

Anomaly Detection in Aircraft Fuel Systems Using Artificial Neural Networks for Maintenance Decision Support

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ABSTRACT

This study proposes a predictive maintenance framework for aircraft fuel systems using Artificial Neural Networks (ANN) integrated with Failure Mode, Effects, and Criticality Analysis (FMECA). Operational flight recorder data consisting of fuel flow, torque, propeller speed, and outside air temperature parameters were processed through cleaning, normalization, and anomaly analysis before ANN training. The results show that the ANN model successfully detected anomalous operational conditions with stable learning performance and satisfactory classification capability. FMECA identified fuel pumps and fuel metering components as the most critical components affecting operational reliability and safety. The proposed framework supports condition-based maintenance by improving anomaly detection, maintenance prioritization, operational reliability, and aircraft safety in defense aviation environments.

INTRODUCTION

In the modern military, the operational readiness of a combat system, including aircraft, is a crucial aspect in supporting mission success. One vital element in a military aircraft system is the fuel system, which is not only responsible for providing energy to the aircraft engine but also affects safety, fuel efficiency, and the continuity of combat missions. Failure in this system can have fatal consequences, causing mission disruption, severe equipment damage, and even the loss of personnel's lives. According to Langton et al. (2009), in aircraft fuel storage systems, fuel contamination is a major problem because it is considered a common mode failure. Fuel contamination can result in the loss of all thrust because the source of the problem affects all engines. Another source of fuel tank contamination involves microbial growth. This occurs as a result of airborne spores from the ventilation system that can grow when the environmental conditions of the fuel tank are favorable. This situation is exacerbated by the fact that fuel tanks are expected to operate without inspection for long periods. Fuel leaks also pose a serious threat to aircraft safety, especially in long-haul flights over water where fuel loss can be potentially catastrophic, as demonstrated by Air Transat Flight TS 236 from Toronto to Lisbon in August 2001, which ended in an emergency landing in the Azores after the loss of both engines due to a fuel leak in the starboard side engine.

The fuel system is a critical system because it has additional functions such as temperature balancing (fuel cooling system), managing fuel distribution between tanks to maintain aircraft balance, and supporting operational continuity in various extreme pressure and temperature conditions. An aircraft fuel system is designed to store, distribute, and precisely regulate the fuel supply to the engine. The main components of this system include fuel tanks, pumps, filters, valves, and pipelines. Each component must function optimally to ensure a stable and clean fuel supply while preventing the risk of contamination or leaks. In addition to the supply aspect, the fuel system also has a significant influence on the aircraft stability margin, making it an indispensable element in aircraft design and operation. Innovations continue to be made in the development of fuel systems, including solutions to fuel combination problems (Tulaev, B. et al., 2019) and modeling the reliability of the fuel system of a diesel engine operating on biofuel (Zhuravel, D. et al., 2022).

Several air accident investigation reports have shown that fuel system components (such as fuel pumps, valves, pressure sensors, or distribution lines) are susceptible to sudden failure, largely due to a lack of early detection systems or delays in maintenance (Li, J. et al., 2023). As a crucial aircraft system, recorded failures related to the fuel system account for more than 30% of all aircraft failures (Shen et al., 2010). To date, the maintenance approach to aircraft fuel systems in the military environment still relies heavily on preventive maintenance based on time or flight cycles. This approach has significant weaknesses because it does not consider the actual condition of components in real time. Fuel system failures not only risk the safety of crew and assets but can also disrupt combat readiness and the smooth running of military operations. In the defense environment, fuel system reliability is becoming increasingly critical because military aircraft are

frequently operated under extreme conditions, with high readiness demands and dense mission cycles. As a result, potential undetected failures can develop into critical failures while the aircraft is on mission, reducing readiness levels and posing a significant risk to military aviation safety. This phenomenon highlights the need for intelligent monitoring systems capable of early failure detection and predicting failures based on real-time data.

Artificial Intelligence (AI) plays a central role in modern predictive maintenance, enabling the analysis of complex sensor data to identify patterns that indicate potential failure (Moghadasnian, S., 2025). Machine learning applications in aircraft maintenance have proven effective in detecting anomalies and predicting failures. Research conducted by Karaoğlu et al also reviews various applications of machine learning in the context of general aircraft maintenance, including damage diagnosis, service life prediction, and maintenance schedule optimization (Karaoğlu et al., 2022). AI can predict component failure times with greater accuracy, optimize maintenance schedules, and reduce unplanned downtime (Tran, M.-Q. et al., 2023 ; Shabbir, A., 2024). The use of AI in fighter aircraft maintenance can also significantly improve the operational readiness of the Indonesian Air Force (TNI AU) (Hermawan, L. et al., 2024).

Although previous studies have demonstrated the effectiveness of Artificial Intelligence and Machine Learning in aircraft maintenance, several important limitations remain. Smarter and more predictive maintenance strategies are needed to minimize the risk of unexpected failures and improve operational efficiency. As technology advances, the application of Artificial Intelligence (AI) and Machine Learning (ML) in aircraft fuel systems has been proven to improve damage diagnosis, performance prediction, and support Condition Based Maintenance (CBM) strategies. This literature review considering the use of Artificial Intelligence (AI) or Machine Learning (ML) to improve the reliability of aircraft fuel systems, with a focus on applications in the defense environment.

As a result, maintenance personnel may detect anomalies without understanding the associated component criticality and operational risk. Therefore, a research gap exists in the development of an integrated framework that combines data-driven anomaly detection with engineering-based criticality assessment for aircraft fuel systems. This study addresses this gap by integrating Artificial Neural Networks (ANN) with FMECA using operational flight recorder data to support anomaly detection, maintenance prioritization, and condition-based maintenance decision-making in defense aviation environments.

THEORETICAL REVIEW

Fuel System Aircraft

The aircraft fuel system is a critical subsystem responsible for fuel storage, management, and delivery to the engine under varying operational conditions. It comprises key components such as fuel tanks, pumps, filters, valves, and distribution lines, which must operate reliably to ensure continuous fuel supply and flight safety. Recent studies highlight that modern fuel systems also

contribute to thermal management and aircraft stability by regulating fuel distribution and temperature (Zhuravel et al., 2022).

Failure in aircraft fuel systems can lead to severe consequences, including engine flameout, thrust loss, and mission failure. According to Li et al. (2023), fuel system components such as pumps and valves are highly susceptible to degradation due to operational stress, contamination, and wear. Fuel contamination caused by water ingress or microbial growth remains a major issue that can block filters and disrupt fuel flow, ultimately affecting engine performance.

Furthermore, fuel system failures often occur as common-mode failures, where a single source of failure can affect multiple engines simultaneously, increasing the risk of catastrophic incidents. Shen et al. (2019) reported that fuel system-related failures account for a significant proportion of aircraft system malfunctions, emphasizing the importance of reliability analysis and maintenance optimization.

Failure Mode, Effects, and Criticality Analysis (FMECA)

Is a widely used reliability assessment method in aerospace systems for identifying potential failure modes, evaluating their effects, and prioritizing risks. The method assesses failures based on three key parameters: severity, occurrence, and detection, which are combined into a Risk Priority Number (RPN) to rank critical components.

Recent applications of FMECA in aerospace engineering demonstrate its effectiveness in identifying high-risk components and supporting maintenance planning. For instance, research by Liu et al. (2020) applied FMECA to aircraft subsystems and showed that it significantly improves failure prioritization and safety management. Similarly, Zhang et al. (2021) emphasized that FMECA provides a structured framework for analyzing complex systems and enhancing reliability.

Artificial Intelligent

According to Tran et al. (2023), AI-based predictive maintenance models can significantly improve failure prediction accuracy and reduce maintenance costs by enabling early detection of system degradation. Common machine learning techniques used in aircraft maintenance include Random Forest, Support Vector Machines, and deep learning models such as Long Short-Term Memory (LSTM) networks, which are particularly effective in analyzing time-series data.

In addition, Shabbir (2024) highlights that AI enhances maintenance scheduling by predicting component failure probabilities and optimizing inspection intervals. Meanwhile, Karaoğlu et al. (2022) demonstrate that AI applications in aviation include fault diagnosis, remaining useful life (RUL) estimation, and maintenance optimization. These capabilities support the transition from traditional preventive maintenance to predictive maintenance strategies.

ANN learns the basic principles of a set of provided symbolic scenarios or tries to understand patterns in the dataset to make predictions. The use of a multi-

layer architecture (Deep/Multi-layer Autoencoder) with a non-linear activation function was chosen empirically and supported by fundamental literature. Based on the pioneering study of Deep Learning by, (Goodfellow et al., 2016) Single-layer architecture with linear activation essentially only replicates the dimensionality reduction of Principal Component Analysis (PCA). Considering that the operational dynamics of aviation sensors (Fuel Flow, Torque, OAT) have highly non-linear multivariate interactions, a Deep Autoencoder architecture is needed to be able to extract hierarchical representations (manifold learning) from the data more comprehensively.

Recent studies suggest that combining FMECA with machine learning improves maintenance decision-making and system reliability. Li et al. (2023) demonstrated that integrating traditional failure analysis with AI-based models enhances the accuracy of failure prediction and supports proactive maintenance strategies.

This hybrid approach is particularly relevant in defense aviation, where system reliability and mission readiness are critical. By integrating FMECA and AI, maintenance systems can transition from reactive and preventive strategies to predictive and intelligent maintenance frameworks, ultimately improving safety, efficiency, and operational performance.

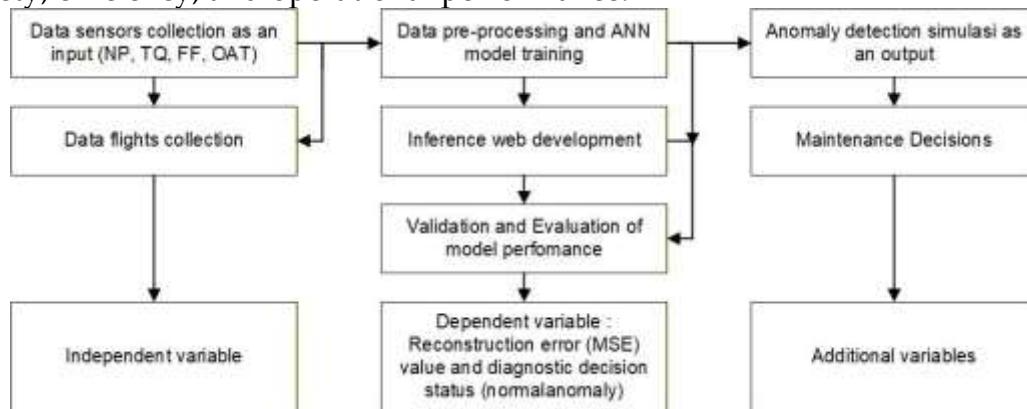


Figure 1. Conceptual Framework

METHODOLOGY

This study was conducted based on a structured literature review combined with the development of a conceptual framework to investigate the application of Artificial Intelligence (AI) in predictive maintenance of aircraft fuel systems. The focus of this research is to develop an Artificial Neural Networks-based system to support the maintenance of the aircraft fuel system, allowing it to monitor the condition of key components in the fuel system and predict potential failures during operation.

This research employed a quantitative approach using measured fuel flow sensor variables in the aircraft fuel system. It focused on identifying critical failure modes, the limitations of conventional maintenance practices, and the potential of AI-based approaches to improve system reliability in defense aviation. Data was collected from peer-reviewed journals, accident investigation

reports, and aircraft fuel system operational records obtained from a national aerospace manufacturer.

The data collection process involved a systematic keyword search across major scientific databases using key terms including "aircraft fuel system failure," "aerospace FMECA," and "AI predictive maintenance." The selected literature was screened for relevance, methodological rigor, and applicability to the military aviation context. The analysis was based on the results of anomaly detection using an ANN program and initialization of FMECA tables based on component criticality.

Based on the synthesized findings, a conceptual hybrid framework integrating FMECA and AI was developed. FMECA is used to identify and prioritize critical components using risk parameters, while an AI model is proposed to detect anomaly probabilities using sensor and operational data. This integration of approaches supports a predictive maintenance strategy that supports decision-making in defense aviation. The proposed methodology provides a systematic foundation for improving reliability, reducing unplanned failures, and enhancing operational readiness, although its implementation may be limited by data availability and validation constraints.

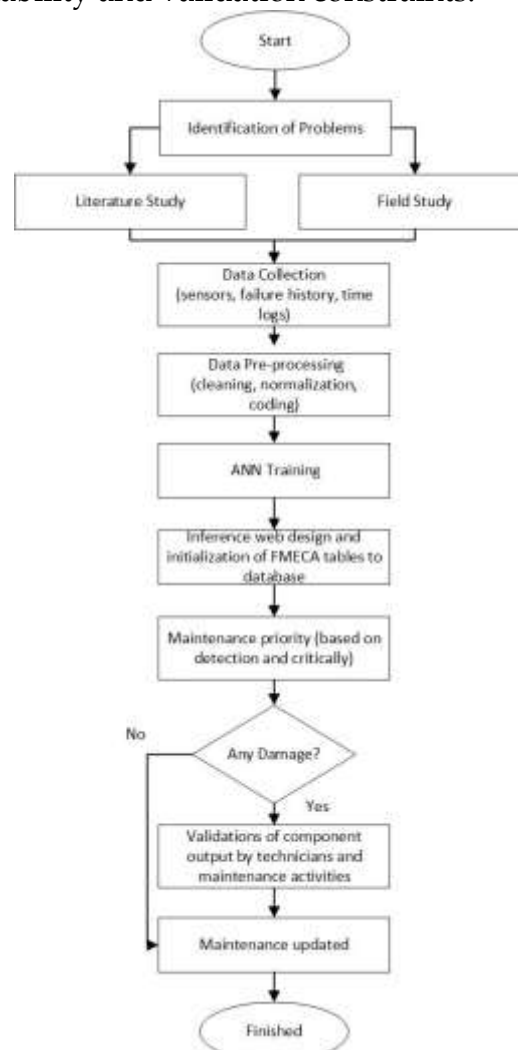


Figure 2. Research Design

The figure above illustrates the research mechanism flow that begins from the initial stage with problem identification to determine the research focus related to the aircraft fuel system, then supported by two parallel approaches: literature studies to obtain a theoretical basis and field studies to understand actual operational conditions and real problems in the field. These two approaches culminate in the data collection stage that includes sensor data, failure history, and operational time records as the main input for the research. The collected data then goes through a pre-processing stage that includes cleaning the data from noise or invalid data, normalization to equalize the scale, and coding so that it can be processed by the computing system, resulting in a dataset ready for use in the ANN training stage. This modeling uses unsupervised learning where the ANN learns the data structure without using previously known target labels. After the ANN model is trained to recognize patterns and predict potential failures, the results are integrated into the creation of a web-based system for inference purposes, while the FMECA table is initialized into the database as a reference for component criticality analysis. Next, the system generates maintenance priorities based on the ANN detection results and the criticality level from the FMECA, which then enters the decision-making stage through the branching of "damage or not"; If no damage is found, the process returns to the monitoring cycle. If an anomaly is detected, the output is validated by technicians through inspection and actual maintenance actions. These validation results are then used to continuously update maintenance data, making the system more adaptive and accurate, until the entire process reaches completion. This demonstrates the iterative nature of this research, integrating failure analysis (FMECA), artificial intelligence (ANN), and feedback from actual maintenance processes to comprehensively improve fuel system reliability.

The population of this study was flight recorder data and fuel system failure logs. The sample used was sensor data affecting fuel flow in the fuel system, consisting of 182,376 rows of data from 10 flight cycles for ANN modeling.

RESULTS

The characteristics and distribution of a dataset in an artificial neural network (ANN) are crucial because ANNs are data-driven learning models. The quality and structure of the data directly impact the model's performance, accuracy, and ability to generalize. The following table shows the statistics of the flight recorder data processing results.

Table 1. Statistics of Flight Recorder Data

Parameter	Description	Min	Max	Mean
TQ1	Engine torque 1	0	3750.98	1783.92
TQ2	Engine torque 2	1228.5	2051.81	1783.96
NP1	Propeller speed 1	3.19	2204.96	931.79
NP2	Propeller speed 2	-2.91	2212.23	927.25
FF1	Fuel flow 1	-0.07	513.5	275.1
FF2	Fuel flow 2	60.95	521.13	278.91
OAT	Outside air temperature	9	539.75	18.74

The dataset consisted of 182,376 rows obtained from 10 flight cycles of the aircraft. Seven operational parameters were selected as ANN inputs, including torque, propeller speed, fuel flow, and outside air temperature. Data preprocessing involved noise filtering, normalization, and missing-value handling to improve model stability.

Here's the FMECA table embedded in the database. This table is crucial because the associated sensor columns serve as the key for the AI to generate recommended actions:

Tabel 2. FMECA Results										
ID	Component		Failure Mode	System effects	S	O	D	RPN	Sensors	Recommended action
F01	Main	Fuel Pump	Pressure drop/leak	Engine starvation	8	4	5	160	FF1, FF2, TQ1,TQ2	Grounded, replace or inspect the main pump
F02	Fuel	Metering Valve	Stuck in closed position	Unstable fuel supply	7	3	4	84	FF1, FF2, NP1,NP2	Metering valve recalibration
F03	Fuel	Filter	Clogging	Gradual decrease in flow	5	6	3	90	FF1, FF2	Filter cleaning or replacement

The FMECA analysis identified the fuel pump and fuel flow sensor as the most critical components. These components exhibited the highest RPN values due to their direct influence on fuel delivery stability and engine performance.

The training curve is a line graph comparing the training loss and validation loss at each epoch to evaluate the performance of the ANN model training process in learning the relationship patterns of the aircraft fuel system parameters. The curve is shown in the figure below.

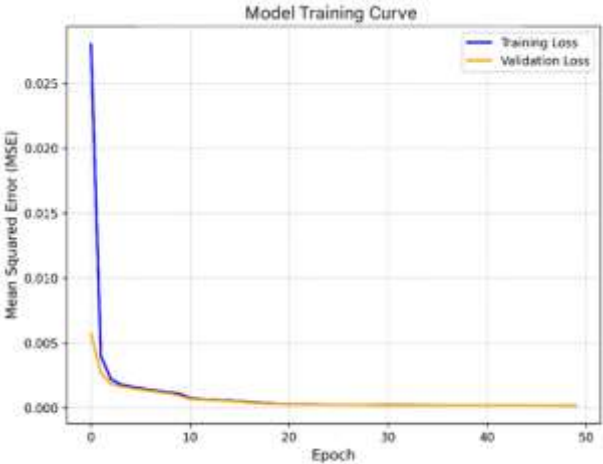


Figure 3. Learning Curve

The training curve shows changes in the training loss and validation loss values with the number of epochs during the training process. Based on the test results, it can be seen that the training loss and validation loss values experienced a significant decrease in the initial epoch, then decreased gradually until reaching a convergent condition in the final epoch. The steady decrease in loss indicates that the model successfully learned the relationship pattern between flight recorder parameters, such as fuel flow, torque, propeller speed, and outside air temperature. Furthermore, the distance between the training loss and validation loss was relatively small during the training process. This indicates that the model has good generalization capabilities and does not experience significant overfitting. The absence of an increase in validation loss in the final epoch indicates that the model is able to maintain its predictive performance on new data outside the training data. The final loss value close to zero indicates that the model's prediction error is very small, allowing the ANN to produce predictions close to the actual conditions of the aircraft fuel system.

The latent data distribution was used to analyze the distribution of reconstruction errors resulting from the ANN model reconstruction of flight recorder data from flight. The latent distribution graph shows the distribution of reconstruction errors, the separation of normal and abnormal data, and the anomaly detection threshold. Based on the visualization, most of the normal data has very small reconstruction errors concentrated around zero. However, some anomalous data has reconstruction errors much higher than the normal distribution. The latent data distribution curve is shown in the figure below.

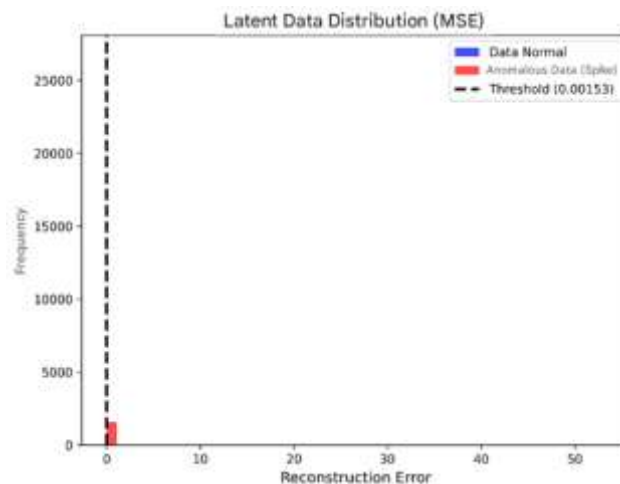


Figure 4. Laten Data Distribution Curve

Performance metrics are used to measure the ability of the ANN model to classify normal and anomalous conditions. The results of the performance metrics are shown in the following figure.

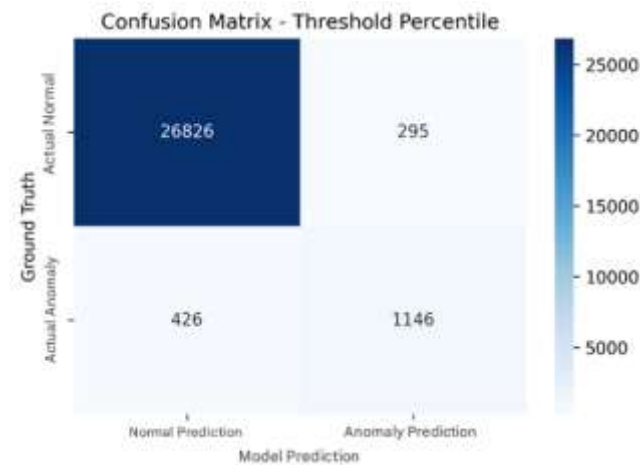


Figure 5. Performance Matrix Result

The image above shows the results of an ANN model performance evaluation using the confusion matrix method on the aircraft anomaly detection system to determine failure detection capability, false alarm rate, risk of undetected failure, and monitoring system reliability. True positives were scored at 1146, indicating data that was truly anomalous and successfully detected as anomalous by the ANN model. True negatives were scored at 26826, indicating normal data that was successfully recognized as normal by the model. Next, false positives, often referred to as false alarms, were scored at 295, indicating data that was actually normal but predicted as anomalous by the model. Finally, with a score of 426, data that was actually anomalous but considered normal by the AI. This is very dangerous because it can cause undetected damage, increase the potential for failure, and compromise flight safety.

Based on the test results, the P99 value was 0.001528, with a recall of 73%, a precision of 80%, and an F1-Score of 76%, indicating the model was able to identify most normal and abnormal data with a high degree of accuracy. The true positive value indicates that the model successfully detected most anomalous conditions, while the relatively low false negative value indicates that the risk of undetected failures is minimized. Furthermore, the low false positive value indicates that the model did not generate excessive false alarms, thus assessing the system as sufficiently stable for use in monitoring the aircraft fuel system.

Time-series inference is the process by which an ANN model reads sensor data sequentially over time (sequential data) to observe changes in system parameter patterns over time. This simulation was conducted to evaluate the ANN model's ability to continuously detect fuel system anomalies based on flight recorder data and how the anomalies appear over time. The results of the time series inference simulation are shown in the following figure.

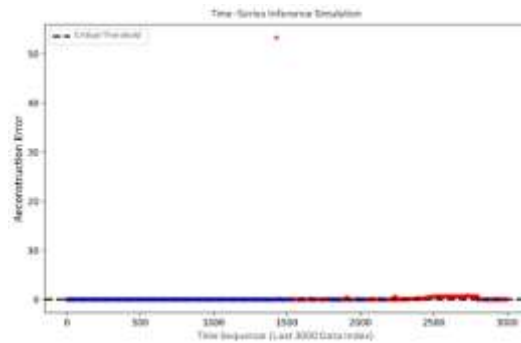


Figure 6. Time-Series Inference Simulation

In the graph, the horizontal axis (x-axis) shows the time sequence or data index (sequence time), while the vertical axis (y-axis) shows the reconstruction error value, or the degree of error in the ANN model's reconstruction of the actual data. Reconstruction error is the difference between the original data and the predicted or reconstructed data from the ANN model. The smaller the reconstruction error, the more the model considers the data normal. The larger the reconstruction error, the more the model detects an unusual pattern or anomaly.

The graph shows that most points are very close to zero, there are several spikes, one very high spike around index 1450, and there is an area of gradual increase in reconstruction error around index 2400–2800, indicating possible gradual degradation in the fuel system. This condition could be related to fuel flow instability, decreased fuel pump performance, or engine torque fluctuations. This indicates that most aircraft operations are normal, with some conditions considered abnormal by the ANN model. Most of the blue points are near 0 to 0.1 reconstruction error, indicating that the ANN model is able to reconstruct the data very well. This indicates that the engine operation pattern is stable, the relationship between parameters is normal, fuel distribution is running well, and there are no major deviations in the fuel system.

The AI-integrated website displays the FileUpload page, which intelligently receives sensor data and is equipped with a data type validation system. This component supports drag-and-drop but will strictly reject archive formats other than the aircraft's native .csv file. StatusBadge and SummaryCards are summary instruments that, after analysis is complete, change their color to a bright green "normal" if the aircraft is fine, or issue a solid red warning "anomaly" when an anomaly is encountered. Next to these indicators is a summary of the peak percentage deviation metrics compared to the operational threshold. The page is displayed as shown in the image below.

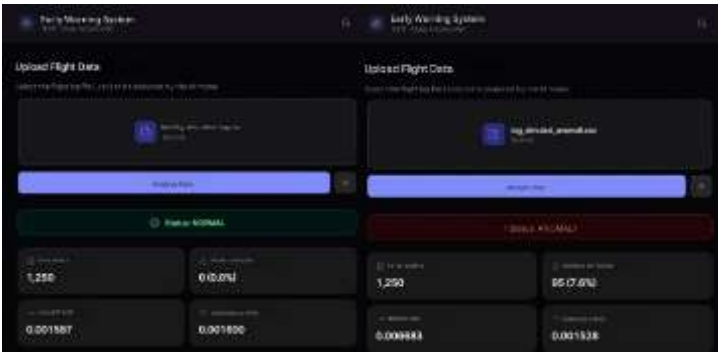


Figure 7. StatusBadge and SummaryCards normal and anomaly condition

The following image represents a time series chart component, which transforms massive amounts of raw data into a comprehensive visual graphical representation. This chart features a red dashed tolerance line. With interactive zoom, users can drill down to the precise second (timestep) where the chart movement intersects the red tolerance line.



Figure 8. Time series anomaly condition

The following is a component of the FMECA diagnostic table. When the AI sounds an anomaly alarm, the expert system matrix automatically retrieves a "repair manual" file from the database. This table synthesizes the problem, analyzes the component's probability of failure, displays the sensor's criticality (RPN value), and then provides operational action. The page will appear as shown below if the uploaded data is anomalous, and under normal conditions, the following page will not appear on the website.

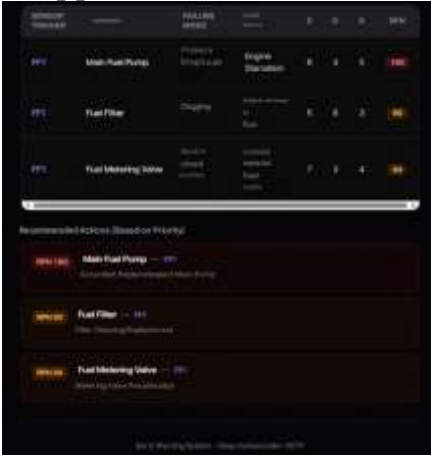


Figure 9. FMECA table page and recommended actions

DISCUSSION

The results of this study demonstrate that the integration of Artificial Neural Networks (ANN) and Failure Mode, Effects, and Criticality Analysis (FMECA) provides a promising framework for predictive maintenance in aircraft fuel systems, particularly within defense aviation environments where operational reliability and safety are critical requirements. The proposed approach not only enables anomaly detection from operational flight data but also supports maintenance prioritization through criticality-based analysis.

The dataset analysis revealed that the operational parameters, including fuel flow, torque, propeller speed, and outside air temperature, exhibit complex multivariate relationships that are highly nonlinear in nature. These operational characteristics justify the use of ANN models, particularly deep autoencoder architectures, which are capable of learning hidden representations and extracting latent operational patterns from large-scale sensor datasets. The preprocessing stage, including data cleaning, normalization, and noise reduction, played an important role in improving the stability and learning capability of the model. The relatively balanced distribution of operational parameters also contributed to the ability of the ANN to generalize effectively during anomaly detection.

The FMECA results identified the fuel pump and fuel metering-related components as the most critical elements within the aircraft fuel system. These components exhibited the highest Risk Priority Number (RPN) values due to their direct influence on fuel distribution stability and engine operational continuity. Fuel pump degradation or pressure instability may interrupt fuel supply to the combustion chamber, potentially causing thrust fluctuation, engine performance degradation, or engine flameout conditions. Similarly, fuel metering valve failures may result in unstable fuel flow distribution and inaccurate fuel regulation. These findings are consistent with previous studies conducted by Li et al. (2023), which emphasized that aircraft fuel system components such as pumps, valves, and sensors are highly vulnerable to degradation caused by operational stress, contamination, and wear mechanisms.

The ANN training performance showed stable convergence characteristics, as indicated by the gradual decrease of both training loss and validation loss during the learning process. The relatively small gap between training and validation loss suggests that the model achieved good generalization capability without experiencing significant overfitting. This indicates that the ANN successfully learned the operational behavior patterns of the aircraft fuel system and was capable of reconstructing normal operating conditions with low reconstruction error values. In predictive maintenance applications, model stability and generalization are essential because the monitoring system must be capable of identifying abnormal conditions under varying operational environments.

The latent data distribution analysis further demonstrated the capability of the ANN model to separate normal operational conditions from anomalous conditions. Most operational data points were concentrated around low reconstruction error regions, indicating stable aircraft operating conditions and consistent fuel system performance. However, several anomalous points exhibited

significantly higher reconstruction error values, suggesting deviations from learned normal behavior patterns. These anomalies may represent early indications of component degradation, unstable fuel pressure, irregular fuel flow distribution, or sensor inconsistencies. This result supports the concept that ANN-based reconstruction error analysis can function as an effective early warning mechanism for aircraft fuel system monitoring.

The confusion matrix evaluation demonstrated that the proposed ANN model achieved strong anomaly classification capability. The high true positive and true negative values indicate that the model was able to correctly classify both anomalous and normal operating conditions with relatively high reliability. In aircraft maintenance systems, minimizing false negative conditions is particularly important because undetected failures may lead to catastrophic operational consequences. The relatively low false positive rate also indicates that the model can reduce unnecessary maintenance actions and excessive maintenance inspections, which are common limitations in conventional preventive maintenance systems.

The time-series inference simulation provided additional insight into the dynamic behavior of aircraft fuel system anomalies during sequential operation. Most operational sequences exhibited low reconstruction error values, indicating stable system conditions. However, several spikes and gradual increases in reconstruction error were identified during specific operational periods. This gradual increase pattern is particularly important because it may indicate progressive degradation rather than sudden failure. In real operational environments, progressive degradation often occurs before critical component failure becomes visible. Therefore, the proposed ANN-based monitoring system has the potential to support early fault detection before the occurrence of severe operational disruption.

Compared with conventional maintenance approaches, the proposed hybrid framework offers several advantages. Traditional preventive maintenance strategies are generally based on fixed flight hours or maintenance intervals without considering the actual health condition of system components. As a result, components may either be replaced too early, leading to increased maintenance costs, or too late, increasing the risk of operational failure. By integrating ANN-based anomaly detection with FMECA criticality analysis, maintenance decisions can be prioritized dynamically according to both operational condition and component criticality level. This supports the implementation of Condition-Based Maintenance (CBM) strategies in military aviation environments.

The findings of this study are also aligned with previous research regarding the application of AI in aviation maintenance. Karaoğlu et al. (2022) stated that machine learning methods can improve fault diagnosis and maintenance optimization in aircraft systems. Similarly, Tran et al. (2023) emphasized that AI-based predictive maintenance models improve failure prediction accuracy and reduce unplanned downtime. The present study extends these findings by specifically focusing on aircraft fuel system anomaly detection and integrating operational sensor analysis with maintenance criticality prioritization through FMECA.

Despite the promising results, several limitations remain in this study. First, the operational dataset was limited to a finite number of flight cycles, which may limit the model's ability to capture wider operational variability. Second, the current ANN framework focuses primarily on anomaly detection rather than detailed fault classification for specific component failures. Third, the implementation remains in an offline analysis environment and has not yet been integrated into a real-time onboard monitoring architecture.

CONCLUSIONS AND RECOMMENDATIONS

This study proposed a hybrid predictive maintenance framework for the aircraft fuel system by integrating Failure Mode, Effects, and Criticality Analysis (FMECA) with Artificial Neural Networks (ANN). The proposed approach successfully identified critical fuel system components and enabled anomaly detection using operational flight sensor data. The FMECA results indicated that fuel pumps and fuel flow sensors possess the highest criticality levels due to their strong influence on fuel distribution stability and flight safety. Meanwhile, the ANN model demonstrated strong predictive capability with high classification accuracy in detecting abnormal operating conditions from multivariate sensor parameters.

The ANN model effectively learned normal operational behavior and identified abnormal patterns through reconstruction error analysis, while the FMECA assessment identified fuel pumps and fuel-related components as the most critical elements affecting system reliability and safety. The integration of these approaches addresses an important gap in previous studies, which typically focused either on anomaly detection or risk assessment separately.

From a practical perspective, the proposed framework provides a foundation for implementing Condition-Based Maintenance (CBM) in defense aviation by supporting early anomaly detection, risk-informed maintenance planning, and improved operational readiness. Therefore, this research contributes both to the advancement of AI-based aircraft maintenance systems and to the development of more intelligent and adaptive maintenance strategies for aircraft fuel systems. In addition, integrating AI-based anomaly detection with engineering criticality analysis such as FMECA can improve maintenance prioritization and operational decision-making. Collaboration between aerospace industries, defense institutions, and academic researchers is also important to improve dataset availability, system validation, and the development of more robust predictive maintenance technologies for aircraft applications.

FURTHER STUDY

Future work should focus on real-time onboard implementation, larger operational datasets, and multiclass failure prediction to improve system robustness and operational applicability.

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