Prediction in Business Aviation Using a Data-Driven Model

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Abstract
Nowadays, aviation companies can anticipate maintenance needs and ensure the availability (in advance) of spare parts for maintaining aircraft airworthiness and to avoid facing an unexpected AOG (Aircraft on Ground) status. The research paper explores supportive data-driven tools for predictive analytics across the civil aviation industry, focusing on how these technologies can transform line maintenance and spare parts inquiry forecasting.

This study focuses on Business Aviation, where operational continuity is highly sensitive to delays due to the need for fast, flexible maintenance support. A structural framework was developed to describe and compare strengths, weaknesses and strategic priorities of relevant data-driven implementation. The priorities on the data-driven maintenance approach were explained in recent studies (Hang et al., 2023).

Recent developments in predictive analytics allow component failure likelihoods to be estimated using historical removal records and aircraft utilization data. However, although failure probabilities can be predicted, the operational decision problem remains unresolved: how spare parts should be stocked, replenished, and allocated over time to minimize AOG risk while controlling logistics and operational costs.

The research problem lies at the intersection of aircraft airworthiness management, maintenance planning, and logistics optimization. The challenge is characterized by uncertainty in component failures, limited inventory capacity, long replenishment lead times, quality of ordered spare part and the high penalty associated with delayed maintenance actions.

1. Introduction
According to the European Aviation Safety Agency (EASA), an aircraft is considered airworthy if it complies with its approved type design and is in safe operating condition. This requirement is not only a technical requirement but also a strategic factor determining operational efficiency and reliability.

Airworthiness is directly linked to dispatch reliability, maintenance planning, and overall operational continuity, as any failure to meet standards can lead to costly interruptions, delays, or cancellations (Stolzer & Goglia, 2015).

The consequences are more severe in the context of business aviation, where, due to small fleets and customer-centric operations, the loss of a single aircraft can jeopardize all customer commitments or business schedules.

Business Aviation (or General Aviation (GA)) industry has been more dynamic for the last decades not only in North American region, but also worldwide. Over the past decade, the global business jet fleet has experienced significant growth. As of 2019, the estimated quantity of business jets worldwide was about 21,979 aircraft (Pangarkar, 2025). From this quantity, North America owns 71%, while Europe held approximately 13% of total jets which means about 2,860 aircraft (Pangarkar, 2025).

The number of technical failures and system errors is increasing apparently. Unfortunately, some technical tasks cannot be solved as quickly as planned due to some factors. Those factors can be related to spare parts logistics, weather conditions, lack of staff, wrong issued documents, maintenance ("MX") facility locations-capabilities. Most times these cases resulted in AOG status, which means

aircraft are not operational or not Airworthy (technically healthy).

The research aim is to predict possible AOG ("Aircraft on Ground") cases in advance in Business Aviation and notifying Airline or Carrier by providing the gap by demonstrating how predictive models can improve spare parts logistics and accordingly, aircraft airworthiness.

Recent studies show that the maintenance support model is evolving from reliability-based scheduled maintenance to condition-based predictive maintenance (Sun et al., 2025).

Business aviation requires particularly high levels of reliability and fast turnaround times, making predictive maintenance a key factor in ensuring operational efficiency and reducing maintenance-related delays. Business aviation operators achieve peak fleet performance and availability levels by adopting their maintenance approach from reactive practices to data-based proactive measures (Daily & Peterson, 2016)

An AOG (Aircraft on Ground) scenario requires immediate corrective action and typically results in high direct and indirect costs. According to research conducted by IATA in 2017, AOG can cost commercial carriers more than US$150,000 per day. Costs vary depending on the type of network configuration on aircraft and the disruption to passenger services. Because they often occur outside planned maintenance windows, these situations are considered serious because they are unplanned events.

Fleet redundancy and well-established supply chain systems help reduce the impact of AOGs on airline operations. Airlines often have extensive networks, typically have multiple aircraft of the same type, allowing capacity to be redistributed in the event of unexpected disruptions (Sebastian et al., 2025).

The relevant research gap is the fact that there is no integrated, validated framework combining predictive maintenance and logistics optimization for business aviation.

The major research questions are collected as per below:

- How can data-driven predictive analytics be effectively applied to prevent or mitigate Aircraft-on-Ground (AOG) events in the Business Aviation industry?
- Which operational, airworthiness, and logistics data variables most significantly influence AOG occurrence in Business Aviation?
- How can predictive insights be operationalized to support proactive maintenance scheduling and spare-parts allocation?

Similar research approaches already exist in regular based operations, products or approaches developed by manufacturers or airlines.

There are some alternative approaches that already exist; however, these are related to preventive (schedule-based) maintenance and reliability centered maintenance (RCM).

The novelty lies in the development of an integrated, data-driven decision-support framework that combines predictive maintenance and spare parts logistics specifically for business aviation, with a focus on reducing AOG events.

The proposed approach applies to a supervised classification model using operational and maintenance-related variables, including component age, maintenance intervals, and logistics lead times, to estimate failure probability and support proactive spare parts planning by using exact data base for exact company where each company may apply the internal data transformation into the proposed model.

2. Procedure, methods or experimental part

For the methodology, predictive modelling and hybrid optimization framework approaches have been selected to develop the model

The research design is structured with flow of 3 steps: Collection and comparison of historical datasets, data preprocessing, and model development to estimate the failure probabilities and remaining useful life of components. The classification model is trained using operational and maintenance-related variables such as component age, maintenance interval, flight activity, and supply delay. A predefined decision threshold is introduced to convert predicted failure probabilities into actionable logistics decisions. Model validation is performed through a supervised classification accuracy assessment, and scenario-based evaluation using a real operational case study.

2.1. Data collection and preparation

A synthetic dataset has been generated to simulate aircraft maintenance planning and operational conditions based on major parameters according to the historical reports.

As is a well-known fact that as much data is being collected in dataset as much accuracy percentage on the results. In this research, a dataset consisting of 500 observations was generated and processed.

To ensure the realism of the proposed dataset and modeling approach, empirical data on component removals from the Bombardier Global Express fleet were considered. Table 1 presents the most frequently removed components over a 12-month

period, highlighting the practical relevance of failure events in business aviation operations.

Table 1: Top 15 removed components

Component	Description	Removals
GG436-1055-3	VALVE	29
09-130021-102	FILTER	28
GX473-0126-1	ACTUATOR ASSY	26
7023300-913	PMAT	25
7900371-203	TOILET ASSY	24
MXP411-9	OXYGEN MASK	23
GG431-2010-3	MACHINE, AIR CYCLE	23
GT415-0100-9	FCU	19
5E2651-8	EIB CONTROL PWS	16
GC584-1001-4	CONTROLR TEMPERATURE	16
G02530001-001-162	MICROWAVE	15
GW415-7125-9	(BCU)	14
GP546-1501-9	FMQGC	11
GS321-0591-9	PAX DOOR ACTUATOR	11
GH582-3001-9	COMPUTER STALL PROTECTION	9

The frequency of component removals supports the selection of failure-related variables in the model and justifies the need for predictive approaches to anticipate such events.

The generated dataset reflects realistic relationships between operational, maintenance, and logistical variables observed in aviation practice. Key parameters such as flight hours, component age, maintenance intervals, and supply delays were modeled based on typical industry ranges reported in the literature. Collected data has been mined in "Orange" tool and obtained percentage of error rate which is shown in below figure 1.

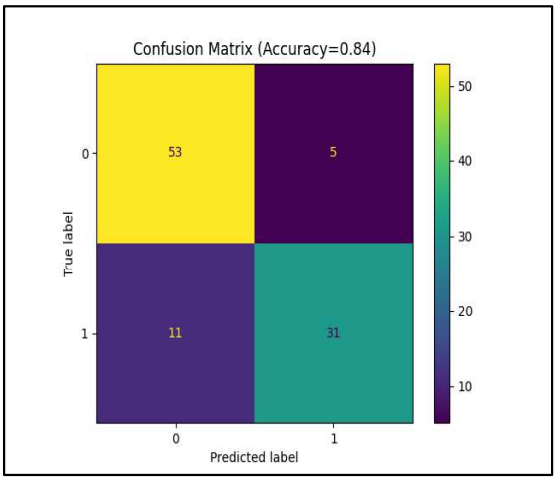

Figure 1: Classification Performance Matrix

A classification performance matrix (also referred to as an error matrix) was used to evaluate the predictive model. The dataset was automatically divided into training and testing subsets by the analytical tool. During the training phase, the model identified relationships between variables, such as higher component age being associated with increased failure risk and longer maintenance intervals contributing to a higher likelihood of AOG events.

The trained model was then applied to the testing data, where predicted outcomes were compared with actual observations. Based on this comparison, the classification performance matrix was generated, indicating an overall prediction accuracy of 84%.

2.2. Logistic regression

To estimate the probability of component failure, logistic regression-based framework is proposed. The probability estimation is as function of operational and maintenance related variables.

The predicted failure probabilities were integrated into a logistics decision-making process. Practically, it's when the threshold was exceeded and spare parts have been ordered in advance, reducing logistics delays and avoiding the risk of AOG events.

One of the key features of the process chain is decision threshold which converts probability into action. A decision threshold was defined such that when predicted probability failure exceeds a predefined value, accordingly, spare parts request is triggered.

3. Validation Strategy

To prove the supposed approach that is useful and practically show reliability, a case study from real case scenario is applied as a validation strategy.

Case study is related to one of the most known business jets, Embraer Legacy 600/650 (also known

as ERJ-135/145). The aircraft tail number will be kept anonymously as per the confidentiality rules.

3.1. Case study: ERJ-135/145 AOG scenario due to the main windshield

The crew of the aircraft tail number XX-XXX have reported the delamination on the main windshield (part number NP-151311-18 RIGHT HAND WINDSHIELD), and accordingly the planning engineers from the continuing airworthiness department started to look for the closest service center or maintenance facility at the destination point to request the troubleshooting. Once the delamination measures are out of limits (as per manuals), aircraft needs immediate replacement of the windshield.

Accordingly, logistics team should be involved in sourcing the required component from the OEM or from the market. All the sources show TBA availability or at least 3 months lead time. This case has caused several negative outcomes for the company. As a decision to solve the problem, components have been ordered with shorter lead time but more expensive from the 3rd party company.

On the other hand, this case helped to make historical analysis by counting on first data of replacement of current windshield (around 2010-2011) and condition. In this accordance, the data of sufficient fleets worldwide has been analyzed by using major parameters such as geography of routing, flight hours/cycles.

Conclusively, it's been stated that all windshields produced (for business jets) by PPG, have operational health in interval of duration between 11-14 years for the new condition. All other conditions like repaired or overhauled are supposed to be replaced in 2-4 years.

By incorporating these patterns into a predictive model, the probability of failure could be estimated in advance. If the predicted failure probability exceeded the defined threshold, a preemptive spare parts request could be initiated, ensuring component availability prior to failure occurrence.

This case study validates the proposed approach by demonstrating that the integration of predictive analytics with logistics planning could have prevented the AOG event, reduced lead time impact, and avoided additional costs. The results highlight the practical applicability of the framework in real-world airworthiness management scenarios.

4. Results and discussion

A synthetic dataset representing aircraft maintenance and operational conditions was used to assess the developed predictive approach.

The classification performance matrix shows that the classification-based model had an overall prediction accuracy of 84%. This demonstrates the model's strong ability to accurately distinguish between failure and non-failure events based on the chosen input variables.

According to the analysis, factors like supply delay, component age, and the amount of time since the last maintenance have a big impact on the likelihood of failure. These results align with real-world observations in business aviation where technical failures are more likely due to aging components and prolonged maintenance intervals.

A significant contribution to this study is the incorporation of predictive outputs into a logistics decision-making process. Predicted failure probabilities were transformed into practical supply chain and maintenance choices by implementing a decision threshold.

Table 2: Model Performance

Metric	Value
Accuracy	84%
Method	Classification model
Validation	Train-test split

Preemptive spare parts provisioning was initiated when the threshold was surpassed, minimizing possible delays brought on by component unavailability. The suggested frameworks operational impact was illustrated through a scenario-based comparison of reactive and predictive maintenance techniques. Failures in the reactive scenario increased the probability of AOG events and caused component sourcing to be delayed.

On the other hand, proactive planning was made possible by the predictive scenario, which minimized AOG incidents and decreased supply

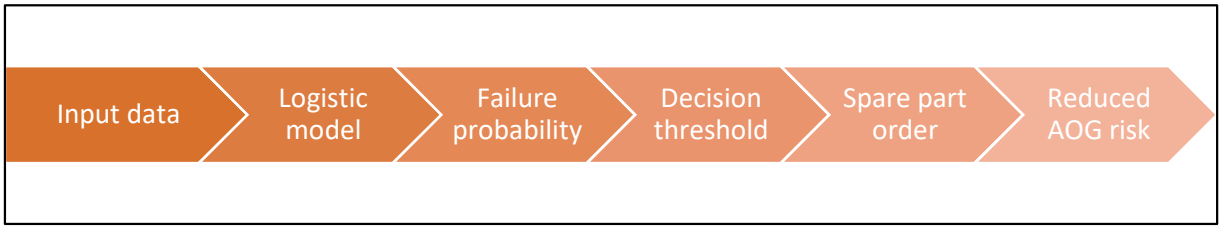

Figure 2: Model development chain architecture

delays. The case study provides additional evidence for these conclusions by presenting a real-world AOG incident brought on by windshield failure where operations were severely impacted by lengthy lead times.

The suggested frameworks application in these kinds of situations shows how early prediction and prompt logistical action can avert similar disruptions. Conclusively, the findings support the idea that combining logistics planning with predictive analytics can improve airworthiness management decision-making, increase aircraft availability and lower operational risks related to AOG events.

5. Limitations and conclusion

5.1. Limitations and future work

Despite the promising results, several limitations should be acknowledged. First, the analysis was based on a synthetic dataset, which, although designed to reflect realistic operational conditions, may not capture all complexities of real-world aviation systems.

Second, the predictive model framework was developed using a supervised classification approach, and further improvements could be achieved by applying more advanced machine learning techniques or hybrid models. As recent studies have already shown, the importance of digital implementations in air transportation (Tafur et al., 2025).

Third, the validation was conducted through scenario analysis and a single case study, which may limit the generalizability of the findings across different aircraft types and operational environments.

Future research should focus on the application of the proposed framework to real operational datasets, the incorporation of additional variables such as environmental and operational uncertainties, and the development of more advanced predictive models. Additionally, integration with real-time data systems and digital twins could further enhance the effectiveness of predictive airworthiness management.

5.2. Conclusion

This study proposed a data-driven decision-support framework for aircraft airworthiness management in business aviation, integrating predictive analytics with logistics planning to mitigate AOG events. The results demonstrate that predictive modeling can effectively identify potential failures, while the introduction of a decision threshold enables the translation of predictions into actionable maintenance and supply chain decisions. A supervised classification approach was applied, as the model was trained on historical data with predefined failure outcomes

The achieved prediction accuracy of 84% and the outcomes of scenario-based analysis indicate that the proposed approach can significantly improve operational efficiency by reducing delays and preventing unplanned aircraft downtime. Furthermore, the inclusion of real-world case study validation highlights the practical applicability of the framework in actual CAMO environments.

The research contributes to the field by addressing the gap between predictive maintenance and logistics decision-making, particularly within the underexplored domain of business aviation. The proposed framework provides a foundation for more proactive, data-driven airworthiness management practices. The classification results are integrated into the aviation logistics process through a threshold-based decision mechanism. When the predicted probability of component failure exceeds the predefined threshold, a spare parts request is initiated in advance. This enables earlier sourcing and inventory planning, reducing lead-time exposure and minimizing the risk of AOG events caused by component unavailability.

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