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APPLICATION OF MARKOV CHAINS, MTBF AND MACHINE LEARNING IN AIR TRANSPORT RELIABILITY

ZASTOSOWANIE ŁAŃCUCHÓW MARKOWA, WSKAŹNIKA MTBF I UCZENIA MASZYNOWEGO W NIEZAWODNOŚCI TRANSPORTU LOTNICZEGO

Abstract

Air transport reliability is a critical aspect in enhancing passenger satisfaction, network connectivity, safety, environmental sustainability, and operational efficiency. In the air transport industry, the reliability of critical components and systems plays an important role in ensuring the safety and efficiency of air transport systems. This article explores the integration of advanced methodologies, including Markov chains, mean time between failure (MTBF) analysis, and machine learning, as promising ways to improve the reliability. In addition, this article provides an overview of in-service data provide insights into prospects and discussions of challenges, regulatory implications, and industry collaboration further contribute to a comprehensive understanding of the application of machine learning and MTBF analysis in air transport reliability. The diverse applications and evolving trends in predictive maintenance underscore its importance in shaping the future of maintenance practices in the air transportation industry.

Keywords: reliability, air transport, Markov chain, MTBF, machine learning

Streszczenie

Niezawodność transportu lotniczego jest kluczowym aspektem w zwiększaniu zadowolenia pasażerów, łączności sieciowej, bezpieczeństwa, zrównoważenia środowiskowego i wydajności operacyjnej. W branży transportu lotniczego niezawodność krytycznych komponentów i systemów odgrywa ważną rolę w zapewnieniu bezpieczeństwa i wydajności systemów transportu lotniczego. Niniejszy artykuł analizuje integrację zaawansowanych metodologii, w tym łańcuchów Markowa, analizy średniego czasu między awariami (MTBF) i uczenia maszynowego, jako obiecujących sposobów poprawy niezawodności. Ponadto, niniejszy artykuł zawiera przegląd danych eksploatacyjnych, wgląd w przyszłe perspektywy i dyskusje na temat wyzwań, implikacji regulacyjnych i współpracy branżowej, co dodatkowo przyczynia się do kompleksowego zrozumienia zastosowania uczenia maszynowego i analizy MTBF w niezawodności transportu lotniczego. Różnorodne zastosowania i ewoluujące trendy w konserwacji predykcyjnej podkreślają jej znaczenie w kształtowaniu przyszłości praktyk konserwacyjnych w branży transportu lotniczego.

Słowa kluczowe: niezawodność, transport lotniczy, łańcuchy Markowa, MTBF, uczenie maszynowe

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1. INTRODUCTION

1.1. BACKGROUND

The critical aspect of the aviation industry is reliability, which affects safety, efficiency, and passenger experience. At its core, aviation reliability ensures that aircraft can perform their intended operations safely and without unnecessary delays. This involves the mechanical integrity of the aircraft, the precision of flight operations, reliable schedules, and effective emergency procedures. High reliability is crucial to maintaining public confidence in air travel, minimising operational costs due to delays and unscheduled maintenance, and meeting stringent regulatory standards. It plays a key role in the protection of human life, highlighting its paramount importance.

As air travel continues to grow, the industry prioritises improving reliability through technological innovation, rigorous maintenance practices, and advanced operational protocols. This commitment not only improves airline competitiveness but also ensures that air transport remains one of the safest modes of travel worldwide. Given the increasing congestion in air traffic and rising passenger expectations, air transport systems must be both efficient and reliable. Advanced analytical methods such as Markov models, machine learning, and time-between-failure analysis are vital to monitoring, predicting, and optimising the performance and reliability of air transport systems. These methods allow for comprehensive analysis of historical and current data, enabling the identification and resolution of potential issues before they affect operations, significantly contributing to enhanced reliability standards in the aviation industry.

1.2. IMPORTANCE OF AIRCRAFT RELIABILITY FOR AIR TRANSPORT RELIABILITY

Aircraft reliability is a crucial aspect of the aviation industry, influencing the efficiency, safety, and effectiveness of air transport operations. The consistently acknowledges the paramount importance of aircraft reliability. For instance, Knotts[1] noted that maintenance activities and their associated downtime significantly impact dispatch reliability and direct maintenance costs, affecting the operational efficiency of airlines. Fan et al.[2] also cited dispatch reliability as a critical metric for evaluating the reliability and operational efficiency of civil aircraft, emphasising its role in determining the performance of individual aircraft and entire fleets.

Another author[3] emphasized the vital nature of aircraft reliability for enhancing performance and survivability, particularly in the reliability of critical components like aeroengine rotors, which directly affect overall aircraft performance and safety.

1 Knotts, 'Civil Aircraft Maintenance and Support Fault Diagnosis From a Business Perspective'.

2 Fan, Zhao, and Jiao, 'Dispatch Reliability of Civil Aviation Simulation Based on Generalized Stochastic Petri Nets (GSPN)'.

3 Liu et al., 'Vibration Reliability Analysis of Aeroengine Rotor Based on Intelligent Neural Network Modeling Framework'.

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Another publication[4] was highlighted that reliable predictions of aircraft turnaround times are essential for improving the punctuality and operational efficiency of airline operations. Furthermore, another researcher underscored the importance of comprehensive maintenance technician training programmes to ensure aircraft safety, highlighting their role in maintaining high safety standards within air transport operations.

In conclusion, the reliability of aeronautical systems, components and operations is fundamental to the success and safety of air transport operations. By striving for maximum reliability, airlines can significantly improve operational efficiency and punctuality, maintain high safety standards, and provide customers with a seamless and hassle-free air travel experience.

1.3. OVERVIEW OF ANALYTICAL MODELS IN AIR TRANSPORT RELIABILITY

Analytical models in air transport reliability encompass a diverse range of methodologies that are utilised to analyse and optimise various aspects of air transport systems. These models play a crucial role in understanding network structures, fault tolerance, and operational parameters within the air transport domain. Several types of analytical models have been applied in the context of air transport reliability, each serving specific purposes and providing valuable insights into system performance.

In Poland, notable research has been conducted by Prof. Lewitowicz[5] and Prof. Żurek[6], who emphasise the importance of reliability in aviation. Two main approaches to reliability theory are evident: the mathematical approach, based on models created from data, and the engineering approach. The mathematical approach relies heavily on probability theory and mathematical statistics to address many reliability issues, despite technological advances and rigorous manufacturing controls[7]. Reliability theory, using stochastic processes, is well-documented in both Polish and international literature, with Prof. Grabski[8] notably using Markov and semi-Markov models.

In the realm of air transport reliability, various analytical models are utilised, including mean time between failures (MTBF) calculations, Markov chain modelling, and machine learning algorithms. Gupta et al.[9] employed MTBF calculations and Markov chain modelling to analyse the reliability of optical wireless communication

4 Schultz and Reitmann, 'Consideration of Passenger Interactions for the Prediction of Aircraft Boarding Time'.

5 Lewitowicz, Podstawy eksploatacji statków powietrznych; Lewitowicz, 'Uncertainty and Dependability of the Risk Model Applicable to Operation of Aircrafts'.

6 Żurek, 'Review of the safety evaluation methods in aviation'; Żurek, Tomaszek, and Zieja, 'Analysis of Structural Component's Lifetime Distribution Considered from the Aspect of the Wearing with the Characteristic Function Applied'.

7 Sadraey, 'Aircraft Design: A Systems Engineering Approach'.

8 'Semi-Markov Processes Applications in System Reliability and Maintenance - Franciszek Grabski w KrainaKsiazek.Pl'.

9 Gupta, Chandra, and Dixit, 'Reliability Analysis of a Fault-Tolerant Full-Duplex Optical Wireless Communication Transceiver'.

transceivers. Wang[10] emphasised the significance of MTBF in the analysis of fatigue reliability of structural components. Furthermore, machine learning models have been increasingly integrated into air transport reliability studies. For example, Salami[11] developed machine learning classifiers to predict historical data on dengue importation from European countries, demonstrating the application of machine learning in forecasting air transport-related phenomena. These diverse analytical models, ranging from traditional reliability calculations to advanced machine learning algorithms, are crucial for evaluating and enhancing air transport reliability, thereby ensuring safe and efficient operations in the aviation industry.

In addition to the models presented below, various analytical models are crucial for evaluating air transport reliability. Percolation theory analyses network reliability and fault tolerance by representing aviation structures as random graphs[12]. Queuing and network decomposition models study delay propagation within air transport networks by decomposing them into queuing components[13]. Uncertainty transformation models convert quantitative data into qualitative assessments, enhancing reliability evaluation[14]. Additionally, Monte Carlo methods determine the reliability of complex technical systems by using random variable concepts, and statistical methods. Together, these models provide comprehensive frameworks for assessing network robustness, delay factors, and operational parameters, ensuring the safe and efficient operation of air transport systems.

1.4. OBJECTIVES OF THE ARTICLE

Reliability of air transport systems is critical to ensuring the safety, efficiency and overall success of the aviation industry. In response to continued advances in technology and, this article explores the integration of advanced methodologies, including Markov chains, mean time between failure (MTBF) analysis and machine learning, as promising ways to improve the reliability of critical components and systems. The following chapters provide a comprehensive analysis of these advanced techniques and highlighting their role in ensuring passenger safety, operational efficiency, and customer satisfaction. Analysis of in-service data provides insights into prospects and discussions of challenges, regulatory implications, and industry collaboration further contribute to a comprehensive understanding of the application of Markov chains, MTBF analysis, and machine learning in air transport reliability.

10 Wang et al., ‘Fatigue Reliability Analysis and Design for Structural Components in Quasi-One-Shot Device’.

11 Salami et al., ‘Predicting Dengue Importation Into Europe, Using Machine Learning and Model-Agnostic Methods’.

12 Lesko, Aleshkin, and Zhukov, ‘Reliability Analysis of the Air Transportation Network When Blocking Nodes and/or Connections Based on the Methods of Percolation Theory’.

13 Wang et al., ‘Fatigue Reliability Analysis and Design for Structural Components in Quasi-One-Shot Device’.

14 Li, Zhang, and Cheng, ‘Reliability Analysis of an Air Traffic Network: From Network Structure to Transport Function’.

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2. MARKOV CHAINS IN AIR TRANSPORT RELIABILITY

2.1. PRINCIPLES OF MARKOV CHAINS

Markov chains, which are stochastic processes that transition between states based on probabilistic rules, have been extensively studied in various fields, including statistics, computer science, and linguistics[15]. Advanced concepts such as large deviation rate functions[16], generalised crested products[17], and Markov-modulated diffusion processes[18] have emerged from these studies. Research has also explored the structure and eigenvalues of heat-bath Markov chains and developed frameworks like the extended Laplace principle for empirical measures. The study of measure-valued Markov chains in Bayesian non-parametrics has enhanced their flexibility. In general, Markov chains have significantly advanced scientific disciplines, providing deep insight into stochastic processes and their applications.

Markov processes are essential to model the dynamic behaviour of complex aviation systems and assess their reliability[19]. They provide a robust framework for reliability evaluation[20], particularly in small sample sizes and dynamic conditions[21]. Advanced applications, such as combining Markov processes with block diagrams, have proven effective for rapid and accurate reliability assessments of systems like electrical power generation, relevant to aviation[22]. Furthermore, Markov processes are flexible in analysing the reliability of control systems, which is essential for safe aviation operations[23]. The versatility and depth of Markov processes in various domains, including semi-Markov models for broader reliability indexes, underscore their critical role in enhancing aviation safety and operational efficiency[24].

15 Levin, Peres, and Wilmer, 'Markov Chains and Mixing Times'; Meyn, Tweedie, and Glynn, 'Markov Chains and Stochastic Stability'; Al-Anziand and AbuZeina, 'A Survey of Markov Chain Models in Linguistics Applications'.

16 Vidyasagar, 'An Elementary Derivation of the Large Deviation Rate Function for Finite State <scp>M</Scp>arkov Chains'.

17 D'Angeli and Donno, 'Generalized Crested Products of Markov Chains'.

18 Huang, Ng, and Chan, 'Wind Shear Prediction from Light Detection and Ranging Data Using Machine Learning Methods'.

19 Oszczypała, Konwerski, Ziółkowski, and Małachowski, 'Reliability analysis and redundancy optimization of k-out-of-n systems with random variable k using continuous time Markov chain and Monte Carlo simulation'.

20 Szkutnik-Rogoż, Małachowski, and Ziołkowski, 'An innovative computational algorithm for modelling technical readiness coefficient: A case study in automotive industry'.

21 Wang and Cheng, 'A Study on Bayesian Method for Reliability Evaluation of Small Sample Size Aviation Support Systems'.

22 Tawfiq et al., 'Reliability Assessment for Electrical Power Generation System Based on Advanced Markov Process Combined With Blocks Diagram'.

23 Wang et al., 'Reliability Analysis for a Hypersonic Aircraft's Wing Spar'.

24 D'Amico, Janssen, and Manca, 'Semi-Markov Reliability Models With Recurrence Times and Credit Rating Applications'.

2.2. CASE STUDIES – REAL-WORLD EXAMPLES OF MARKOV CHAIN APPLICATIONS

The study of the readiness of aircraft to perform flight tasks should begin with a strict definition of the operating states in which the tested machine may be located, along with a determination of whether these states meet all readiness conditions. Although this model is applied specifically to transport aircraft, it is important to note that its underlying principles can be adapted and applied to any transport system, reflecting its versatility and applicability across different modes of transportation. This adaptability underscores the potential for broader application of the model, offering insight into the operational readiness and efficiency of various transport systems beyond just aircraft.

The aircraft can be in the following states:

- S_1 – Waiting before launching – The aircraft is in a state of readiness for flight;
- S_2 – Pre-flight maintenance – replenishment of fuel, operating fluids, and check of the aircraft by technicians carried out each time before the start of the flight (according to the provisions of the "norms of current maintenance" the duration of the service is 15 minutes);
- S_3 – Flight – The time from the start of the engine with the intention of performing an air task to its shutdown after taxiing;
- S_4 – Post-flight maintenance – replenishment of fuel, operating fluids, and securing the aircraft, carried out after the last flight of each flying day (according to the provisions of the "time standards for the performance of ongoing maintenance" the duration of the service is 30 minutes);
- S_5 – Pilot's takeover of the aircraft – control by the pilot of the efficiency of the aircraft each time before the flight (the duration of the takeover was set at 10 minutes based on the observation of the pilots' behaviour);
- S_6 – Aircraft malfunction: After diagnosing the malfunction in the previous states, the aircraft is in the flight malfunction state. The next step is to move to the S-7 state;
- S_7 – Operation – During this state, the readiness and efficiency of the aircraft are restored after a malfunction is detected in previous states;
- S_8 – Awaiting Flight – Time when no activities are performed on the aircraft, however, it is ready to perform an aviation task.

In addition to carefully analysing the states in which the aircraft may be in, attention should also be paid to the characteristics of the transitions between these states. In Table 1 is presented a matrix that illustrates the characteristics of transitions between states of an aircraft and additionally the transitions between operation states are presented in Figure 1.

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Table 1. The possibilities of transitions between states [own elaboration]

	λ_{ij}	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	Sum from
S_1 – Waiting before launching	S_1	–	1	0	0	0	1	0	1	3
S_2 – Pre-launch service status	S_2	0	–	1	0	0	1	0	0	2
S_3 – Flight status	S_3	0	0	–	1	0	0	0	0	1
S_4 – Post-flight service	S_4	0	0	0	–	1	1	0	1	3
S_5 – Acceptance of aircraft	S_5	0	0	0	0	–	1	1	0	2
S_6 – State of repair	S_6	0	0	0	0	0	–	1	0	1
S_7 – State of service	S_7	0	0	0	0	0	1	–	1	2
S_8 – State of waiting for flight	S_8	1	0	0	0	0	0	0	–	1
	Sum to	1	1	1	1	1	5	2	3	15

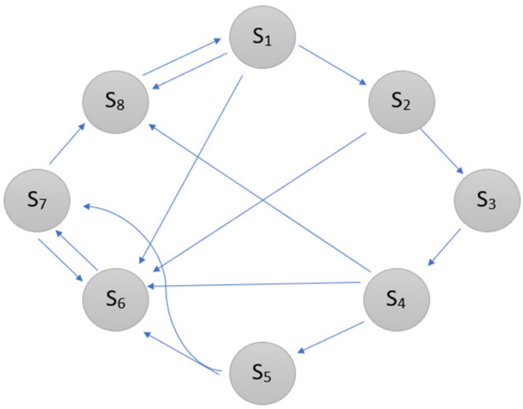

Fig. 1. Graph showing transitions between aircraft operational states [own elaboration]

2.3. ANALYSIS OF THE OPERATION PROCESS USING MARKOV PROCESSES

Transition of the aircraft from the state S_a to the S_b state, where $b \neq a$ in the time interval Δt is determined by the corresponding relation:

$$p_{a,b}(t, t + \Delta t) = F_{a,b}(t + \Delta t)\Pi_{a,b}$$

where:

– $F_{a,b}$ – the distributor of the residence time of the process in the state S_a, provided, that the next state will be S_b.

– $\Pi_{a,b}$ – The conditional probability of the Markov chain inserted in the process (the probability of jump transition).

The probability of occurrence of each state is determined by the probability of occurrence of the states included in Figure 1, and can be described by the equations:

$$\frac{dP_1(t)}{dt} = -(\lambda_{1,2} + \lambda_{1,8} + \lambda_{1,6})P_1(t) + \lambda_{8,1}P_8(t)$$
$$\frac{dP_2(t)}{dt} = -(\lambda_{2,3} + \lambda_{2,6})P_2(t) + \lambda_{1,2}P_1(t)$$
$$\frac{dP_3(t)}{dt} = -(\lambda_{3,4})P_3(t) + \lambda_{2,3}P_2(t)$$
$$\frac{dP_4(t)}{dt} = -(\lambda_{4,5} + \lambda_{4,6} + \lambda_{4,8})P_4(t) + \lambda_{3,4}P_3(t)$$
$$\frac{dP_5(t)}{dt} = -(\lambda_{5,6} + \lambda_{5,7})P_5(t) + \lambda_{4,5}P_4(t)$$
$$\frac{dP_6(t)}{dt} = -(\lambda_{6,7})P_6(t) + \lambda_{7,6}P_7(t) + \lambda_{5,6}P_5(t)$$
$$\frac{dP_7(t)}{dt} = -(\lambda_{7,6} + \lambda_{7,8})P_7(t) + \lambda_{6,7}P_6(t) + \lambda_{5,7}P_5(t)$$
$$\frac{dP_8(t)}{dt} = -(\lambda_{8,1})P_8(t) + \lambda_{1,8}P_1(t) + \lambda_{4,8}P_4(t) + \lambda_{7,8}P_7(t)$$

where:

- $P_1(t)$ – the probability of being in a “pre-flight day service” state.
- $P_2(t)$ – the probability of being in a “pre-launch service” state.
- $P_3(t)$ – the probability of being in a “flight” state.
- $P_4(t)$ – the probability of being in a “post-flight service” state.
- $P_5(t)$ – the probability of being in a state of “adopting an aircraft.”
- $P_6(t)$ – the probability of being in a “repair” state.
- $P_7(t)$ – the probability of being in a “service” state.
- $P_8(t)$ – the probability of being in a “waiting to fly” state.

The intensity of transitions from state a to state b, was expressed by the frequency of transitions per hr., $\lambda_{(a,b)}$ {1,2,3,4,5,6,7,8},

Matrix notation:

$$\frac{d}{dt}P(t) = \wedge P(t),$$

where:

$$P(t) = \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \\ P_5 \\ P_6 \\ P_7 \\ P_8 \end{bmatrix}$$

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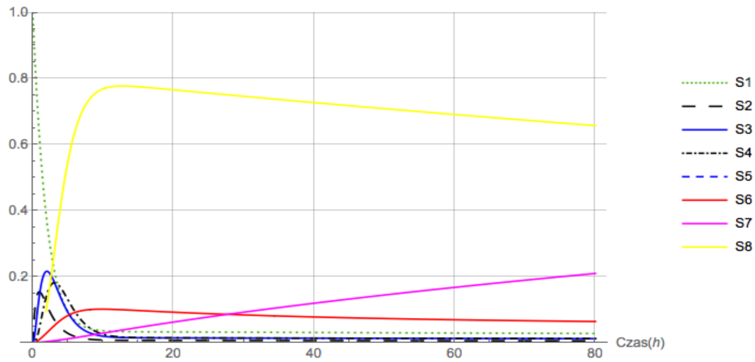

Fig. 2. The probability of an aircraft being in one of the operating states [own elaboration]

$$\Lambda = \begin{bmatrix} -(\lambda_{1,2}+\lambda_{1,8}+\lambda_{1,6}) & 0 & 0 & 0 & 0 & 0 & 0 & \lambda_{8,1} \\ \lambda_{1,2} & -(\lambda_{2,3}+\lambda_{2,6}) & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \lambda_{2,3} & -(\lambda_{3,4}) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \lambda_{3,4} & -(\lambda_{4,5}+\lambda_{4,6}+\lambda_{4,8}) & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \lambda_{4,5} & -(\lambda_{5,6}+\lambda_{5,7}) & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \lambda_{5,6} & -(\lambda_{6,7}) & \lambda_{7,6} & 0 \\ 0 & 0 & 0 & 0 & \lambda_{5,7} & \lambda_{6,7} & -(\lambda_{7,6}+\lambda_{7,8}) & 0 \\ \lambda_{1,8} & 0 & 0 & \lambda_{4,8} & 0 & 0 & \lambda_{7,8} & -(\lambda_{8,1}) \end{bmatrix}$$

From the analysis, the transitions among the various operational states of the aircraft reveal significant tendencies of the aircraft to be in particular states. According to the results of the analysis, the aircraft is most likely to be in state S_8 (waiting for flight) and state S_1 (pre-flight service). Thus, the aircraft is generally in a phase of preparation at this stage before it takes off. Further, a high probability being in state S_3 (in flight) is also evident, which means that once the aircraft transitions from being grounded to being in the air, it generally behaves as operational as normal and efficient as possible.

Conversely, the states with the least tendency to occur are state S_5 (pilot of aircraft takeover) and state S_2 (pre-takeoff service). These states have a probability of being transitioned to that decreases as the time in the operational distributions of the aircraft increases. This pattern could result from operational efficiencies and standard procedures that are realized as both the aircraft and the crew gain experience and activities are perfected for each flight. In total, the overall comprehensive analysis provides a likely portrait of the aircraft as it cycles through its operational states, and further, provides a sense of the dynamic nature of aircraft readiness and operations in their flow. The aircraft will more commonly be in states of preparation before it moves to take off, and actual flights as opposed to transitioning services or pilot take over. This distribution of states provides useful insights into the operational characteristics and efficiency of the aircraft.

2.4. SUMMARY OF MARCOV MODEL

The application of analytical models in air transport reliability, while highly beneficial, faces several limitations and challenges. However, case studies have also provided valuable insights into overcoming some of these issues:

1. Complexity of Systems: Air transport systems are inherently complex, involving numerous interdependent components and processes. This complexity can make it difficult to create accurate models that capture all relevant variables and interactions. Case studies have shown that breaking down the system into smaller, more manageable subsystems can improve model accuracy and reliability.
2. Data Availability and Quality: Reliable data is crucial for the effectiveness of models such as Markov processes and queuing models. However, obtaining high-quality, comprehensive data can be challenging due to issues like data fragmentation, proprietary restrictions, and variability in data collection methods[25]. Case studies suggest that implementing standardized data collection protocols and investing in advanced data integration platforms can mitigate these challenges.
3. Computational Requirements: Advanced models, particularly those involving large networks or stochastic processes, often require significant computational resources. This can be a barrier for some organizations, especially smaller ones, limiting their ability to implement such models effectively. Insights from case studies indicate that usage of proper numerical methods can provide scalable and cost-effective solutions.
4. Model Assumptions: Many analytical models rely on assumptions that may not hold true in all real-world scenarios. For instance, Markov models assume memoryless processes, which may not accurately reflect the behavior of certain aviation systems components.
5. Scalability: Applying models like the Monte Carlo method and Markov-modulated diffusion processes to large-scale systems can be challenging. Ensuring that these models remain scalable and efficient as system size and complexity grow is a significant hurdle. Successful case studies highlight the importance of iterative model refinement and validation to maintain scalability.
6. Interdisciplinary Integration: Effective reliability analysis often requires integrating knowledge from various disciplines, such as engineering, statistics, and economics. Case studies recommend establishing interdisciplinary teams and fostering continuous communication among experts to enhance integration.
7. Real-Time Application: Implementing these models for real-time monitoring and decision-making in air transport systems can be challenging due to the need for rapid data processing and analysis. The deploying real-time data analytics platforms and usage of other techniques like machine learning algorithms can improve responsiveness and decision-making.

[25] Wang and Cheng, 'A Study on Bayesian Method for Reliability Evaluation of Small Sample Size Aviation Support Systems'; Reyes-Garcés et al., 'Advances in Solid Phase Microextraction and Perspective on Future Directions'.

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Addressing these limitations and challenges is crucial for the continued advancement and effective application of analytical models in enhancing air transport reliability and safety. Insights from case studies demonstrate practical approaches to overcoming these hurdles, contributing to more robust and reliable aviation systems.

3. MEAN TIME BETWEEN FAILURES (MTBF) MODEL

3.1. DEFINITION AND SIGNIFICANCE OF MTBF

The Mean Time Between Failure (MTBF) is a crucial metric in air transport reliability, impacting safety, operational efficiency, maintenance planning, cost reduction, regulatory compliance, design and development, and customer confidence[26]. Higher MTBF values are indicative of more reliable components and systems, directly contributing to improved safety in air transport operations[27]. Systems with elevated MTBF scores experience fewer downtimes, essential for adhering to schedules, reducing delays, and ensuring seamless air transport services[28]. Understanding MTBF facilitates enhanced maintenance scheduling, prediction of potential system failures, and efficient allocation of repair or replacement resources[29]. MTBF is also essential for meeting regulatory requirements and industry standards established by aviation authorities, providing a quantifiable measure to showcase compliance. Airlines operating fleets with high MTBF rates can leverage this reliability to enhance customer confidence[30]. In summary, Mean Time Between Failure is a foundational metric in the aviation industry, crucial for ensuring the safety, efficiency, and reliability of air transport. Its application influences a broad spectrum of operational, economic, and regulatory aspects, underscoring its significance in upholding the high standards expected in the aviation sector.

3.2. CALCULATION AND APPLICATION OF MTBF IN AIR TRANSPORT SYSTEMS

The reliability index of aircraft includes MTTF and MTBF. The calculation formula for the point estimation of MTTF is as follows:

$$m = \frac{T_0}{N},$$

26 Lee et al., 'Critical Parameter Identification for Safety Events in Commercial Aviation Using Machine Learning'; H. Barrett, Britter, and Waitz, 'Global Mortality Attributable to Aircraft Cruise Emissions'; Gössling, 'Risks, Resilience, and Pathways to Sustainable Aviation: A COVID-19 Perspective'; Post et al., 'Changes in Vital Signs, Ventilation Mode, and Catecholamine Use During Intensive Care Aeromedical Evacuation Flights'.

27 Żyluk et al., 'Implementation of the Mean Time to Failure Indicator in the Control of the Logistical Support of the Operation Process'.

28 Aksoy et al., 'Complex Fuzzy Assessment of Green Flight Activity Investments for Sustainable Aviation Industry'; Tien et al., 'Critical Care Transport in the Time of COVID-19'.

29 Woch et al., 'Statistical Analysis of Aviation Accidents and Incidents Caused by Failure of Hydraulic Systems'.

30 Baxter, Srisaeng, and Wild, 'An Assessment of Airport Sustainability, Part 1—Waste Management at Copenhagen Airport'.

Where T_0 is the sum of working time before the first failure of all samples, in hours (H); N is the total number of samples.

The calculation formula for the point estimation of MTBF is as follows:

$$m = \frac{\sum_{i=1}^{N} t_i}{r} = \frac{\sum_{i=1}^{N} t_i}{\sum_{i=1}^{N} r_i},$$

where *r* is the total number of failures; t_i is the accumulated working time of the aircraft in the evaluation period, in hours (h); r_i is the cumulative number of the i-th aircraft in the evaluation period.

If the products do not failure in the fixed time test, the lower confidence limit of MTBF is:

$$m_L = \frac{T}{-\ln(1-\alpha)}$$

Where T is the total test time of all samples for the fixed time test, in hours (h); α is the confidence level.

3.3. RELIABILITY

The technical reliability of an object means that it can meet all the demands placed on it. Mathematically, it is a conditional probability that describes the chance that a given piece of equipment will operate from the time it starts working to the time t without any damage. With this condition is that at the time of startup (t = 0) the device was fully operational. In other words, reliability is the probability that an object will operate correctly for a certain period, given its initial state as a working device. Reliability function $R(t)$

$$R(t) = P(T \geq t),\ t \geq 0$$

where:

T – time of correct operation,
P – probability.

The function refers to the probability of a situation in which the device, at least until time *t*, was not damaged (was operational).

Reliability and unreliability are terms that describe the characteristics of a particular aircraft in some characteristic way. By analysing this data, we can assess the suitability and capability of an aircraft to perform certain aviation tasks. Today, thanks to technological advances, designers already at the stage of research and design can predict the service life of individual systems or equipment, which allows us to determine the appropriate serviceability period for aircraft.

Reliability is a broad term, and it can apply to a wide variety of equipment. This paper focuses mainly on aircraft reliability, and on the engine of the M-28 Bryza aircraft. In general, however, reliability refers to the ability of aircraft technology to meet specific requirements at a specific time and under specific operating conditions.

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Expanding on this definition, it can be said that reliability means that a given unit, under appropriate operating conditions, will meet the condition of trouble-free operation for a certain predetermined period, which involves a certain objective degree of confidence. In the case of an aircraft, reliability requirements include, among other things:

- limit the number of permissible damages to the aircraft,
- minimizing the number of damages incurred during flight,
- reducing the time spent repairing the aircraft to a minimum,
- ensuring maximum suitability of the aircraft to perform the tasks/requirements set for it.

$R(t)$ the reliability function (survival function/survival function) is the complement of the distribution to the singularity. The probability of continuous operation over a certain time interval.

It is expressed by the formula[31]:

$$R(t) = 1 - F(t)$$

where:

$F(t)$ – damage density function.

When damage intensity remains constant (unaffected by passing service life) it is relevant to the device or instrument in reliability modeling[32].

$$\lambda(t) = \lambda = const.$$

The reliability function is expressed in such a situation:

$$R(t) = e^{-\lambda t}$$

The average time to failure, in such a situation, is expressed by the formula:

$$MTBF = \frac{1}{\lambda}$$

The above equations show that the determination of the ultimate reliability of an instrument or device depends on the damage intensity function $\lambda(t)$. When $\lambda(t) = \lambda$ (the function takes a constant value), the distribution of operating time that is failure-free is represented as an exponential probability distribution. However, when the intensity function is not constant, we use approximation using other probability distributions, such as normal, log-normal, Weibull, exponential.

3.4. CASE STUDIES: MTBF FOR TRANSPORT AIRCRAFT

The case study analysed the time between damage occurrences for the M-28 aircraft engine using data from 2012 to 2019. The STATISTICA program was employed to determine the best-fitting statistical model for describing the Time To Failure (TTF). Among various models, the normal distribution was found to best describe

31 Żurek, 'Review of the safety evaluation methods in aviation'.
32 Ibidem.

the TTF, with an average of 846 minutes and a standard deviation of 446 minutes. This significant scatter in TTF is attributed to diverse operational conditions, including varying aircraft use intensity, atmospheric conditions, maintenance quality, and engine age. Identifying the normal distribution as the best fit allows for accurate reliability measures such as Mean Time Between Failures (MTBF) and failure intensity (λ), which are crucial for effective maintenance planning and continuous airworthiness.

3.5. FAILURE INTENSITY, RELIABILITY AND UNRELIABILITY FOR INDIVIDUAL AIRCRAFT VERSIONS M-28 BRYZA

To enhance the consistency and readability of the analysis on damage intensity, reliability, and unreliability as functions of time for various versions of the aircraft across different years, it's practical to organize the data, especially the intensity calculations, into a table format. In the Tables 2 and Table 3 is a structured presentation of this information, including the number of airframes for each version of the aircraft over the given years and the calculated intensity of incidents (Λ) per hour of operation.

Table 2. Number of Raids by Different Variants of the Aircraft [own elaboration]

Year	M-28 B (Hours)	M-28B/ PT (Hours)	M-28B/ PT/ GC (Hours)
2016	3894 h	1389 h	1510 h
2017	3822 h	1417 h	1631 h
2018	4498 h	1298 h	1608 h

Table 3. Incident Intensity Calculations (Λ = Incidents / Hours) [own elaboration]

Year	M-28B	M-28B/PT	M-28B/PT/GC
2016	0.003595 1/h	0.00504 1/h	0.017881 1/h
2017	0.003663 1/h	0.004234 1/h	0.01962 1/h
2018	0.002223 1/h	0.005393 1/h	0.020522 1/h

This structured approach not only simplifies the comparison of data across different years and aircraft variants but also highlights trends in damage intensity, reliability, and unreliability. From the tables, it's evident that the basic version of the Bryza aircraft consistently showed the lowest damage intensity over the three years, with a gradual improvement in 2018. Conversely, the version with glass cockpit avionics (M-28B/PT/GC) exhibited the highest damage intensity, indicating a potential area for further investigation and improvement.

Such tabulation and analysis are crucial for understanding the operational performance and reliability of aircraft variants over time, aiding in maintenance planning, design modifications, and the overall enhancement of air transport reliability.

Reliability and unreliability charts for each version of the Bryza aircraft in 2016 will be presented in Figure 3.

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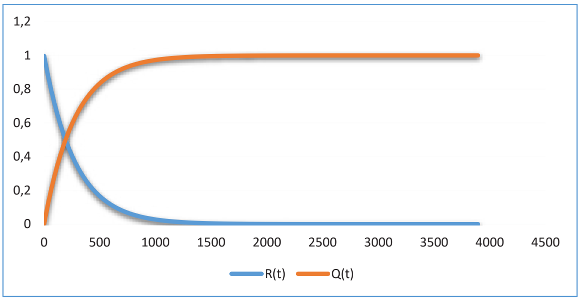

Fig. 3. Example of reliability function [own elaboration]

3.6. SUMMARY OF MTBF METHOD

Following the discussion on the importance of Mean Time Between Failure in aviation, exploring the MTTF method within the same context reveals both its advantages and challenges. MTTF provides a quantitative approach for evaluating the reliability of aviation components and systems, essential for maintaining operational integrity. It offers tangible outcomes, enabling aviation professionals to make informed decisions based on anticipated failure times and enhancing decision-making processes. Being widely recognized, MTTF fosters unified discussions and comparisons of reliability across the aviation sector. By estimating mean time to failure, organizations can adopt predictive maintenance strategies, significantly reducing downtime and optimizing maintenance schedules. Using MTTF to examine historical data assists in identifying trends and potential improvements within aviation systems, ensuring continuous performance and safety enhancements.

In summary, while the MTTF method offers valuable insights into aviation system reliability, effectively addressing the complexities of uncertainties, human factors, policy implications, and the evolving aviation and space landscape is crucial for its successful application. Addressing these challenges is key to fully leveraging MTTF benefits in enhancing aviation reliability and safety.

4. MACHINE LEARNING FOR PREDICTIVE MAINTENANCE

4.1. INTRODUCTION TO MACHINE LEARNING IN AVIATION

Introduction to Machine Learning in Aviation Machine learning (ML) has emerged as a transformative technology with multiple applications in various industries, including aviation. To improve safety, efficiency and decision-making, the aviation sector has increasingly adopted ML techniques in recent years. The integration of ML in aviation involves a wide range of applications, from predictive maintenance and safety risk identification to anomaly detection and flight parameter optimization. Predictive maintenance of aircraft systems is one of the key areas where ML has been extensively applied.

Using feature extraction and data analysis, ML models have been developed for the prediction and prevention of failures in aircraft systems[33]. As well as reducing downtime and maintenance costs, it improves overall plant safety and reliability. In addition, ML techniques have been instrumental in addressing safety concerns in the aviation industry. ML algorithms have been used to analyse flight data and improve understanding of safety-critical parameters, from identifying in-flight risk factors to predicting and preventing aviation accidents[34]. Furthermore, applying ML to anomaly detection has helped improve aviation safety by identifying abnormal patterns and potential threats. In addition, in the optimization of flight parameters and trajectory planning, ML has played a key role. Interpretable ML methods have been used to address approach and landing safety issues, contributing to the overall safety and efficiency of flight operations[35]. Additionally, ML models have been integrated with Kalman filtering for wind nowcasting problems, demonstrating the potential of hybrid frameworks to address aviation-specific challenges[36]. The use of ML in aviation extends beyond operational aspects to include passenger demand forecasting, airport delay prediction, and even satellite navigation. ML models such as artificial neural networks, linear regression, gradient boosting, and random forest have been used to forecast passenger demand and optimise airport operations[37]. In addition, ML techniques have been applied to satellite navigation systems, demonstrating the potential to improve the accuracy and reliability of navigation in both manned and unmanned aircraft[38]. In summary, the integration of ML into aviation represents a significant step forward, with far-reaching implications for safety, efficiency, and decision-making within the industry. The diverse applications of ML, ranging from predictive maintenance and safety risk identification to flight parameter optimisation and anomaly detection, highlight its transformative potential in shaping the future of aviation.

4.2. TYPES OF MACHINE LEARNING ALGORITHMS FOR RELIABILITY

Each machine learning algorithm has some uniqueness in terms of its learning model and parameter optimisation. However, there are some common steps, such as the preparation of datasets, feature selection methods and performance evaluation approaches. These steps are discussed later in the paper. Figure 4 illustrates a schematic representation of a general classification/prediction protocol using a machine learning approach.

33 Karaoğlu, Mbah, and Zeeshan, 'Applications of Machine Learning in Aircraft Maintenance'.
34 Lee et al., 'Critical Parameter Identification for Safety Events in Commercial Aviation Using Machine Learning'.
35 Ding et al., 'Implementation of Decision Tree for Maintenance Policy Decision Making - A Case Study in Semiconductor Industry'.
36 Kim and Lee, 'Unscented Kalman Filter-Aided Long Short-Term Memory Approach for Wind Nowcasting'.
37 Zachariah, Sharma, and Kumar, 'Systematic Review of Passenger Demand Forecasting in Aviation Industry'.
38 Golda and Zieja, 'Risk Analysis in Air Transport'.

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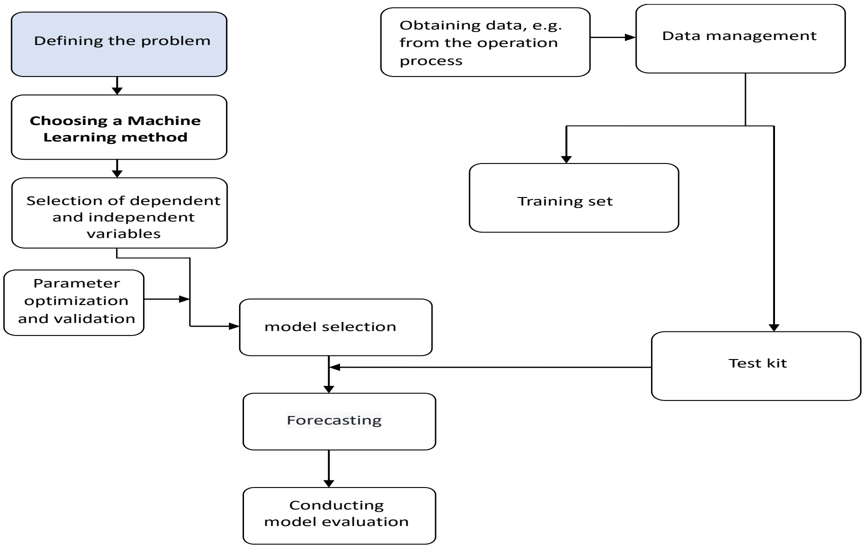

Fig. 4. Schematic representation of general classification/prediction using machine knowledge [own elaboration]

4.3. CASE STUDIES: SUCCESS STORIES IN PREDICTIVE MAINTENANCE

In the initial phase of the analysis, data describing the transport aircraft's operating process were selected for analysis. This data included:

- Occurrence of adverse events,
- Date and time of departure,
- Aircraft operating time,
- Information on pilot experience.

The selection of the best models was performed using the Data Miner tool in STATISTICA. This tool allows for the simultaneous development of several models, facilitating the selection of the most suitable one for further analysis. The model development process involves several steps:

- Preparing data for analysis,
- Preparing a training sample (for model development) and a test sample,
- Selecting variables,
- Removing redundancies in the data,
- Modifying variable selection,
- Model development and evaluation.

During the analysis, variables were selected, and their type and role were defined using a stratified random sampling method. This method allows for the selection of equal subgroups for undesirable events (which account for less than 10% of all events) and successful task performance events. After creating subgroups for adverse and non-adverse events, 20% of the cases were drawn to form a test sample for assessing model quality.

The model used in the study ensures equal sample sizes for incidents and non-incidents. The data sample is first checked for the number of incidents, and then an equal number of non-incident cases are added using methods such as algorithms or Gauss elimination. Due to the sensitivity of the data, exact numbers are not disclosed. The entire sample (50% incidents, 50% non-incidents) is then divided into two groups: a learning sample (usually 80% of all cases) and a test sample. Models are built using the learning sample and subsequently tested with the test sample. All these steps are conducted in STATISTICA. Upon completion, tables are generated to evaluate the model's quality.

Table 4. Table of numbers. Predictions. C&RT [own elaboration]

	Decision	Prediction YES	Prediction NO	
	YES			
% from the column		59.72%	42.25%	
% from the line		58.90%	41.10%	
% of total		30.07%	20.98%	51.05%
	NO			
% from the column		40.28%	57.75%	
% from the line		41.43%	58.57%	
% of total		20.28%	28.67%	48.95%
	Total			
% of total		50.35%	49.65%	

In Table 4, when a decision is predicted, YES means that an incident has occurred, NO means no incident. The percentages shown show how many such decisions were predicted. When the cases where an incident occurred are considered, it is apparent that out of the total, 30.07% of the cases were predicted correctly, and in 20.98% of the cases, even though an incident occurred, the model shows that it did not. Where there were no incident 20.28% of cases were predicted correctly and 28.67% incorrectly. Overall, this results in 50.35% of predictions being checked and 49.65 being incorrect. The C&RT model allows work on binary data.

Table 5. Table of numbers. Prediction. Neural network [own elaboration]

	Decision	Prediction YES	Prediction NO	
	YES			
% from the column		65.43%	32.26%	
% from the line		72.60%	27.40%	
% of total		37.06%	13.99%	51.05%
	NO			
% from the column		34.57%	67.74%	
% from the line		40.00%	60.00%	
% of total		19.58%	29.37%	48.95%
	Total			
% of total		56.64%	43.36%	

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When the cases where an incident occurred are considered, it can be observed that, of the total, 37.06% of the cases were predicted correctly and 13.99% incorrectly. When the incident did not occur 29.58% of the cases were predicted correctly and 29.37% incorrectly. Overall, this gave 56.64% accurate predictions and 4.,36% incorrect predictions.

Table 6. Table of numbers. Predictions. Boosted tree [own elaboration]

	Decision	Prediction YES	Prediction NO	
	YES			
% from the column		59.21%	41.79%	
% from the line		61.64%	38.36%	
% of total		31.47%	19.58%	51.05%
	NO			
% from the column		40.79%	58.21%	
% from the line		44.29%	55.71%	
% of total		21.68%	27.27%	48.95%
	Total			
% of total		53.15%	46.85%	

Based on Table 6, it can be observed that when an incident occurred, of the total, 31.47% of cases were predicted correctly and 19.58% incorrectly. In contrast, when the incident did not occur 21.68% of cases were predicted correctly and 27.27% incorrectly. Overall, this gives 53,15% predicted correctly and 46.85% incorrectly.

The model evaluation results indicate that the Classification and Regression Trees (C&RT) model had the lowest error rate at 50.35%. The Boosted Trees model followed with an error rate of 53.15%, while the Neural Network model had the highest error rate at 56.64%. These results suggest that the C&RT model is the most accurate among the tested models for predicting adverse events in the aircraft's operating process.

Aviation safety standards are extremely high, and it is crucial for both pilots and passengers to avoid incidents, accidents, and malfunctions. The models discussed above are not very accurate, especially the neural network model, which is also the most challenging to interpret. The C&RT model has the smallest error rate and is the easiest to use for determining the intensity of adverse events or damage. However, each of these models has an accuracy of only about 50%, whereas aviation demands a minimum of 90% accuracy. If these models were to be used to decide, for example, whether a flight could proceed under certain weather conditions with a specific pilot and aircraft, their errors would need to be considered. The results do not meet the high standards of aviation safety, so these models could not be the sole basis for decision-making. However, they could provide insights into potential incident risks, such as a pilot's inexperience with a particular aircraft type. These models can help identify situations that pose safety risks, thereby strengthening current safety rules. Their application requires further analysis, but preliminary results are promising, and with more parameters, these models could become useful tools for the safe operation of aircraft.

4.4. SUMMARY OF MACHINE LEARNING MODELS

A second trend that has seen intensive development recently is the application of machine learning methods in aviation. These methods offer several advantages, including:

- Anomaly Detection and Predictive Maintenance: Machine learning techniques provide advanced capabilities for detecting anomalies in flight data and conducting predictive maintenance. This is critical for identifying potential issues and proactively managing aircraft system reliability.
- Flexibility and Adaptability: Methods such as ensemble learning and reinforcement learning offer flexibility and adaptability, addressing complex reliability challenges in aircraft systems. These techniques can learn from data and adapt to changing operational conditions, enhancing their applicability in dynamic aviation environments).

However, there are notable disadvantages and challenges associated with machine learning in aviation:

- Data Labeling and Surveillance Challenges: Machine learning techniques often struggle with appropriately labeling aerospace system condition data, which limits the effectiveness of supervised learning techniques. This can impact the reliability assessments based on these methods.
- Computational Complexity and Resource Requirements: The application of certain machine learning techniques, particularly deep learning models, involves significant computational complexity and resource demands. This can be challenging in resource-constrained aviation environments.

Despite these challenges, the strong points of machine learning, such as its capability for advanced anomaly detection and flexibility, make it a promising tool for enhancing aviation safety and reliability. Further research and development are needed to address its limitations and fully leverage its potential in aviation.

5. CONCLUSION

This research explores the application of three distinct methodologies: Markov chains, mean time between failures (MTBF), and machine learning, to improve the reliability of the same transport aircraft. Each method presents unique possibilities to improve air transport reliability.

Markov Chains:

- Strengths: Effective for modeling the dynamic behavior of complex systems, particularly in scenarios with limited data, and adaptable to changing conditions.
- Weaknesses: The assumption of memoryless processes can be a significant limitation, as it may not accurately represent real-world aviation systems.
- Future Perspective: Future research could focus on developing hybrid models that integrate Markov processes with other techniques to improve accuracy in various operational conditions.

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Mean Time Between Failures (MTBF):
- Strengths: Provides valuable quantitative reliability metrics, facilitates maintenance planning, and enhances operational efficiency.
- Weaknesses: Its effectiveness depends on high-quality data and may not capture the complexity of all potential failure modes.
- Future Perspective: Integrating MTBF with real-time data analytics could significantly enhance predictive maintenance strategies.

Machine Learning:
- Strengths: Offers advanced anomaly detection, predictive maintenance, and adaptability to dynamic environments.
- Weaknesses: Challenges include extensive data labeling, high computational requirements, and complexity in interpretation.
- Future Perspective: Addressing these challenges by improving data quality, reducing computational demands, and developing more interpretable models is crucial for future research.

Differences and Applications:
- Markov Chains: Best suited for modeling and predicting system states and transitions.
- MTBF: Primarily used to provide reliability metrics for maintenance planning.
- Machine Learning: Offers robust predictive capabilities and adapts to new data for ongoing reliability assessment.

This study demonstrates that each of these three models – Markov chains, MTBF, and machine learning – provides a unique approach to assessing and enhancing the reliability of transport aircraft. They are not integrated but rather represent different strategies to achieve the same goal of improving aviation safety and operational efficiency. Future research should continue to explore these methodologies independently and in combination with advanced data analytics and real-time monitoring to further enhance air transport reliability.

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