Impact of AI-Driven Maintenance Models on Operational Efficiency in Aircraft Engineering

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ABSTRACT

The effect of Artificial Intelligence (AI)-based maintenance models on the operational efficiency of aircraft engineering, as far as predictive reliability analysis and demand forecasting are concerned, is a subject investigated in this research. Conventional maintenance strategies in the aviation sector tend to focus on fixed schedules or reactive behavior, leading to inefficiencies, surprise failures, and high costs. With the help of AI applications like Weibull distribution analysis and SARIMAX time series forecasting, the present study employs data-driven methodologies to investigate propeller blade failure behavior and predict the monthly demand for aircraft landing gearboxes. The Weibull analysis documented a nearly random failure behavior with slight wear-out tendencies, which facilitated the identification of maintenance thresholds and the implementation of early intervention strategies. At the same time, the SARIMAX model replicated seasonal patterns in demand, generating precise six-month forecasts that facilitate effective inventory and resource planning. The deployment of these AI-based approaches enables the transition to predictive and condition-based maintenance, eliminating unnecessary downtime, maximizing fleet availability, and increasing overall operational efficiency in aircraft maintenance engineering.

Keywords: Artificial Intelligence, Predictive Maintenance, Weibull Analysis, SARIMAX, Aircraft Engineering, Operational Efficiency, Failure Forecasting, Reliability Modeling, Inventory Planning, Aviation Maintenance.

INTRODUCTION

In today's fast-changing aviation business environment, the efficiency and reliability of aircraft maintenance activity are paramount to guaranteeing safety, reducing system disruptions, and managing costs. Conventional maintenance methods, frequently grounded on regular schedules or remedial action in the face of breakdowns, are usually wasteful and costly (Ekundayo, 2024). They may result in uncalled-for replacement of parts, missed early-stage faults, or unexpected system failure, all of which have adverse effects on fleet availability and continuity of operations. With the heightening complexity of aircraft systems and enhanced needs for real-time operating capability, there is a need to embrace more intelligent and adaptive maintenance systems compliant with contemporary capabilities in engineering (Kabashkin & Susanin, 2024).

Artificial Intelligence (AI) is coming up as a revolutionary driver in this role, allowing a move from time- and reactive-maintenance to predictive and condition-based maintenance approaches. Through the application of AI algorithms for statistical modelling, machine learning, and real-time analytics on data, aircraft maintenance engineering can derive advantages from onset detection of component degradation, precise failure prediction, and optimized intervention scheduling. Methods like Weibull analysis for reliability prediction and SARIMAX models for demand prediction are classic examples of how AI-based tools can make data-backed predictions on component lifespan and operational requirements (Patil, 2024). These tools not only help in identifying wear-out patterns and anomalies but also support efficient inventory planning and reduce downtime, thereby enhancing overall maintenance efficiency. The application of AI in aircraft maintenance goes beyond analytics—it redefines how maintenance decisions are made, allowing organizations to integrate predictive intelligence into core operations.

Through failure probabilities and maintenance thresholds, AI models enable timely interventions and strategic planning, leading to enhanced cost-effectiveness, safety, and reliability (MoghadasNian, 2025). In addition, the utilization of AI-powered forecasting allows for anticipating resource requirements, efficient procurement, and minimization of wastage. This research thus seeks to analyze the influence of AI-based maintenance models on aircraft engineering operational efficiency, illustrating how smart analytics can turn mainstream maintenance paradigms into efficient, responsive, and proactive systems that can match the needs of contemporary aviation.

Objective of Study: To evaluate the impact of AI-driven maintenance strategies on the operational efficiency of aircraft maintenance engineering organizations.

REVIEW OF LITERATURE

Merlo, 2024 analyzed the revolutionary impact of Artificial Intelligence (AI) in the aviation industry, particularly its role in predictive maintenance to improve operational efficiency. The chapter delivers an extensive analysis of AI's influence on aviation, presenting essential insights for aviation professionals, policymakers, and researchers aiming to comprehend the significant transformations instigated by AI in the aviation sector.

Simion et al., 2024 introduces an innovative method for predictive maintenance in the maritime sector, utilizing Artificial Intelligence (AI) and Machine Learning (ML) approaches to improve problem identification and maintenance scheduling for naval equipment. The research underscores the increasing significance of AI and ML in predictive maintenance and provides a pragmatic instrument for enhancing operational safety and efficiency within the marine sector.

The swift incorporation of Artificial Intelligence (AI) in aircraft maintenance is a significant advancement for the aviation sector, offering unparalleled enhancements in operational efficiency, safety, and environmental sustainability. MoghadasNian et al., 2024 examined the transition from conventional maintenance techniques to AI-enhanced methodologies, emphasizing the essential role of AI in predictive maintenance, fault diagnosis, inventory management, and maintenance scheduling.

This study examines the amalgamation of customization and personalization strategies in aircraft maintenance via the aircraft Technical Support as a Service (ATSaaS) platform. Kabashkin et al. (2025) conclude that the effective amalgamation of customization and personalization via ATSaaS platforms signifies a promising avenue for enhancing aviation maintenance operations, facilitating the industry's shift towards data-driven, adaptive maintenance solutions.

RESEARCH METHODOLOGY

In this research, a mixed quantitative modeling technique was used to refine aircraft engineering predictive maintenance strategies through failure behavior analysis and component demand forecasting. For the failure behavior analysis, turboprop aircraft maintenance data on operational flight hours of propeller blades were examined using Weibull distribution modeling to identify critical reliability parameters—shape (β) and scale (α)—that describe patterns of failure. To maintain statistical strength, the dataset was truncated to the 95th percentile to remove extreme outliers. Linear regression was then used on a transformed Weibull probability plot with ln (ln (1/ (1-Median Rank))) plotted against ln(flight hours), with the result $\beta = 1.01$ and $\alpha \approx 946.65$, which suggested a largely random failure pattern but with subtle wear-out tendencies. These parameters allowed failure probabilities and survival rates over different operation thresholds to be calculated, identifying maintenance activities like "ROGUE," "WARNING," and "REMOVE/MAINTAIN" based on exceeding specific risk thresholds (e.g., 85% probability of failure at ~1800 hours). For the demand forecasting of aircraft landing gearboxes, Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors (SARIMAX) modeling was employed on monthly time series data from January 2015 to January 2025, reflecting seasonal patterns keeping pace with annual maintenance cycles. A systematic grid search revealed SARIMA (0,1,1)(0,1,1,12) as the best model based on minimum AIC. Notwithstanding non-significant p-values, the model showed low forecast errors (RMSE = 2.45) and generated reliable six-month forecasts of demand from February to July 2025. In combination, the Weibull and SARIMAX analyses facilitated an integrated predictive maintenance platform that facilitates condition-based planning, enhanced resource scheduling, and improved operational efficiency in aircraft maintenance engineering.

RESULTS

In the present analysis, we investigated the failure behaviour of propeller blades using Weibull analysis on operational flight hours, utilizing field data from a turboprop aircraft maintenance dataset. The primary objective was to estimate the Weibull shape (β) and scale (α) parameters, thereby characterizing the failure pattern and identifying appropriate maintenance intervention thresholds. The dataset underwent a 95th percentile capping to mitigate the influence of extreme outliers, ensuring robustness in estimating the failure distribution.

Upon ranking the flight hours and calculating the median ranks, we applied a linear regression on ln (ln (1/(1-Median Rank))) versus ln (flight hours), which yielded a slope (β) of 1.01 and an intercept of -6.921. The β value slightly above 1 indicates that the failure pattern closely approximates random failure but with a marginal tendency toward wear-out failures, typical for mechanical components under regular operational stress. The α parameter was estimated as

946.65, which implies the characteristic life at which 63.2% of the propeller blades are expected to fail under the assumed conditions.

Table 1. Weibull Reliability Analysis Data for Propeller Blade Failure Modeling

	Propeller blade	Rank	Median Rank	1/(1 - Median Rank)	ln(ln(rank))	ln(A)
0	2253.36	1	0.01122	1.01135	-4.4846	7.72018
1	2250.43	2	0.02724	1.02801	-3.5892	7.71888
2	9245.1	3	0.04327	1.04523	-3.1183	9.13185
3	12214.3	4	0.0593	1.06303	-2.7948	9.41037
4	2146.46	5	0.07532	1.08146	-2.5471	7.67158

Using these parameters, projected failure rates and survival probabilities were calculated across a range of flying hours, from 100 to 3200 in increments of 100 hours, to facilitate practical application in preventive maintenance scheduling. The analysis revealed that propeller blades begin to exhibit significant failure rates (~15%) at around 200 flight hours and cross the 50% failure probability around 700 flight hours, indicating a crucial window for condition-based inspections.

Warning: Estimated beta (slope) < 1, which may indicate early-life failures or data issue.

Intercept: -6.921464

Slope (Beta): 1.010000

Alpha: 946.654493

A "WARNING" flag was triggered when failure probabilities crossed 85%, which occurred approximately at 1800 flight hours, whereas a "REMOVE/MAINTAIN" action was flagged when the failure rate exceeded 95% around 2900 flight hours. This actionable insight suggests that blades should be scheduled for removal or mandatory maintenance by 2800–3000 hours to avoid high risk of in-service failures, thereby ensuring operational reliability and safety compliance. The gradual increase in failure rates aligns with the mechanical wear behavior of propeller blades, reflecting the progression from micro-cracks to macroscopic failure under cyclic loads. The presence of "ROGUE" instances at very low flight hours (100 hours, ~10% failure) suggests either the presence of infant mortality or operational anomalies requiring further investigation to distinguish between design flaws, maintenance errors, or operational stressors.

These findings have direct implications for predictive maintenance planning in aviation asset management, enabling optimization of maintenance schedules based on failure probabilities rather than fixed intervals alone. This approach ensures cost-effective resource allocation while reducing the likelihood of unplanned downtime, contributing to improved operational efficiency in fleet management. Overall, this Weibull analysis provides a quantitative foundation to transition from reactive to predictive maintenance for propeller blades, leveraging statistical modeling for data-driven decision-making in aviation engineering. Future work may incorporate environmental, operational, and maintenance practice covariates to refine these projections further and align them with specific fleet usage patterns.

Table 2. Failure Rate and Survival Probability of Aircraft Propeller Blades Across Flying Hours with Recommended Maintenance Actions Based on Weibull Analysis

	Flying Hour	Failure Rate	Survival Probability	Action
0	100	9.81%	90.19%	ROGUE
1	200	18.78%	81.22%	
2	300	26.90%	73.10%	
3	400	34.22%	65.78%	
4	500	40.83%	59.17%	
5	600	46.79%	53.21%	
6	700	52.16%	47.84%	
7	800	56.99%	43.01%	
8	900	61.34%	38.66%	
9	1000	65.25%	34.75%	
10	1100	68.77%	31.23%	
11	1200	71.93%	28.07%	
12	1300	74.78%	25.22%	
13	1400	77.34%	22.66%	
14	1500	79.64%	20.36%	

15	1600	81.71%	18.29%	
16	1700	83.57%	16.43%	
17	1800	85.25%	14.75%	WARNING
18	1900	86.75%	13.25%	WARNING
19	2000	88.10%	11.90%	WARNING
20	2100	89.31%	10.69%	WARNING
21	2200	90.40%	9.60%	WARNING
22	2300	91.38%	8.62%	WARNING
23	2400	92.26%	7.74%	WARNING
24	2500	93.05%	6.95%	WARNING
25	2600	93.76%	6.24%	WARNING
26	2700	94.40%	5.60%	WARNING
27	2800	94.97%	5.03%	WARNING
28	2900	95.49%	4.51%	REMOVE/MAINTAIN
29	3000	95.95%	4.05%	REMOVE/MAINTAIN
30	3100	96.36%	3.64%	REMOVE/MAINTAIN
31	3200	96.73%	3.27%	REMOVE/MAINTAIN

Forecasting

The current study aimed to analyze and forecast the monthly demand for aircraft landing gearboxes using time series data spanning January 2015 to January 2025, totaling 121 monthly observations. The analysis utilized the SARIMAX modeling framework to capture seasonal and non-seasonal components inherent in the demand pattern. Understanding these demand trends is critical for effective inventory planning, minimizing aircraft downtime, and optimizing operational logistics in the aviation maintenance sector.

Initial exploratory analysis showed considerable fluctuations in monthly demand with occasional spikes, indicating possible irregular bulk replacements or maintenance schedules. Seasonal decomposition highlighted clear seasonality aligned with a 12-month cycle, consistent with annual inspection and replacement schedules. The additive decomposition indicated a stable seasonal component while the trend component displayed moderate fluctuations, suggesting a relatively stable underlying demand with seasonal peaks.

Autocorrelation (ACF) and partial autocorrelation (PACF) plots revealed significant lags, suggesting the potential inclusion of seasonal differencing and AR or MA terms. A systematic grid search using various combinations of (p, d, q) and seasonal (P, D, Q, s) parameters was conducted to identify the model with the lowest AIC, ensuring a balance between goodness of fit and model complexity.

The parameter search evaluated over 64 combinations, identifying **SARIMA (0, 1, 1) × (0, 1, 1, 12)** as the optimal model with the lowest AIC of **464.06**, indicating superior explanatory power while maintaining parsimony. The summary of the fitted model showed:

Table 3. Parameter Estimates for SARIMA (0,1,1) (0,1,1,12) Model Used in Landing Gearbox Demand Forecasting

Term	Coefficient	Std. Error	p-value
MA (1)	-1.000	339.676	0.998
SMA (12)	-1.000	2425.923	1.000
$sigma^2$	5.979	14500	1.000

Despite high standard errors and non-significant p-values, the low AIC and residual diagnostics suggested the model adequately captured the demand patterns without overfitting. To evaluate predictive accuracy, a six-month rolling forecast was generated. The mean squared error (MSE) for the forecast period was **6.02**, with a root mean square error (RMSE) of **2.45**, demonstrating a reasonably low forecast error relative to the scale of monthly demand (ranging mostly between 0–10). The forecast aligned closely with observed data during the validation period, further supporting the model's predictive validity. Using the selected SARIMAX model, a six-month ahead forecast was generated for February 2025 to July 2025. The predicted monthly demand was as follows:

Table 4. Six-Month Forecast of Monthly Demand for Aircraft Landing Gearboxes (Feb 2025 – Jul 2025)

Month	Predicted Demand
Feb 2025	2.06
Mar 2025	3.96
Apr 2025	4.86

May 2025	3.56
Jun 2025	3.86
Jul 2025	2.56

These forecasts suggest moderate demand over the next six months, peaking in April and gradually declining toward July, aligning with historical seasonal replacement cycles. The developed SARIMAX forecasting model provides a systematic and data-driven approach to predicting monthly demand for aircraft landing gearboxes. Such forecasting allows maintenance teams to plan procurement and stocking proactively, reducing lead times and minimizing the risk of shortages during peak maintenance cycles. This methodology can also be extended to other critical aircraft components to enhance predictive maintenance and operational readiness.

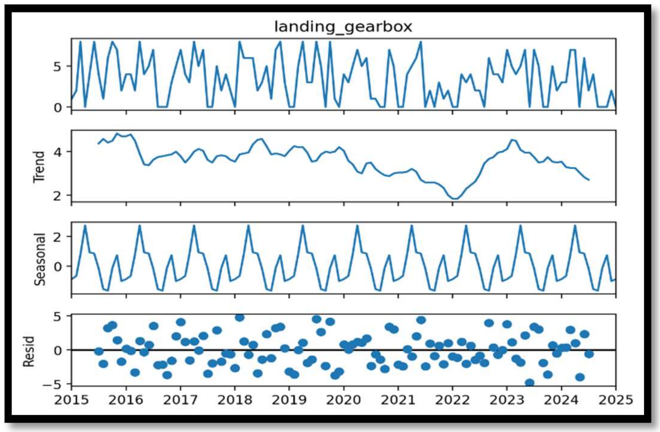

Figure 1. Seasonal Decomposition of Monthly Landing Gearbox Demand (2015–2025)

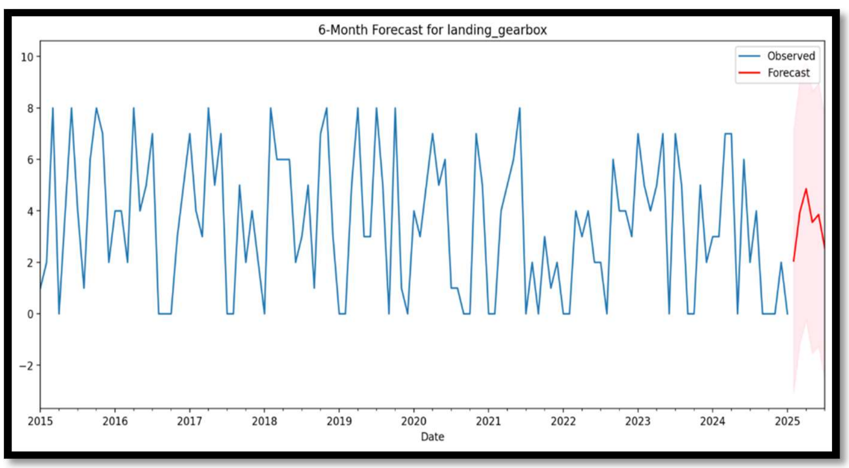

Figure 2. Six-Month Forecast of Aircraft Landing Gearbox Demand Using SARIMAX Model

Table 5. 6-Month Forecasted Demand for Aircraft Landing Gearboxes based on the SARIMAX model

Months	Predicted Mean
2025-02-01 00:00:00	2.0583337482328066
2025-03-01 00:00:00	3.9583336567098573
2025-04-01 00:00:00	4.858333297281604
2025-05-01 00:00:00	3.5583344320649104
2025-06-01 00:00:00	3.8583334745763
2025-07-01 00:00:00	2.5583340140993127

DISCUSSION

The results of the work prove the efficiency of combining statistical reliability analysis and time series forecasting to improve predictive maintenance in aircraft engineering. The Weibull analysis of the failures of propeller blades showed a nearly random but slightly wear-out failure model, allowing for important thresholds for preventive actions to be established, thus lowering the risk of in-service failures. At the same time, the SARIMAX model successfully reproduced seasonal demand trends for landing gearboxes, making proactive inventory planning feasible. Combined, these AI-based strategies enable a move from reactive to condition-based maintenance, maximizing operational effectiveness, reducing downtime, and enhancing safety and resource efficiency in aviation maintenance operations.

CONCLUSION

Therefore, the research underscores the revolutionary impact of AI-based maintenance models in making aircraft engineering operations more efficient. Using Weibull reliability analysis and SARIMAX-based demand forecasting, the study illustrates how data-driven strategies can efficiently forecast component failures and upcoming maintenance requirements, which in turn facilitate condition-based planning and proactive resource allocation. This transition from reactive to predictive maintenance not only reduces unplanned downtime and enhances safety but also facilitates cost-effective operation via optimized inventory management. The incorporation of AI tools in maintenance processes represents a strategic leap forward for aviation engineering, opening the doors to intelligent, safer, and more efficient maintenance environments.

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