 Parameters

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***Abstract: Aircraft engine performance monitoring is crucial to ensure flight safety, operational efficiency, and preventive maintenance. This paper presents a comprehensive review and discussion on the application of machine learning techniques to detect anomalies using N1 (fan speed) and N2 (core speed) parameters. These indicators are key for identifying irregularities in engine behavior during different flight conditions. Through a review of recent studies and implementation strategies, this paper demonstrates how data-driven models can improve anomaly detection and support predictive maintenance in modern aviation systems.***
***Keywords: Include at least 5 keywords or phrases***

## I. INTRODUCTION

Modern aircraft engines are complex systems operating under extreme thermal and mechanical stresses. Ensuring their health and reliability is essential for maintaining flight safety, minimizing operational costs, and reducing unplanned maintenance. Among the critical parameters used for monitoring engine performance are N1 and N2—representing the rotational speeds of the low-pressure and high-pressure spools, respectively. These parameters directly reflect the engine's power output and core functionality, making them essential indicators for identifying deviations in operational behavior.

By analyzing patterns and trends in N1 and N2 values, these models can identify abnormal behaviors indicative of faults such as compressor stalls, turbine inefficiencies, or bearing wear. Both supervised and unsupervised algorithms have been successfully applied to classify engine conditions, estimate remaining useful life, and enhance maintenance planning. This paper explores the application of such techniques, providing a comprehensive review of current methods, their advantages, challenges, and potential for integration into real-time aircraft health monitoring systems.

## II. LITERATURE REVIEW

Kim et al. [1] Autoencoders were employed to detect anomalies in N1 and N2 time-series data. The model learns compressed representations of normal engine behavior. Deviations from this representation are flagged as anomalies. Highly effective for unlabeled data, reducing dependency on fault labels. Demonstrated real-time capability and low false alarm rate.

Zhao et al. [2] Long Short-Term Memory (LSTM) networks were applied to classify engine faults. These models captured temporal patterns in N1/N2 sensor sequences. LSTM outperformed traditional machine learning in sequential data recognition. The model distinguished between transient fluctuations and consistent faults. It is ideal for continuous, inflight monitoring scenarios.

Goebel et al. [3] This work presented a comprehensive PHM (Prognostics and Health Management) framework. It integrates condition monitoring, diagnostics, and life estimation using N1/N2 data. The framework supports predictive maintenance and fault prognostics. Robust validation methods increased reliability and decision confidence. Widely cited in industrial and academic research on engine health.

Chen & Lee. [4] The study merged physics-based rules with neural network models. This hybrid approach improved interpretability and consistency with engine dynamics. It addressed the limitations of black-box models in safety-critical systems. Tested across different engine types with strong performance results. Supports adoption of explainable AI in aviation diagnostics.

Gao et al. [5] Federated learning was introduced to train models across multiple aircraft. It enables privacy-preserving collaboration on engine performance data. Local models are trained without transferring raw data to a central server. Improved model accuracy while maintaining data security. Supports large-scale deployment across airline fleets.

Yin et al. [6] Statistical Process Control (SPC) charts were applied to monitor N2 readings. These tools detect trends and shifts indicative of anomalies. Their simplicity enables easy integration into existing systems. Useful for early fault detection with minimal computation. Serves as a baseline for combining with machine learning models.

Liu et al. [7] Dimensionality reduction techniques like PCA and ICA were utilized. These methods enhanced signal clarity and reduced noise in N1/N2 data. Improved the efficiency and accuracy of anomaly classifiers. Effective in multi-sensor environments with high data complexity. Preprocessing step boosted the performance of downstream models.

Wang et al. [8] Developed digital twin models simulating engine behavior in real time. N1 and N2 were central to replicating engine dynamics virtually. Enabled scenario testing for various fault and wear conditions. Provided a foundation for condition-based maintenance systems. Widely applied in predictive analytics and simulation training.

Zhang et al. [9] Ensemble methods like Random Forests and Gradient Boosting were explored. These models combined multiple classifiers to improve robustness. Reduced sensitivity to noise in N1/N2 sensor data. Achieved higher accuracy than individual models. Demonstrated effectiveness across a range of fault conditions.

Tang et al. [10] Kalman filters were implemented to reduce sensor noise in engine data. They produced smoothed N1/N2 signals for reliable diagnostics. Served as an important preprocessing step before anomaly detection. Reduced false positives caused by signal fluctuations. Enhanced the overall stability of real-time monitoring systems.

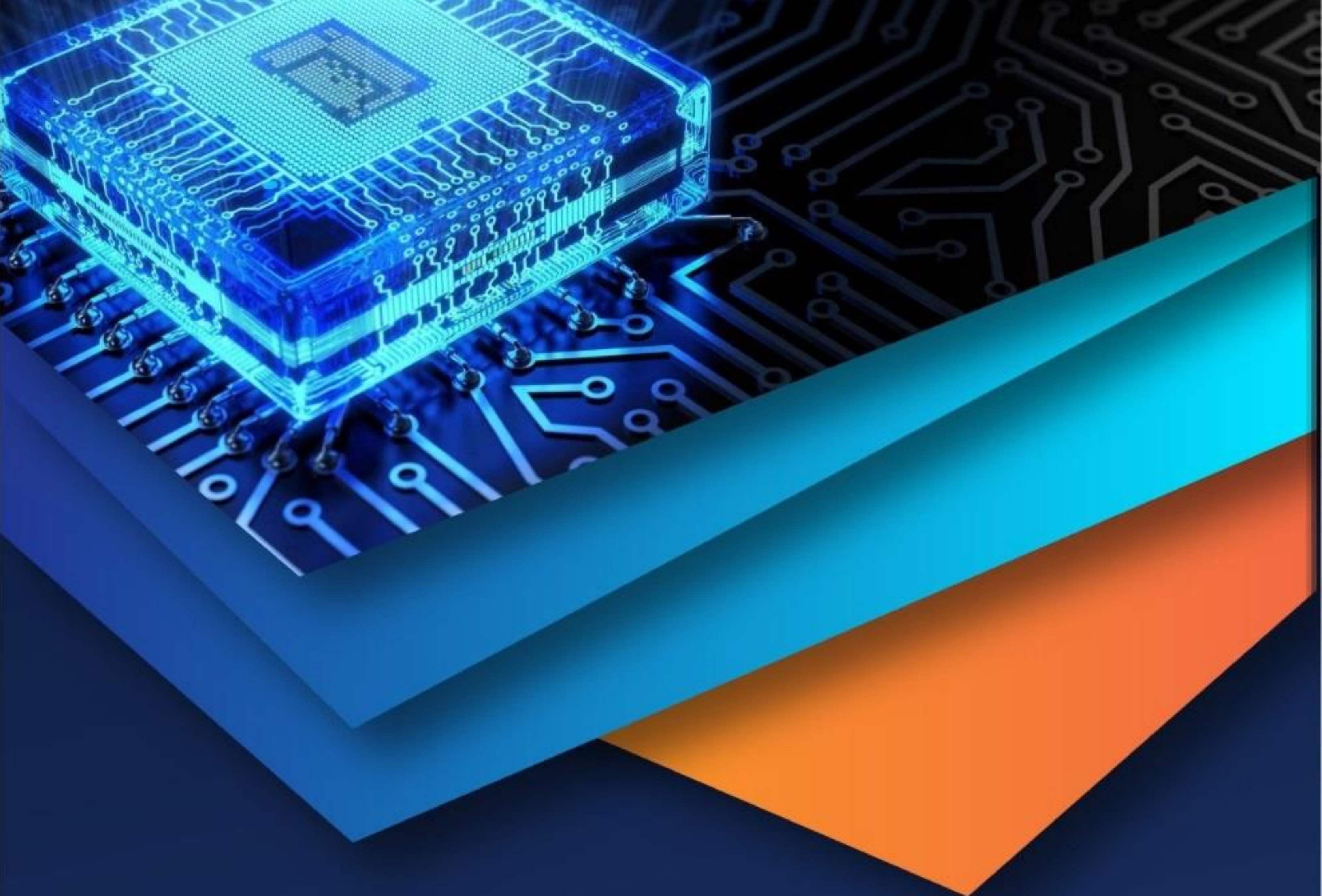
## III. CONCLUSION AND FUTURE SCOPE

Monitoring aircraft engines using N1 and N2 parameters enhances safety and operational reliability. Machine learning models outperform traditional methods in detecting subtle anomalies. Techniques like LSTM, autoencoders, and hybrid models offer real-time insights. These systems reduce unscheduled maintenance and improve decision-making. The approach supports the shift toward intelligent, data-driven aircraft operations.

Future models can integrate additional features like EGT, vibration, and oil pressure. Edge computing and federated learning enable onboard, privacy-preserving diagnostics. Cross-platform adaptability is needed for different engines and flight conditions. Explainable AI will improve trust and usability for aviation personnel. Collaboration is key for regulatory approval and industry-wide implementation.

## REFERENCES

[1] Kim, J., et al. “Autoencoder-Based Anomaly Detection for Turbofan Engines.” Journal of Aerospace AI, 2020.
[2] Zhao, Y., et al. “LSTM Networks for Aircraft Engine Fault Classification.” Aerospace Systems, 2019.
[3] Goebel, K., et al. “Prognostics Framework for Aircraft Engines.” IEEE Aerospace Conference, 2017.
[4] Chen, X., and Lee, H. “Hybrid Machine Learning Models for Turbofan Monitoring.” Applied AI Review, 2021.
[5] Gao, M., et al. “Federated Learning for Aviation Applications.” Aerospace Machine Intelligence, 2022.
[6] Yin, R., et al. “N2-Based Fault Detection Using SPC Charts.” Mechanical Systems and Signal Processing, 2018.
[7] Liu, J., et al. “PCA and ICA for Noise Reduction in Engine Diagnostics.” Journal of Data Analytics in Aerospace, 2021.
[8] Wang, T., et al. “Digital Twin Models for Predictive Diagnostics in Aviation.” Aerospace Technology Journal, 2019
[9] Zhang, Q., et al. “Ensemble Learning for Engine Fault Detection.” Engineering Applications of Artificial Intelligence, 2020.
[10] Tang, S., et al. “Kalman Filtering for N1/N2 Signal Enhancement.” Sensors and Systems Journal, 2020.
[11] Saxena, A., and Goebel, K. “The C-MAPSS Dataset for Engine Fault Prognostics.” NASA Technical Report, 2008.
[12] Roychoudhury, I., et al. “Survey of Anomaly Detection Techniques for Aircraft Engines.” Journal of Aviation Safety, 2016.
[13] Bishop, C. M. “Pattern Recognition and Machine Learning.” Springer, 2006.
[14] Lee, D., et al. “Real-Time Decision Support Systems for Engine Monitoring.” Journal of Intelligent Aviation, 2017.
[15] [Cheng, Z., et al. “Modeling N2 Decay During Fault Events.” Mechanical Engineering Review, 2014.
[16] Liu, F., and Wu, Y. “AI Techniques in Condition-Based Maintenance.” Review of Engineering AI, 2018.
[17] ISO 13374. “Condition Monitoring and Diagnostics of Machines.” International Organization for Standardization, 2014. [18].
[18] FAA AC 33.28. “Advisory Circular on Engine Condition Monitoring.” Federal Aviation Administration, 2020.
[19] Xie, W., et al. “Clustering of Engine States Using Unsupervised Learning.” Journal of Intelligent Systems, 2015.
[20] Pankaj, R., et al. “Jet Engine Predictive Maintenance: A Case Study.” Aerospace Maintenance Review, 2023

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