TRIBHUVAN UNIVERSITY

INSTITUTE OF ENGINEERING

PULCHOWK CAMPUS

THESIS NO: M-110-MSMDE-2024-2026

Data-Driven Reliability Assessment and Maintenance Planning of A320 Aircraft Using Operational Records in Nepal Airlines Corporation

By

Sagar Neupane

A THESIS SUBMITTED TO THE DEPARTMENT OF MECHANICAL AND AEROSPACE ENGINEERING

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF

SCIENCE IN MECHANICAL SYSTEMS DESIGNAND

ENGINEERING

DEPARTMENT OF MECHANICAL AND AEROSPACE ENGINEERING

LALITPUR, NEPAL

April, 2026

COPYRIGHT

TRIBHUVAN UNIVERSITY

INSTITUTE OF ENGINEERING

PULCHOWK CAMPUS

DEPARTMENT OF MECHANICAL AND AEROSPACE ENGINEERING

The undersigned certify that they have read, and recommended to the Institute of Engineering for acceptance, a thesis entitled " **Data-Driven Reliability Assessment and Maintenance Planning of A320 Aircraft Using Operational Records in Nepal Airlines Corporation"** submitted by Sagar Neupane in partial fulfillment of the requirements for the degree of Master of Science in Mechanical Systems Design and Engineering.

Supervisor, Sudip Bhattarai, PhD
Assistant Professor
Department of Mechanical and Aerospace Engineering, Pulchowk Campus

Supervisor, Kamal Darlami
Assistant Professor
Department of Mechanical and Aerospace Engineering, Pulchowk Campus

External Examiner, Bimal Bhattarai
Sr. Technical Officer
Nepal Airlines Corporation, Kathmandu

Tribhuvan University
Institute of Engineering
Department of Mechanical and Aerospace Engineering
Pulchowk Campus

Supervisor, Sudip Bhattarai, PhD
Head of Department
Department of Mechanical and Aerospace Engineering, Pulchowk Campus

Date:27th April,2026

ABSTRACT

This study develops a data-driven framework for reliability assessment and maintenance planning of Airbus A320 aircraft operated by Nepal Airlines Corporation. Operational record data from 2017 to 2024, including pilot reports, component change records, and aircraft logbooks, were analyzed to understand utilization patterns such as operating days, Flight cycle, and Flight hours. Fault analysis across major ATA (Air Transport Association) chapters identified recurring premature failures, particularly in the landing gear system, including the nose wheel, main wheel, and braking components. This study is divided into two parts. In the first part, a relevance analysis is conducted using the ANOVA method to determine which variable has the greatest impact on the number of cycles a wheel assembly performs between failures. In the second part, Weibull analysis was further used to model failure behavior, revealing the presence of early-life failures and supporting improved maintenance planning. We have used the predictive method of ARIMA and the Exponential moving average. We got the coefficient of determination (R^2) to be 0.758 in EMA (α =0.6), which is best among other methods and error percentage on an annual failure prediction of NWA and MWA of A320 aircraft is 6.67% and 5%.

Keywords

Aircraft Reliability, Maintenance Planning, A320, Weibull Analysis, ANOVA.

ACKNOWLEDGEMENT

I would like to express my deepest and most sincere gratitude to my Supervisor, Assistant Professor Dr. Sudip Bhattarai, and Assistant Professor Kamal Darlami, for their exceptional guidance, continuous encouragement, and invaluable academic support throughout the course of this research. His profound knowledge, critical insights, and meticulous supervision played a pivotal role in completing this thesis. His constructive feedback, patience, and unwavering commitment to academic excellence were instrumental in bringing this research to completion, and I am truly indebted to him for his mentorship.

I am also sincerely grateful to the M.Sc. Programme Coordinator, Professor Dr. Surya Prasad Adhikari, for his motivation, guidance, and academic counselling from the initial stages of this research. His support and direction were crucial in refining the research focus and ensuring steady progress throughout the study.

I would like to extend my appreciation to the Department of Mechanical and Aerospace Engineering, HOD, and Campus Chief for providing a supportive academic environment, necessary resources, and institutional encouragement that facilitated the successful completion of this thesis.

My heartfelt thanks go to my friends and colleagues at Nepal Airlines Corporation for their cooperation, encouragement, and moral support during the course of this research.

Finally, I express my deepest gratitude to my family for their unwavering love, patience, and emotional support. Their constant encouragement and belief in me provided the strength and motivation necessary to overcome challenges and complete this academic journey.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS AND ABBREVIATIONS

AFL	Aircraft Flight Log Book
AI	Artificial Intelligence
AMP	Aircraft Maintenance Program
ANNs	Artificial Neural Networks
ANOVA	Analysis of Variation
AOG	Aircraft on Ground
ARMS	Airline Resource Management System
ATA	Air Transport Association
CMS	Central Management System
CNNs	Convolutional Neural Networks
EMA	Exponential Moving Average
FMEA	Failure Mode and Effect Analysis
FMECA	Failure Modes, Effects, and Criticality Analysis
FOD	Foreign Object Debris
FTA	Fault Tree Analysis
KDE	Kernel Density Estimation
LSTMs	Long Short-Term Memory Networks
LWEMA	Local Weight Exponential Moving Average
MA	Moving Average
MAE	Mean Absolute Error
MAREPs	Maintenance Reports
MTBF	Mean Time Between Failure
MWA	Main Wheel Assembly
NAC	Nepal Airlines Corporation
NWA	Nose Wheel Assembly
PdM	Predictive Maintenance
PHM	Prognostics and Health Management
PIREPs	Pilot Reports
RCA	Root Cause Analysis
RMSE	Root Mean Square

RUL	Remaining Useful Life
SVM	Support Vector Machines

CHAPTER 1: INTRODUCTION

1.1 Background

Aircraft worldwide is essential for maintaining operational efficiency as well as ensuring the safety of the passenger, including promoting financial sustainability. Reliability in aircraft systems majorly impacts cost, operational efficiency, and safety results, and also develops through ongoing loops of design, testing, operation, failure assessment, and enhancement. Mostly, reliability is considered during the stage of design, where differences between testing environments, as well as actual operating conditions, mostly result in service failure. Reliability mostly includes fault gathering, analysis, and feedback in the operational stage. Planning systems used in airlines help to minimize failures and improve the availability of the aircraft. Particular drawbacks are seen in small airlines, including a lack of technical staff, limited resources, and insufficient data to perform predictive analysis.

Aircraft, since history, have relied heavily on scheduled and time-driven approaches based on guidelines provided by the manufacturer. However, time-driven methods do not completely fulfill the variability seen by actual operational conditions. Nowadays, data-driven maintenance methodology has been popular as operational data aids to improve system performance, predict failures, and improve maintenance scheduling. By doing so, it allows airlines to change from reactive & preventive maintenance to obtain proficiency in predictive and reliability-based technology.

In the context of Nepal, reliability in aircraft systems poses extra setbacks because of specific geographical, environmental, and operational factors. The aircraft industry enhances national connectivity, advances in tourism sectors, emergency facilities, and economic development. Due to distinct factors affecting setbacks in airlines, air travel is important to gain mobility & integration rather than just a convenience.

Distinct stressors seen in Nepal include airports at high elevations, small runways, multiple takeoff and landing cycles, frequent changes in weather and temperature, pollution, and terrain turbulence, which causes extra mechanical as well as environmental stresses on aircraft systems. This is the major cause leading to wear and changing failure. More setbacks like small fleet sizes, limited financial resources and availability of spare parts, and reliance on strict flight schedules cause unscheduled maintenance leading to operational disturbances due to small malfunctions. These scenarios majorly result in delays and cancellations of flights, financial losses, and negative PR for the reputation of the airlines.

Contemporary aircraft consist of intricate engineering systems categorized into ATA chapters or subsystems. Each intricate systems effects readiness of the aircraft, the expenses involved in maintenance, and consistency in operational efficiency. Even a small malfunction may lead to delays, cancellations, higher expenses, and potential safety hazards. Operational data from airlines reveal that unscheduled issues are localized within particular ATA chapters, and repeated issues have been majorly recognized in:

- ATA 32 – It is a landing Gear System where significant mechanical stresses are endured during takeoff and landing in specific cases, such as short runways and higher altitudes. Major malfunctions seen here are wear, structural strain, hydraulic setbacks, and vibrations.
- ATA 21 – It is an Air Conditioning and Pressurization System which is highly impacted by changes in altitude, environmental factors, and a series of operations conducted.
- ATA 33 – It is a Lighting System in aircraft that poses high risk to vibration, intrusion in moisture, fluctuations in load, and several environmental scenarios.

Repetitive faults show that current maintenance approaches will not properly represent the true operating conditions of aircraft in Nepal. Also, failure examinations are minimal to understand if the ATA chapters are connected or if they all lead to broader disturbances in operation.

Environmental variability is also another complication in Nepal. Changes in weather conditions, i.e., temperature, humidity, flow of wind, and rainfall, dust, and disturbances in airflow (due to terrain) affect both mechanical and electrical systems. However, the connection between environmental factors and system failure patterns is not properly examined.

Utilization of major operational data, such as technical log entries, pilot reports, schedules, and logs of maintenance and unplanned defects reports, is not fully done since advanced analytical techniques are not available for reliability evaluation and improvement in maintenance. Thus, it's necessary to reduce the gap between data collection and using advanced technologies to ensure decision-making and increase effectiveness in maintenance. For instance, in NAC flies Airbus A320 planes, it can be seen that stress is elevated in several systems like landing gear, braking systems, environmental controls, and communication systems, mainly because of short-distance flights and environmental changes. This causes Breakdowns in these systems, which hugely impact response operations, increasing cost and safety issues. Earlier research focused on major ATA chapters, which are highly focused on problems due to fuel, landing gear, communication systems, and air conditioning.

Data collections majorly utilized now are PIREPS, AFL, and MAREPS for determining aircraft utilization and observing patterns of failures. Statistical data analysis methodologies and Weibull analysis are mostly utilized to see the behavior of failure behavior and determine reliability. This study aims to provide proper insights into system performance by examining major influential factors and investigating failure rates per thousand cycles

1.2 Problem Statement

The operation of Airbus A320 aircraft in Nepal is majorly impacted by challenging conditions in Nepal, which cause maintenance difficulties and reliability issues. Analysis of operational data shows irregular utilization patterns between two aircraft, which may result in uneven wear of components and reduced operational efficiency.

There are different reason that is premature fault, limited authorized manpower, limited infrastructure, limited component, and other operational events. So, all of these, mainly, we have focused on a component-level analysis, which can be incorporated or solved within the organization. We have particularly focused on the landing gear chapter, which is a critical chapter during take-off and landing.

1.3 Research Objectives

1.3.1 Main objective

Data-driven reliability assessment and maintenance planning of A320 aircraft using operational records.

1.3.2 Specific objective

- To analyze the utilization pattern of A320 aircraft.

- To identify and classify major Premature faults affecting operations.
- To perform a component-level reliability analysis of the landing gear system, focusing on the nose wheel and main landing gear assemblies.
- To apply statistical methods to evaluate failure behavior and predict future component failures.

1.4 Scope of the Research

This study primarily focuses on the Airbus A320 landing gear system of NAC. The study is primarily limited to the NWA and MWA, where failure analysis and reliability assessment are performed in detail. It also involves analysis of aircraft annual utilization and failure with reference to historical data. Other ATA chapters and aircraft systems are only taken into account on a general level, primarily to detect significant failure components. A maintenance strategy is intended to minimize unscheduled downtime, improve system reliability, and sustain airworthiness under demanding operating environment conditions in Nepal.

1.5 Limitations

The sample sizes of data from the NAC are small because we have changed from the Boeing to the Airbus aircraft, which may affect the statistical accuracy. These small datasets may fail to capture the true randomness of operational events, which may increase variability in model estimates and decrease forecast accuracy. There are several limitations of this study, including environmental factors such as bird strikes, lightning, climate, FOD on the runway, and firm or hard landings. These can impact aircraft performance, increase maintenance time, and increase downtime and operational constraints, such as limited facilities, lack of qualified technicians, and unavailability or access to spare parts, also contributing to extended ground times for aircraft, which is not considered in this study. In addition, this study of failure analysis considers only the wheel assembly and does not consider very short-interval failures (e.g., 4-20 cycles) and deep cut, tire burst due to other reasons or other landing gear problems such as leaks, sensors, and other system-related failures.

CHAPTER 2: LITERATURE REVIEW

2.1 The Shift to Data-Driven Predictive Maintenance

The aviation industry was increasingly moving away from traditional scheduled and reactive maintenance toward predictive as well as data-driven strategies. It was seen that the aviation industry operated as a complex, dynamic system generating large amount of data from aircraft sensors, flight schedules, and other sources. Effective management of this data is crucial for solving major issues and costly events, including delays in flight and mechanical failure. Predictive analysis and machine analysis such as one-dimensional CNNs and LSTMs, can lead to an accuracy resulting in 97% in predicting RUL. From the research paper, it was seen that PdM systems had 4 major parts, including data acquisition & preprocessing, diagnostics of fault, prognostics of fault, and maintenance-related decision-making process. These systems utilized industrial big data and AI techniques such as deep learning, transfer learning, and support vector machines. These techniques helped to anticipate failures before they occur, minimize unplanned downtime, and enhance safety (Marevac, E., Kadušić, E., Živić, N., Hamzić, D., & Hadžajlić, N., 2025).

Further, research conducted in 2009 introduced a methodology to predict RUL (Xu, G., Liu, M., Wang, J., Ma, Y., Wang, J., Li, F., & Shen, W. , 2019, August) of an unspecified complex system. without requiring prior domain-specific knowledge, highlighting the efficiency of machine learning techniques in forecasting degradation (Peysson, F., Boubezoul, A., Ouladsine, M., & Outbib, R., 2009). Similarly, research works conducted by the team of G. Nichhiotti in 2018 demonstrated how CMS data and maintenance logs can be integrated into PHM systems. These systems helped to predict unscheduled replacements between 2 and 10 flights using techniques such as SVM and eigenface-based classification. This approach helped in providing information regarding prognostics and also provided low false alarm rates (Nicchiotti, G., & Rüegg, J., 2018).

Finally, a paper published by P. Korvesis and team illustrated predictive maintenance using post-flight reports. The researchers used regression and multiple time learning to anticipate landing gear failures occurring in the aircraft (P. Korvesis, S. Besseau, and M. Vazirgiannis, 2018). Meanwhile, research conducted by Skormin highlighted the role of environmental and operational stress parameters that impacted aircraft systems. This paper utilized data mining as well as techniques for knowledge determination to predict failures based on different kinds of exposure (Skormin, V. A., Gorodetski, V. I., & Popyack, L. J., 2002).

Moreover, when delving into another research conducted by I. Dagal and team used ANNs with FMECA, which is a hybrid framework. It was concluded from this paper that this hybrid framework achieved 94.3% accuracy while predicting failures. This also helped to reduce maintenance costs by 35.3%. Moreover, it was witnessed that unplanned outages were reduced by 40.5% (I. Dagal, B. Erol, W. Fendzi Mbasso, A. Harrison, A. Demirci and U. Cali,, 2025). Likewise, another paper published by F.S Cetin mainly highlighted the major challenges of data collection and its maintenance. For this, a different analysis was proposed, i.e., survival analysis (Deep-Hit) and latent space classifiers. By doing so, predictions could be made even when data was limited (Çetin, F. S., Üngör, U., Koyuncu, E., & Özkol, İ., 2026).

2.2 Maintenance Planning and Resource Allocation

While reviewing the Maintenance planning and resource allocation conducted by M.Ward and team, it was concluded that resource allocation is one of the crucial factors that could balance major factors, including safety, operational efficiency, and also resilience in flights. This paper mainly highlighted that their maintenance required an ecologically valid model of operations where normal scenarios and different potential procedures were seen. Here, it was also explained in detail how identifying and resolving issues related to performance could enhance transparency, efficiency, as well as identification of hazard identification. (M. Ward, N. McDonald, R. Morrison, D. Gaynor, and T. Nugent, 2010).

Another research paper that was reviewed provided quantitative proof that maintenance planning directly reduced downtime and turnaround time. This will thus improve profitability, workability, reliability, and serviceability in the aircraft system. It was concluded from this paper's regression analysis that the planning function and activities done to improve maintenance play a vital role in reducing downtime. It was concluded from this paper that proper execution and availability of reports could only be ensured with detailed Aircraft Maintenance Programs (AMPs). (Chandola, D. C., Chandola, P., Verma, S., & Kamal., 2023).

In another research paper conducted by van Kessel, Freeman, and Santos, they highlighted the difficulties faced during maintenance scheduling in disruptive environments. In this paper, they introduced a linear programming framework of mixed type for task rescheduling. This framework introduced reduced ground time by 3% and also minimized frequent schedule changes by 50%. This model greatly improved the stability. The use of mixed linear programming highlighted the importance of dynamic resource allocation methods, which balance efficiency with feasibility in operation. (Kessel, Freeman, & Santos, 2023) .

It was concluded from all the papers mentioned above that human factors knowledge, structured planning of the maintenance, and optimized models could be used to reduce several inefficiencies, including the reduction of downtime, improvement of reliability, and enhancement of safety management systems. This approach ensured that maintenance organizations could meet regulatory requirements while also leading to high reliability, effectiveness, satisfaction of clients, and cost-effectiveness.

2.3 Root Cause Analysis on Key Aircraft Systems

A paper published by Allan majorly demonstrated that preventative maintenance, along with root cause analysis, was essential for improving the life span of the equipment, reducing costs associated, and enhancing safety. It was highlighted in this paper that 4 major ways could be utilized to lower the cost of operations. These were basic care, early detection of faults, predictive type of maintenance, and root cause analysis. These factors all improved the life span of associated aircraft equipment. Different modern techniques, including vibration and analysis, infrared imaging, and nondestructive testing, were used. These techniques reduced several problems, such as misalignments or wear, and also provided precise data for determining structural or alignment issues. Thus, different causes of failures could be determined by this approach, and it would be possible to implement corrective actions before breakdown occurs in aircraft parts. (Allen, 2015). Similarly, another paper in 2019 applied RCA to aviation systems. This system helped to assess the deflections seen in the landing performance and to perform a root cause analysis. RCA techniques such as FTA and FMEA were widely used across avionics, landing gear, and bleed valve systems. These techniques used were crucial in airlines to identify issues that caused deviations and implement corrective measures to prevent the issues before they occur.(Ramamurthy, P., & Sundaramurthy, A., 2019).

From both papers, it was concluded that RCA was a strategic process that integrated monitoring of operations, engineering analysis, and preventive maintenance.

2.4 Risk Assessment and Reliability Frameworks

A quantitative model was developed in 2006 for determining aviation safety risk factors. The quantitative model used in this paper introduced the fuzzy linguistic scale method, FMECA, which was combined with the as low as practicable approach. The combination of both these approaches improved risk factors based on importance, hazardousness, detectability, probability, and criticality in aircraft systems. A diagram was developed that could monitor and categorize risks into intolerable, ALARP, or broadly acceptable zones. This approach helped to prioritize corrective actions in a systematic way, where emphasis was mainly given to critical hazards.

Another research published by Yang also followed this approach, where a reliability growth process was developed based on operational fault analysis. His framework emphasized collecting fault data during service and analyzing the causes of the faults. For this, different methods were used, including FTA and the Corrective Analysis approach. Reliability growth models such as AMSAA and Duane were then applied to track improvements in MTBF after corrective actions. For example, improving film cable durability and tightening the clamps of the resolver led to a more than 75% increase in reliability.

These frameworks explained the dependency between risk assessment and reliability growth. Risk-based models by Lee provided a way to identify and prioritize hazards. Meanwhile, Yang ensured that we could develop corrective measures that are used to implement, track, and resolve over time in the process of reliability growth.

2.5 Aircraft Reliability and Maintenance Planning

This paper mainly focused on proactive maintenance planning so that there is a reduction of turnaround time and improvement in serviceability of the fleet. Their regression analysis majorly highlighted that maintenance activities and continuous improvement in planning functions exert the strongest influence on reducing the downtime caused. This approach ensured that aircraft were available for revenue flights during high-demand times. By doing so, profitability and operational resilience would be enhanced (Chandola, D. C., Chandola, P., Verma, S., & Kamal., 2023).

It was concluded from the literature that preventive, corrective, and predictive maintenance strategies were essential to reduce operational complications. Different types of Preventive checks (A, B, C, D-checks) ensured compliance with regulatory requirements before they occur. It was concluded from the paper that Airlines that aligned reliability with proactive planning, along with continuous improvement, reduce costs and downtime. Furthermore, it also strengthens safety as well as the confidence of the customer. (Chandola, D. C., Chandola, P., Verma, S., & Kamal., 2023).

2.6 Data-Driven Maintenance and Reliability Analysis

The purpose of this paper was to build a data-driven predictive maintenance model. To overcome the issues of sparse observations and unbalanced data. In this study, they compared survival analysis (Deep-Hit) with a latent space classifier. This latent space classifier was constructed from an auto-encoder and was found to be more resilient. This led to better predictions for fault and inventory management for a fleet of more than 500 aircraft. The key takeaway from the paper was that the utilization of advanced machine learning could address the issue of reliability at small, medium, and large scales.

Similarly, research conducted by Nicchiotti, G., highly emphasized the importance of CMS logs combined with maintenance records. This combination of both could predict unscheduled replacements in two major steps. The first was anomaly detection with Support Vector Machines, and the second was component identification using Eigenfaces. This combination of steps provided high accuracy results, kept the false positives very low, and failures could be anticipated in between 2 and 10 flights in advance. Thus, this approach not only reduced costly disruptions but also played a vital role in improving spare part logistics. By detailed analysis of operational records, predictive models could supplement conventional types of reliability analysis. This would surely reduce downtime caused and also could support smarter maintenance planning.

2.7 Importance of the ATA Chapter Analysis

It was highlighted from this paper that the C-check for Boeing 737 had a significant negative impact on all ATA100 categories. Thus, this experiment indicated how the ATA chapter-wise analysis was a powerful tool for determining as well as categorizing faults and maintenance activities by the system.

The data could be structured according to the ATA chapters, which would help in recognizing huge risk systems such as landing gear (ATA 32) or air conditioning (ATA 21). Moreover, maintenance planning prioritization could make sure that high-priority operational systems receive timely maintenance and checks. Besides that, this will also support sustainability assessment since the impact of the environmental conditions can be traced and recognized in particular system categories. This will lead to strengthened reliability.

2.8 Relationship Between Unscheduled Faults and Operational Impact

According to a journal from van Kessel and team, it was concluded that corrective issues arrive every 4 hours and also require more than 17 hours of daily ground time. This was predicted for a fleet of 60 aircraft, and it clearly showed that unscheduled faults were mainly due to high ground time, decreased reliability dispatch, and irregular delays for smaller airlines. By using predictive analysis, airlines could minimize unexpected groundings. Moreover, this will also aid in maintaining schedule integrity as well as increase profitability in the aircraft industry. Predictive methodologies through reliability growth models, ATA chapter analysis, along with data collected prognostics, were essential to improve sustainability and reliability in modern aviation systems (van Kessel, P. J., Freeman, F. C., & Santos, B. F., 2023).

2.9 Small Airline Operational Challenges

The paper highlighted that predictive maintenance with data mining could reduce maintenance costs. In addition, it could avoid preventive maintenance actions while also reducing unexpected failures. This holds for major airlines, but in the case of small airlines, they had to face unique challenges, which include limited data sets, resource constraints, and irregular disturbances (Okoro, O. C., Zaliskyi, M., Serhii, D., & Abule, I., 2023).

2.10 Environmental and Operational Influences on Fault Behavior

This paper mainly pointed out that waste and emissions from maintenance (lubricants, solvents, paints) would pollute and damage the ecosystem. Chemicals used in batteries, fluids, and paint residues pose a serious impact and hazards to soil, water, and human health if not managed properly. High energy use during the heavy maintenance (e.g., C-check) would impact resources, particularly in the ATA100 categories. The worst-case scenario, such as operating at high altitude, humid air conditions, or a number of flights, would cause wear and failure of the system. Thus, it was concluded from this paper that airlines must meet safety & reliability standards but must also increase operational stability (van Kessel, P. J., Freeman, F. C., & Santos, B. F., 2023).

2.11 Research Gaps

2.11.1 Resource Constraints

It was observed from the literature review that the current airline scheduling and optimization systems have been used with the resource constraints of manpower, materials, and hangar slots, mostly for large airlines. But small airlines were constrained by resource issues such as a lack of manpower (both skill and number), less material (spare parts), a lack of advanced tools (equipment), and a lack of hangar facilities. Current models do not capture the improper operational impact of these limitations in small fleets. This can be seen on many occasions, like failure in the ATA chapters, such as the landing gear or air conditioning.

2.11.2 Disproportionate Impact of Disruptions

Disruption management tools, such as MILP-type rescheduling, were built for major airlines where you could have the right resources, and a major source of delay can be compensated with redundancy. The minor faults, like a lighting system fault in ATA 33 or a landing gear fault in ATA 32, could result in major disruption to small airlines. So, certainly, there is a need for adaptive disruption management. Thus, there is certainly a need for adaptive disruption management tools. Also, these tools must prioritize critical ATA chapter faults even with limited resources.

2.11.3 Integration of Environmental Considerations

Environmental impact assessments, such as the ATA chapter, were only pertinent to large airlines and were not stressed in small airline maintenance planning due to resource constraints. However, small airlines are also subject to regulatory and sustainability challenges. Therefore, an opportunity exists in creating simple tools that employ reliability assessment with environmental impact. This combined assessment can aid small airlines in balancing operational stability with sustainability

2.11.4 Scalable Reliability Growth Models

Reliability growth frameworks, such as tracking using MTBF, worked only for large-scale operations as they were designed for them. However, small airlines had to focus on scalable as well as low-data methodologies that could track reliability improvements in particular ATA chapters, such as landing gear, lights, and air conditioning. This is when there is no extensive infrastructure or manpower.

2.11.5 Simplified Decision Support Tools

Cutting-edge methods such as FMEA, semantic technologies, and digital twins provide Major IT infrastructure as well as expert teams. But small airlines have this limitation, which will certainly create a gap for developing tools with limited expertise and integrating sparse datasets. These tools must focus on premature fault analysis in major and crucial ATA chapters for regular maintenance planning.

The condition and maintenance of aircraft wheel assemblies were of great importance, as these components were subjected to a wide range of stresses and conditions during taxiing, takeoff, and landing. In NAC, there were continuous flights of A320 aircraft; however, to avoid the delay in aircraft operations, it is essential to make a prediction of the annual failure of wheel assembly and the efficient use of available resources.

To mitigate this issue, another thesis proposed by Castilho demonstrated a failure prediction or estimation based on a time series model, and a relevance analysis was conducted using the ANOVA method to determine which variable had the greatest impact on the number of cycles a wheel assembly lasted between failures. (Castilho, 2015)

CHAPTER 3: METHODOLOGY

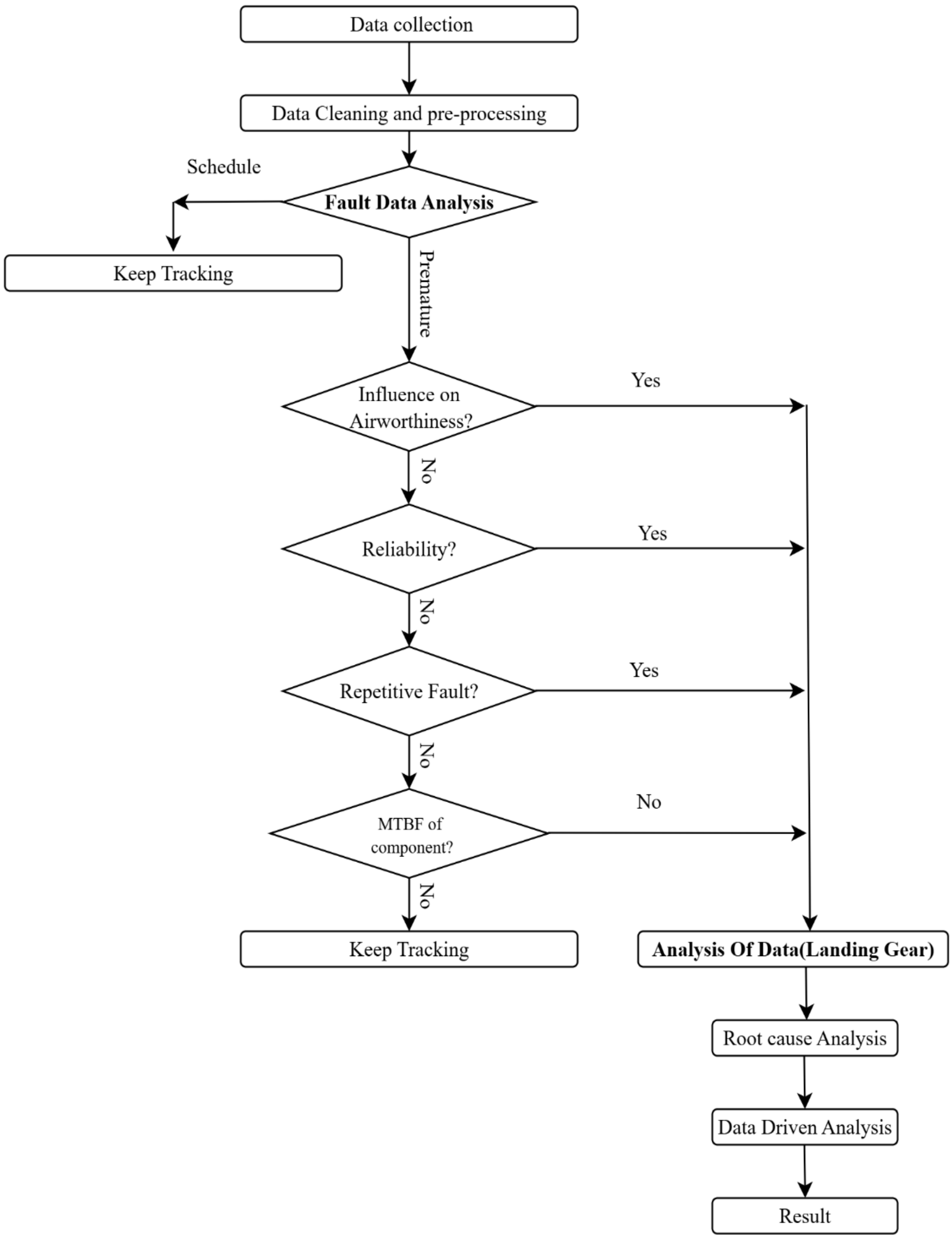

Figure 3.1: Methodology

3.1 Research Design

This study adopts a quantitative data-driven reliability analysis approach to investigate aircraft system faults and maintenance trends. Operational and maintenance records of two Airbus A320 aircraft from a small airline were analyzed to identify recurring faults, determine root causes, and evaluate maintenance reliability.

There is a integration of different analysis like fault analysis, pareto analysis, Root cause analysis (RCA) and descriptive statistical analysis to evaluate aircraft most failure component and their prediction of failure component to aid on decision of maintenance planning.

3.2 Data Collection

Operational and maintenance data were collected from the airline's technical records department.

3.2.1 Sources

Several data sets are used from NAC (Airbus A320 fleet) for the period 2017-2024, including operation data (FH, FC, and operating days). The PIREPs (pilot reports) are gathered, describing in-flight anomalies and technical irregularities, component change logs detailing unscheduled removals, replacements, and part changes in key ATA chapters from the reliability section, and maintenance logbooks, which provide a complete description of daily operations (including other factors or uncertainties, maintenance, and system observations) from the reliability section. Aircraft logbook offers all data due to one of the communication channels between the operations and technical personnel. Some data was collected from ARMS for 2019-2024. These provide quantitative and qualitative information on the patterns of use, fault events, un-schedule event, and wear-out failure of components, which can be used as the basis for statistical verification and reliability assessment in the NAC.

AFL and Reliability Report

Aircraft logbook data were collected for approximately 8 years of operation for two Airbus A320 aircraft. The logbook records contain:

- Component Part Number (P/N)
- Serial Number (S/N)
- Component removal and installation records
- Maintenance actions
- Scheduled and unscheduled component replacement

These records were used to evaluate component reliability and replacement trends.

PIREPs and MAREPs Records

Pilot and maintenance reports were collected for 5 years of aircraft operation.

PIREP: Reports submitted by pilots describing operational abnormalities during flight.

MAREP: Reports written by maintenance engineers detailing faults, troubleshooting, and corrective actions in AFL. These were used to detect fault occurrences, system faults, and operational problems. Maintenance records were categorized into:

- Scheduled maintenance events (routine inspections, planned component replacements)
- Unscheduled maintenance events (unexpected faults, in-service failures, defect rectifications)

3.3 Data Cleaning and Pre-processing

Data is cleaned and pre-processed for analysis. AFL, PIREPs, and component change cards from 2017 to 2024 were used in the dataset. Continuous data, such as FH, with missing values, is removed, while categorical data, like fault type, is grouped or removed. Failure interval (time between failures) outliers were detected using box-plots, Q-Q plot, and KDE were checked before removing them in some component, otherwise, directly because of missing data. Data integrity is checked by Premature Failure Analysis by cross-checking pilot reports with component change logs to check for faults on a chapter wise. If there is any component change in the component replacement, log in a short interval or unusual time period, then we have also verified with the AFL to find their reason. The conflicting and inconsistent data records for data consistency are also excluded. The data are then standardized and normalized in consideration of the aircraft utilization. Once the data are cleaned, they are sorted by the ATA chapter. Further, the data are split into two groups: faults reported by pilots per 1,000 FH and component changes per 1,000 FH. This allowed us to pinpoint the most common fault chapters and component changes. Failure rates are calculated from component change data for each ATA chapter, such as Landing Gear (ATA 32), Air Conditioning (ATA 21), Lights (ATA 33), and so on.

ATA Chapter-Wise Segregation

Initially there is a separation of PIREPs and MAREPs according to their respective ATA chapters. Each fault entry is allocated to its relevant system chapter e.g., ATA 32 (Landing Gear), ATA 21 (Air Conditioning), ATA 33 (Lights), and similarly so on.

From this we can evaluate:

- Chapter wise fault frequency analysis
- Identification of high occurrence chapter
- Comparison of their impact across the different system

3.4 Utilization pattern of aircraft

To understand the utilization pattern of aircraft, there is a study of key operational parameter, including FC, FH, and operating days. They are critical and important parameter which described the aging of aircraft and help to analyzing the operational intensity of the aircraft and their effects on component degradation and premature. They have also used the evaluation of the efficiency and performance of aircraft in the real field. So, there is initiation of the analysis of operational data from Nepal Airlines, which reveals significant variability in aircraft utilization. The observed ranges are as follows:

- FH: 1,842 to 4,011 hours annually,
- FC: 534 to 1,391 cycles annually and
- Operating Days: 202 to 360 days/year.

These variations are summarized in Table 3.1 and Table 3.2 based on the annual performance of both aircraft. The results indicate that aircraft utilization within the fleet is highly unsteady, with some aircraft operating under relatively low utilization conditions while others experience significantly higher operational loads. The utilization pattern is significantly different in aircraft by year. Such variability in FC, FH, and operating days can have a direct impact on aircraft performance and efficiency. In particular:

- Higher FC indicates fatigue-related failures and also leakage of hydraulic problems, especially in systems such as the landing gear,

- Increased FH contributes to wear in systems like air conditioning, avionics, and so on.
- Reduced operating days may indicate extended maintenance downtime or aircraft in AOG.

Furthermore, inconsistent utilization patterns complicate maintenance planning for whole organizations and may lead to either over-maintenance or unexpected unscheduled failures if not properly accounted for. Maybe it could be a disaster. Thus, it is necessary and mandatory for actual usage data to be included in the reliability assessment and predictive maintenance models. Time-based maintenance is not suitable for the actual operation of the aircraft, so usage-based maintenance should be considered. In conclusion, the study shows the fleet is operating at an average of about 9 FH per day and 3 FC per day with an average ratio of 3 FH/FC in NAC. This is considered medium-haul in nature, in contrast to the standard short-haul parameters. Likewise, our airlines offer short-haul flights (Thailand, Hong Kong, India, Dubai, Malaysia, and so forth). The usage pattern analysis also shows that there is considerable variability in the usage patterns of the fleet. This variability, in turn, affects system performance, degradation, and failure characteristics. In particular, variability in flight cycles and intensity can result in inconsistent wear between key systems, thus impacting maintenance and reliability. These results demonstrate a strong connection between aircraft use and failure behavior, which is a key component of the reliability analysis and failure analysis covered in this ATA chapter.

Table 3.1: Annual Utilization of 9N-AKW

Year	Flight Hours(FH)	Flight Cycles(FC)	Operating days
2016	2548	1040	347
2017	3505	1095	344
2018	2980	980	269
2019	3610	1225	348
2020	1939	553	213
2021	1842	534	229
2022	2202	757	210
2023	4095	1229	329
2024	3610	1066	332

This is the annual utilization of aircraft A320 in Tables 3.1 and 3.2 where there is easily seen their utilizations pattern in terms of FH, FC and operating days.

Table 3.2: Annual Utilization of 9N-AKX

Year	Flight Hours(FH)	Flight Cycle(FC)	Operating days
2016	2042	805	309
2017	2629	1167	340
2018	4352	1391	360
2019	3580	1237	343
2020	1874	534	202
2021	2029	628	236
2022	4011	1332	353
2023	2517	798	226
2024	2667	800	239

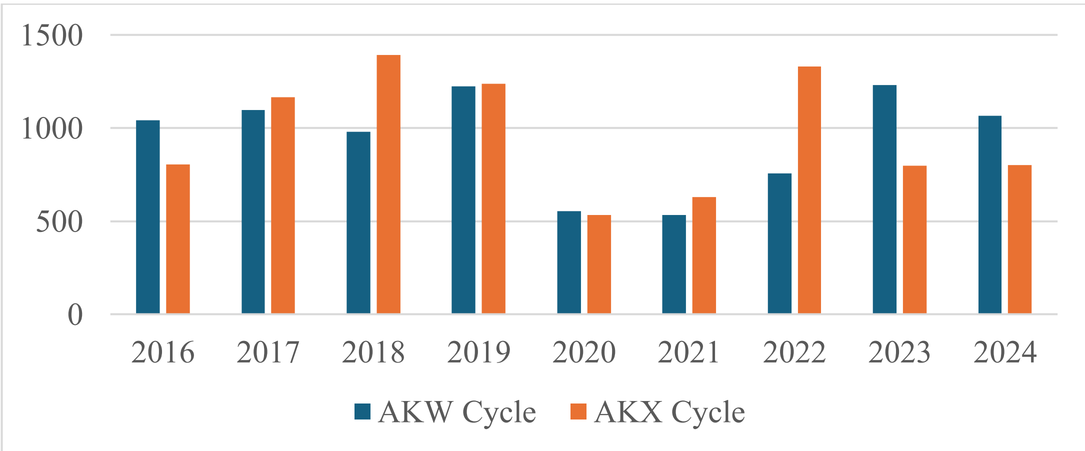

Figure 3.2: Bar Diagrams of the Utilization Cycle

There is utilization FH and FC of two aircraft in a Bar-diagram as Shown in Figures 3.2 and 3.3.

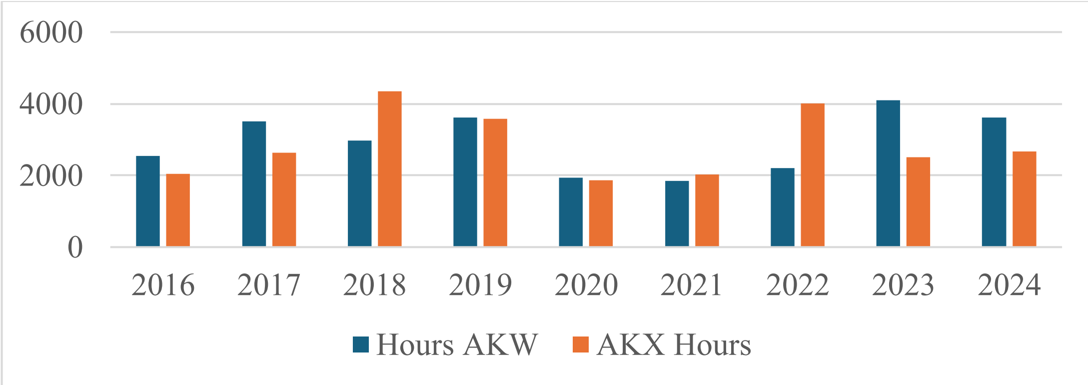

Figure 3.3: Bar Diagrams of Utilization Hours

3.5 Premature Failure Analysis

In the premature failure analysis, there is a gathering of all data from different sources as a chapter-wise PIREP, MAREP, and part replacement data. The data are grouped in to separate scheduled repaired and premature failure for each chapter of the system. Then, the premature failure is examined through chapter-wise to identify the systems and components that were more prone to premature failure. This method enables a focused view of which system areas are the major contributors to unscheduled maintenance and downtime. For ease of visual comparison, the premature failures are represented in a bar diagram, which shows the number of failures for each chapter. The diagram (Figure 3.4) illustrates the systems, such as Landing Gear, Air Conditioning, Lighting, and Communication systems, with the most premature failures.

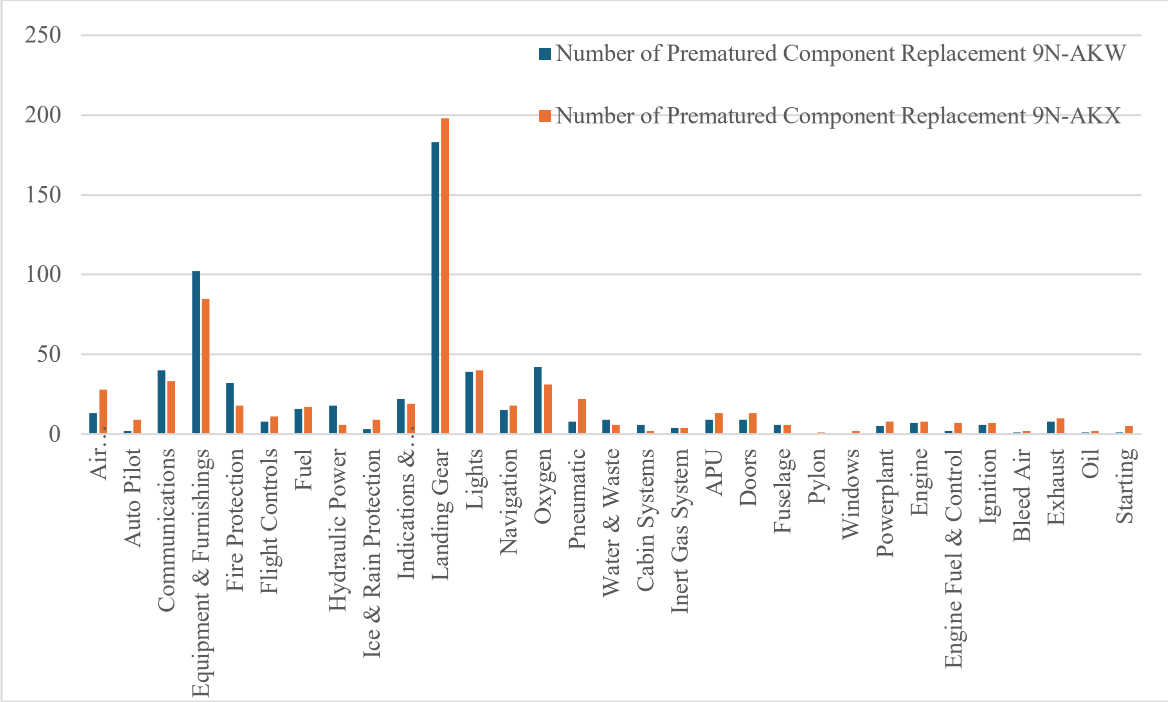

Figure 3.4: Bar Diagrams of Premature Failure

A general table was developed summarizing the most frequently failing components in each ATA chapter, providing a clear overview of critical areas that contribute to unscheduled maintenance, as shown below in Appendices. This table also includes the part number and helps to:

- Identify components with high failure recurrence
- Prioritize maintenance actions based on failure frequency and criticality

This chapter-based evaluation offers valuable information on component reliability and maintenance priorities and provides a basis for further analysis, such as Pareto and Weibull reliability analysis. It was found that most of the premature failures of components affect system operation, which could result in more maintenance and delay. But other components, though not safety-critical, can impact the service reputation and reliability of Nepal Airlines. These non-critical component failures can result in passenger inconvenience, delays, or frequent maintenance interventions, impacting the airline's reputation. Understanding the difference between safety-critical failures and reputation-impacting failures is critical to prioritizing maintenance tasks and identifying the strategies to improve reliability.

3.6 Detailed Analysis of Landing Gear Systems

The chapter-wise inspection of the data set gave us some inside information, and we have done a more specific analysis for the Landing Gear system, which has the maximum number of premature failures. A majority of these failures occurred in ATA Chapter 32, which relates to the landing gear and related systems (such as the chapter hydraulic, avionics, and so on). But we conducted our analysis inside this chapter and mainly focused on the impact of failures on the operations; failure rates were measured in faults per 1,000 FC per year. We have quantified the results in terms of the FC, as the landing cycle has a direct impact on the system. This measure facilitates the comparison of different aircraft with different utilization patterns and provides a consistent measure of failure.

Table 3.3: Fault Analysis per 1000 Cycles

Year	Flight Cycle(FC)	Fault	Fault per 1000 cycles
2016	1773	52	29.32
2017	2209	50	22.634
2018	2318	46	19.844
2019	2479	59	23.79
2020	1115	19	17.04
2021	1186	19	16.02
2022	2086	60	28.76
2023	2028	54	26.62
2024	1754	43	24.51

The results of this analysis are presented in Table 3.3, highlighting the frequency of failures per 1,000 cycles for each year. In which failure includes both the A320 fleet in the organization.

3.7 Qualitative and Root Cause Analysis

To find out the causes of premature fault in aircraft system and assess their influence on reliability, various methods are used to analyze the maintenance data. These methods include Pareto Analysis, Fishbone Diagram, and 5-Why Analysis. These techniques are used to examine fault patterns, study repetitive fault, establish root causes, developed the inspection plan, and guide maintenance actions.

Root cause analysis was used to resolve and conclude the causes of most prone premature system faults find out during the data analysis process. The analysis will help determine why certain premature fault are repetitive and assist potential solutions to improved aircraft system reliability.

3.7.1 Pareto Analysis

The maintenance records are analyzed using the Pareto method to determine the most repetitive faults in the landing gear. This technique is founded on the Pareto principle (80/20 rule), which states that main problems are caused by a minor factor.

For this research, the premature faults written in the AFL, PIREP, and MAREP are segregate into ATA chapters and their fault types. The occurrence of each fault type was determined and ranked in descending order. Using these data, a Pareto chart was created to identify the major causes of aircraft system faults. This approach allows us to focus maintenance efforts on the systems that produce the greatest percentage of aircraft system faults.

3.7.2 Fishbone Diagram (Cause-and-Effect Analysis)

The Fishbone diagram (Ishikawa diagram) is applied to identify possible causes of faults in aircraft systems. The diagram divides the causes into primary categories: Man, Machine, Method, Material, and Environment.

In this study, the Fishbone diagram is focused on landing gear system faults (ATA 32). Contributing factors like maintenance, wear, operation, and environment were considered. This approach can map the various contributing factors to the system fault and can be used to drill down into the root causes.

3.7.3 5-Why Analysis

The 5-Why analysis method was employed to identify the root causes of the recurrent aircraft faults identified from the Pareto and Fishbone analyses. This technique is based on the process of asking "Why did this happen?" until the root cause is discovered.

In this study, the 5-Why analysis is applied to major fault conditions such as:

- Wheel assembly wear out and deep cuts
- Brake unit wear
- Nose wheel vibration

By examining the cause-and-effect step by step, the analysis helps to identify root causes such as maintenance practices, operating conditions, or material life. The findings guide maintenance and reliability improvement strategy.

3.8 Data Properties and Tools

3.8.1 Kernel Density Estimation – KDE

One of the most widely used method to estimate the density of the distribution resulting from discrete data is to draw a histogram. To achieve this, the range of the variable to be shown is divided into intervals, and the count (or the density) of the measured values in each interval is represented. The problem with this approach is in the choice of the range of the intervals. If the intervals are too large (see the left-hand side figure in Figure 3.5), the changes in the distribution, such as the dip around the low value, may be overlooked. Conversely, since the data is discrete, if the intervals are too small(as in the right figure in Figure 3.5), Then, overfitting to the data might happen. Variations in the distribution may show up in the plot that will not be present in a larger sample.

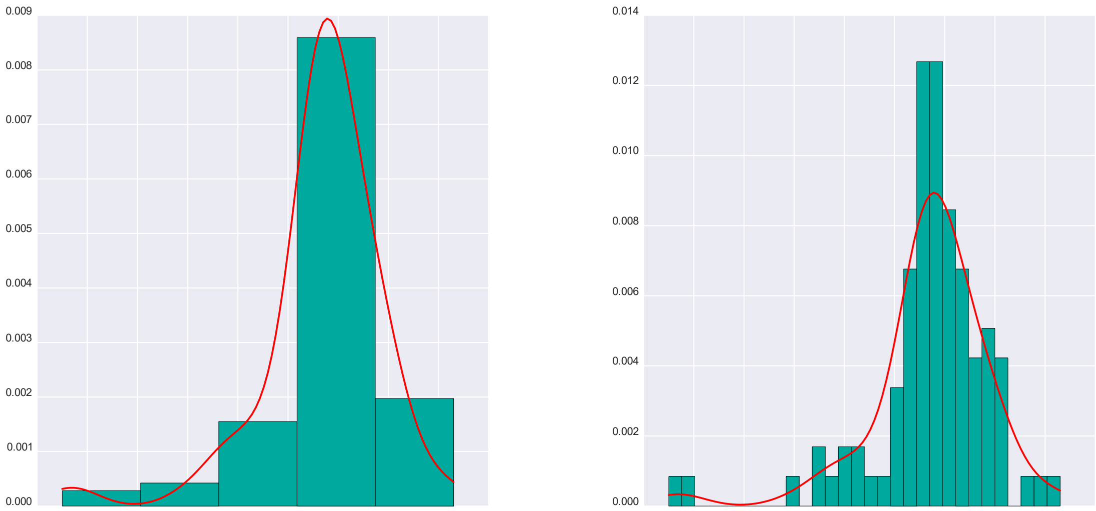

Figure 3.5: Impact of interval range definition for histograms in the shape of distribution extracted (in blue) *(Castilho, 2015)*.

A further drawback of the description with histograms is that the choice of the limits of the intervals may have a large influence on the shape of the distribution. One way to avoid some of the problems mentioned previously with the choice of interval widths in the histograms and obtain a continuous representation of the distribution, is through KDE with a continuous kernel, which is represented in red in Figure 3.5 in the example above. The selection of the bandwidth has the same problems as the choice of the interval width for the histogram; the KDE approach, however, allows for obtaining a continuous representation and resolves the issues arising from the choice of the limits of the intervals on the histograms.

3.8.2 Kurtosis and Skewness of a Distribution

To describe the shape of a distribution, parameters like kurtosis and skewness are used. The kurtosis is a measure of summit of the normal distribution with respect to standard normal distribution, whose graph of the shape of a distribution are shown in Figure 3.9.

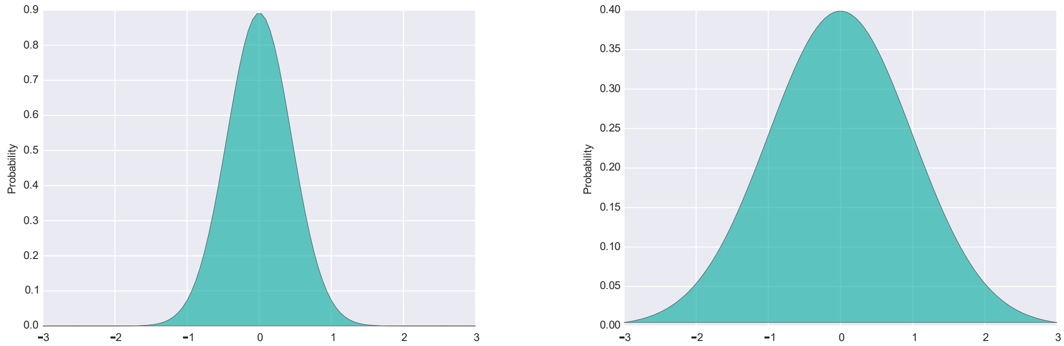

Figure 3.6: High Kurtosis and low Kurtosis *(Castilho, 2015)*

The skewness, on the other hand, is a measure of the symmetry of a distribution and represents the right skewness or left skewness as shown in Figure 3.7.

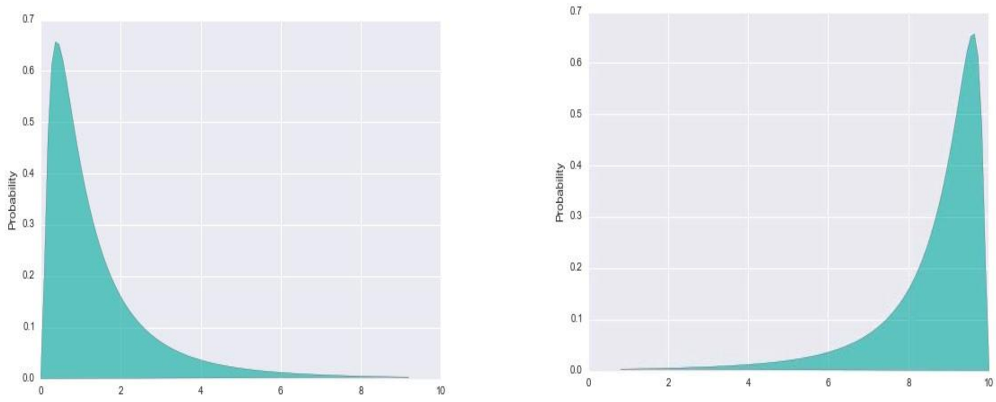

Figure 3.7: Left Skewness and Right Skewness *(Castilho, 2015)*

3.8.3 Normality tests

To test whether a distribution is normal, the most common and obvious approach is to analyze the coefficient of kurtosis and skewness of the distribution and compare them with the kurtosis and skewness of the normal distribution. In this work, there are two tests for kurtosis and skewness in order to obtain probabilities of normality for each coefficient.

3.8.4 Balanced and Unbalanced Data

When analyzing a dataset, it is important to check if the data is balanced. If an unbalanced dataset is known, the analysis of this dataset will be constrained to a set of methods or will require an adaptation of these methods. A dataset is balanced if all the possible sets of features have the same number of observations. Thus, the sets of features above would have the same number of observations, and the dataset would be balanced.

3.8.5 Datasets

To predict the failure of aircraft wheel assembly, initially, data were collected from a different source, as mentioned above. A structured dataset was developed using the collected AFL number, date, installed part number, serial number, removal part number, position, and ATA chapter from relevant operational and maintenance records. The dataset includes key parameters that (explains in above) capture both the component identification number, component position, and operational exposure. The collected fields are as follows:

- Wheel part number
- Wheel serial number
- Date of installation and failure
- Aircraft tail number
- Wheel position
- Number of landings cycle of wheel perform between failure
- Type of tire- There are MAIN or NOSE relative to the corresponding landing gear of the tire.
- Nose tire size - Nose gear tires
- Main tire size - Main gear tires

The wheel layout for the A320 aircraft is shown in Figure 3.8.

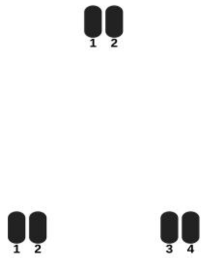

Figure 3.8: Wheel Position
Layout of A320 *(Castilho, 2015)*

3.9 Analysis of Variance - ANOVA

If there are two sets of data and a measure of the difference of their distributions is required, some tests can be used, such as a t-test if the distributions are assumed to be normal or a Mann-Whitney test if not. But, if there are more than two groups of data, in order to compare the distributions of the groups with each other, methods such as the above would have to be carried out for each pair of groups. So, for a comparison of distributions when data is divided into more than two groups, ANOVA is a more accessible solution.

3.9.1 One-way ANOVA

In this project, ANOVA is used to determine the relevance of variables to the number of cycles a wheel completes before failure. This is achieved by considering a measurement variable and a nominal variable. The measurement variable will be the number of cycles a wheel does between failures, and the nominal variable will be the variable to be evaluated. And then several observations of the measurement variable are obtained for each value of the nominal variable and grouped.

3.9.2 Assumptions

One-way ANOVA assumes that observations from each group follow a normal distribution. But in certain circumstances, this approach is robust to non-normal data. In order to test for normality, the difference between each measurement and the mean of the group (residuals) should be graphed and tested. If the distribution is non-normal, then the data should be transformed to normalize the residuals.

The second assumption is that the data is homoscedastic (i.e., the standard deviations of the groups are equal). When the data is balanced, one-way ANOVA can provide accurate results. For unbalanced heteroscedastic data, Welch's ANOVA is more accurate than one-way ANOVA. The preferred method is to balance the data by deleting some of the sample points or obtaining data by regression and performing one-way ANOVA.

3.9.3 Null hypothesis

After collection of the sample data from the source, which includes mainly measurement variable and nominal variables that measures the means of all sample groups. After that, they are tested for how relevant the nominal variable is to the measurable variable for every sample group, that concludes how significant to each other. Therefore, the hypothesis is tested here to determine the means of all sample groups, and this hypothesis will have to be rejected or accepted in different groups, which can be known from the ANOVA analysis.

3.9.4 Method

For one-way ANOVA, the mean of the measurements for each group is calculated, and the variance between these means is compared with the average variance within the groups. In order to test the null hypothesis, if the P value is less than 0.05, then we reject the Null hypothesis; otherwise, we accept.

3.9.5 ANOVA with unbalanced data

The results from one-way ANOVA can be affected by data in certain situations. One-way ANOVA results are not always perfect because heteroscedastic data can change them. One-way ANOVA is a tool, but it has its limits, especially when the data is heteroscedastic. In an ANOVA table 3.4, the Between Groups row indicates the variation arising from differences among group means, while the Within Groups row depicts random variation within each group, and the Total signifies the overall variation in the dataset; the Sum of Squares (SS) quantifies variability so that total variation is the combination of between and within variations, and the degrees of freedom (d.f.) represent independent information and is employed to assess significance, while the P-value reflects the likelihood of observing such results under the null hypothesis, and the F-critical value serves as the benchmark from statistical tables at a specified significance level (typically 0.05); the null hypothesis (H_0) asserts that all group means are equal, and the decision rule states that if the computed F-value exceeds the F-critical value or if the P-value is less than or equal to 0.05, the null hypothesis is dismissed (indicating a notable difference between groups); otherwise, it is not dismissed, signifying no statistically significant difference among the group means.

Table 3.4: Layout of ANOVA Table *(Castilho, 2015)*

	Sum of squares	d.f.	Mean Square	F_s	P-value	$F_{Critical}$
Between Groups	x	x	x	x	x	x
Within Groups	x	x	x			
Total	x	x	x			

The methodology adopted in this paper to equalize the data to be used in the ANOVA study will be to delete some sample points from the group with the largest sample size. This method is applicable when the data has a large amount of sample size and is significantly uneven, to have a lot of measurements per sample size.

CHAPTER 4: DATA ANALYSIS

This section presents the analysis of aircraft maintenance data collected from operational records. The purpose of this analysis is to identify the most frequent faults, determine the aircraft systems most affected by failures, and investigate the root causes of these faults. The collected data are analyzed using statistical methods, Pareto analysis, and root cause analysis techniques described in the methodology section.

4.1 Fault Frequency Analysis

To better understand the significance of each system failure, the percentage contribution of each fault category was also calculated using the following relationship:

Fault-Percentage = (Number of faults in a specific system / Total number of recorded faults) × 100%

This calculation helps to determine the relative importance of each system premature failure compared to the total number of faults recorded during the study period. The outputs of the fault frequency analysis give the most frequent aircraft failure chapter and their maintenance problems. High-frequency faults and repetitive fault may represent systems with potential reliability issues caused by operational factors, component degradation, or maintenance procedures. The identified high-frequency faults are then further analyzed using Pareto charts and root cause analysis techniques to determine the most critical maintenance issues affecting aircraft reliability.

Table 4.1: Premature Failure in the ATA Chapter

ATA Chapter	Aircraft System	No. of Fault	Percentage (%)
ATA 32	Landing Gear	381	30.31
ATA 21	Air conditioning	41	3.26
ATA 33	Lighting system	79	6.28
ATA 25	Equipment and Furnishing	187	14.87
ATA 23	Communications	73	5.807
ATA 71 To 80	Engine and powerplant	80	6.36

4.2 Pareto Analysis of Landing Gear Failures

When we have a high premature failure rate per 1000 FC, then we have to go into further analysis of the Landing Gear system, which was conducted using a Pareto analysis approach to identify which components contribute most significantly to failures. The Pareto analysis reveals that the majority of faults were wheel assemblies and the braking system, as shown in Figure 4.1, specifically:

- Main Wheel Assembly (MWA)
- Nose Wheel Assembly (NWA)
- Carbon Brake System
- Other minor components

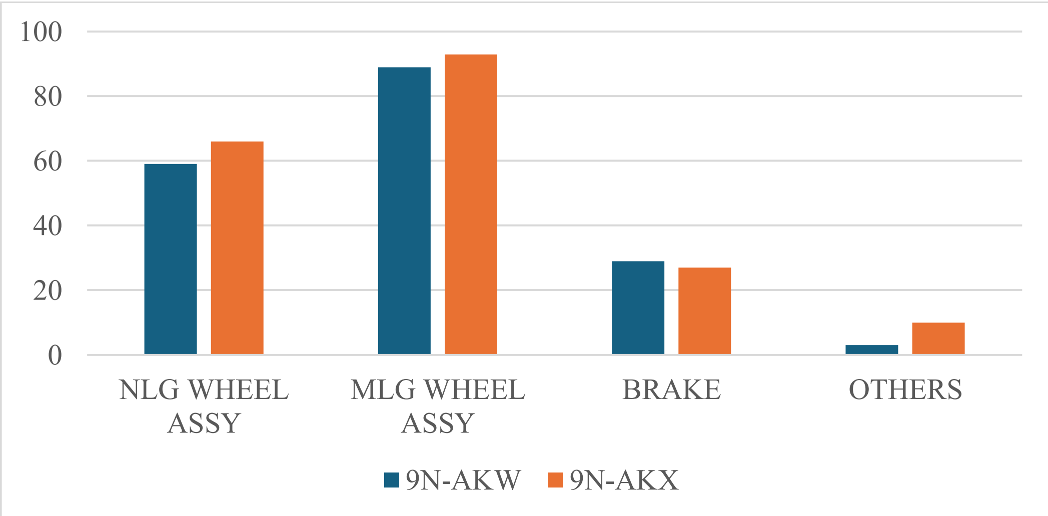

Figure 4.1: Pareto Analysis of Component

At the component level, the most repeated fault types, as shown in Figures 4.2 and 4.3, observed include:

- Worn-out and deep cuts on tires
- Nose wheel misalignment or offset
- Brake unit malfunctions
- Nose wheel vibrations
- Other miscellaneous faults

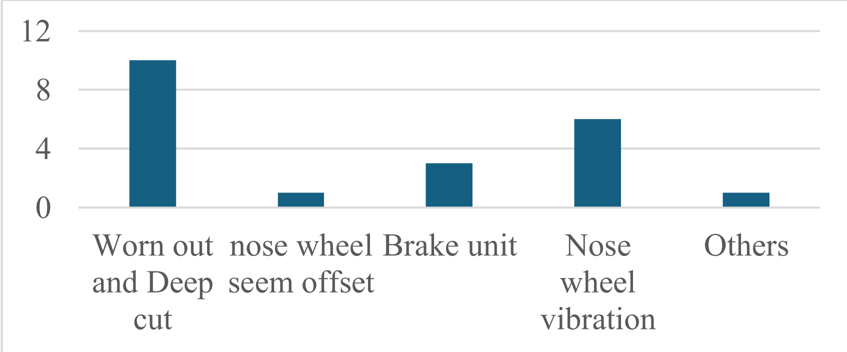

Figure 4.2: Bar Diagram of Fault Types in 2020

There is repeated failure of NWA and MWA in a bar diagram of fault types in 2020 and 2024 but there is analysis of component wise failure from 2020 to 2024.

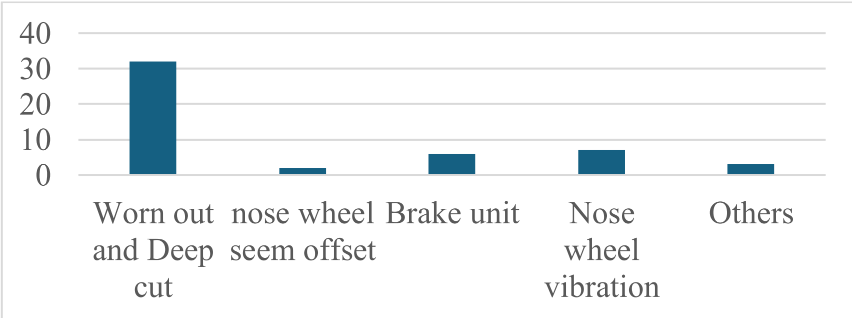

Figure 4.3: Bar Diagram of Fault Types in 2024

4.3 Root Cause Analysis

In NAC, Fleet has operated A320-233 model aircraft and used the V2500 series engine in a commercial flight. There is a maximum take-off weight of 73500 kg to 78000 kg and a maximum landing weight of 64500 kg to 66000 kg for the A320 aircraft. The TIA runway length is 3050m. From the paper, we know that the ideal touchdown of 300m and the airport height is 4390 ft. We know that the landing speed of 136 knots at a landing weight of 66000kg in an aircraft, which is mentioned in "A320 Aircraft Maintenance Performance," but in an actual scenario, the aircraft landed at 142 knots, and the maximum used runway length was 1700m. Runway requirement for A320 aircraft is 1700 to 1900m at normal conditions and 1850m to 2100m at wet conditions (Ugnenko, Evgeniya and Perova, Elena and Voronova, Yelizaveta and Viselga, Gintas, 2017) (family, 2006). Maybe there is an extra factor that affects the aircraft wheel assembly, for ex. landing weight, landing environmental temperature, runway condition, and so on, but it is also affected by manual braking condition in the aircraft and the landing distance used by the aircraft.

- Wheel assembly deep cuts
- Brake unit wear
- Nose wheel vibration

Each of these faults is analyzed step by step to identify the underlying causes contributing to their occurrence. The results of the 5-Why investigation help reveal deeper issues related to operational conditions, component limitations, and maintenance practices, as shown in Table 4.2.

Table 4.2: 5-Why Root Cause Analysis for Landing Gear System Faults

Fault Type	**Why-3**	**Why-4**	**Why-5**	**Corrective Action**
Wheel Deep Cut	contact with sharp or abrasive objects	FOD, worn pavement sections, Steering side loads increase, tread shear, High braking energy increases surface stress.	High landing frequency, Short-runway braking demand, Firm landing, Steeper approach	Increase runway inspection and control manual breaking.
Brake Unit Wear	Short runway operations	High braking load during deceleration	Maintenance interval not optimized for operational conditions	Used a long runway length and control manual braking
Nose Wheel Vibration	Frequent taxi operations	Surface irregularities on the runway	Environmental conditions affecting landing gear components	Pressure difference less than 5PSI, check bearing.

The findings of the root cause analysis indicate that several factors contribute to the occurrence of landing gear premature faults, including operational stress on components, runway conditions, environmental effects, and limitations in maintenance scheduling.

4.4 Analysis of variable relevance using ANOVA

Table 4.3: Wheel study and flight data summary

Type of wheel	2
Position of the wheel	6
Time period under study	2017 to 2024
PIREP study	2017 to 2024
Component Change Study	2019 to 2024
Flight hours	52032
Flight Cycle	17171
Failure rate per thousand cycles	23.41

Table 4.4: Tire Configuration of A320-233

Aircraft Model	'A320-233"
Tire Manufacturer	'Michelin"
Retreading	'1","2"
Wheel position	'N1","N2","M1","M2","M3","M4"
Type of tire	"Nose", "Main"

Initially, the statistical properties of the dataset are evaluated by calculating the p-values of skewness and kurtosis for variables such as wheel position and wheel type. The skewness test is used to evaluate the symmetry of the sample data, and the skewness test was used to evaluate the peaked ness of the data. There is calculated the skewness and kurtosis p-value to check the effect of the data on sample data as shown in Table 4.5 and 4.6. There is computed the Skewness and kurtosis p-value to assess their impact on the sample data to develop the predictive model. Then, there is performed normality tests to check whether the data met the requirements for parametric tests. The results shows that the nose wheel data and its placement are close to normal and no transformation is needed. But the main wheel data showed substantial departures from normality. In this case, a Yeo-Johnson transformation is used to effectively normalize the data while maintaining the integrity of the data. This data transformation allows the dataset to be used for statistical analysis such as analysis of variance (ANOVA), which in turn increased the validity and accuracy of the results.

Table 4.5: P value at different positions

Group	Kurtosis P-Value	Skewness P-value
N1	0.69	0.135
N2	0.812	0.795
M1	0.921	0.965
M2	0.003	0.685
M3	0.166	0.925
M4	0.056	0.658

There is a calculation of Kurtosis P value and Skewness p value at a different position as well as different type of wheel assembly to define their effect on normally distribution of data respectively.

Table 4.6: P value at NWA and MWA

Group	Kurtosis P-Value	Skewness P-value
Main tire	0.000163	0.109
Nose Tire	0.87	0.51

The standard deviation of each variable (type-wise and position-wise) group is calculated to quantify the dispersion of the data around the mean value. In addition, the respective error relative to the variable mean standard deviation (E) is determined, providing a normalized measure of variability across different groups. There is calculated the tentative error with the mean Standard deviation is calculated in both groups. A one-way ANOVA (Analysis of Variance) is conducted to evaluate which variables are most relevant to the number of cycles performs between failures of wheel. If there are more than three samples, then we have to analyze the variation of the samples through one-way ANOVA. In this analysis, the measurement variable is defined as the number of cycles between installation and failure or mean time between premature failure, while the nominal variables included factors such as wheel position and tire type that were already mentioned above, whose influence on failure behavior was to be determined. We have assumed the Null hypothesis, which means there is a very slight difference in the variation of the mean among different samples. An appropriate sample size is selected to ensure the robustness of the one-way ANOVA test, as already mentioned above, as shown in Tables 4.9 and 4.10. There is different sample sizes for the different wheel types due to their total data size. The sample size is determined based on the variability observed in each group (position-wise and type-wise), the required statistical power, and the significance level, ensuring that the analysis could reliably detect differences between group means and also check their skewness and kurtosis values, as shown in Tables 4.5 and 4.6. By selecting a representative, sufficient, and small sample, the ANOVA analysis results provide a valid and correct assessment of the influence or effect of variables such as wheel position and tire type on the number of cycles between failures. Standard Deviation of each variable group and respective error relative to the variable mean standard deviation is shown here in Tables 4.7 and 4.8.

Table 4.7: Standard Deviation and respective error percentage position-wise

Group	**Standard Deviation**	**E(%)**
N1	73.33	8.49
N2	66.6	16.89
M1	91.32	13.95
M2	98.25	22.6
M3	63.03	21.34
M4	88.28	10.16
Overall Mean	80.135	

There is a calculation of the standard deviation of data from each and every position and their respective error percentage position wise as well as wheel wise.

Table 4.8: Standard Deviation and respective Error Percentage of wheel-wise

Group	**Standard Deviation**	**E (%)**
Main wheel	83.035	8.68
Nose wheel	69.784	8.65
Overall Mean	76.4	

Table 4.9: Sample Size for the type of wheel

Group	**Sample size**	**Minimum sample size**
Main wheel	173	20
Nose wheel	112	28

In Table 4.9, there is a selection of sample size for ANOVA analysis. There is a selection of a minimum sample size be 28 for NWA and 20 for MWA.

Table 4.10: Sample size for Wheel positions

Group	**Sample size**	**Minimum sample size**
N1	56	20
N2	56	20
M1	43	20
M2	43	20
M3	45	20
M4	42	20

In Table 4.10, there is a selection of sample size for ANOVA analysis. There is a selection of a minimum sample size be 20 for every position of wheel.

Table 4.11: ANOVA of NWA

	Sum of squares	d.f.	Mean Square	F_s	P-value	$F_{critical}$
Between Groups	4435.384	3	1478.461	0.298	0.827	2.6887
Within Groups	536117.4	108	4964.05			
Total	540552.8	111				

A one-way ANOVA is performed to evaluate whether there are statistically significant differences in the mean landing cycle across the groups defined by the selected operational variable. When the analysis is done through the single-factor ANOVA analysis in Excel, have found the result as shown in Table 4.11, which describes that there is no variation of mean between the sample data. This result indicates that the variation between the groups defined by wheel position in NWA, as well as MWA, is not statistically significant when compared to the variability within the groups. The ANOVA findings show that there is no significant statistical difference among the groups. This is due to the computed F-value (0.298) being significantly less than the critical value (2.689), and the p-value (0.827) being considerably higher than the usual significance threshold of 0.05. As a result, the null hypothesis remains accepted, indicating that any differences seen in the data are probably a consequence of random variation instead of genuine group effects. In practical terms, this indicates that the groups display comparable behavior, and grouping does not significantly affect the outcomes.

Table 4.12: ANOVA of Wheel Position

	Sum of squares	**d.f.**	**Mean Square**	**F_s**	**P-value**	**$F_{critical}$**
Between Groups	495453.2	5	99090.63	9.65	1.06E-07	2.29
Within Groups	1170593	114	10268.36			
Total	1666046	119				

When there is analysis of single-factor ANOVA analysis on a wheel assembly as a position-wise result, as shown in Table 4.12. The ANOVA findings indicate a significant statistical difference among the groups. This is due to the F-value (9.65) being significantly greater than the critical value (2.29) and the p-value (1.06×10^{-7}) being well below the significance threshold of 0.05. Hence, the null hypothesis is dismissed, suggesting that the differences among groups are not a result of random chance. In practical terms, this implies that the group's exhibit varied behavior or traits, and their classification significantly influences the outcomes.

4.5 Weibull Analysis

To analyze the reliability and failure behavior of the nose wheel, a Weibull distribution analysis was conducted, and we have small sample data that is easy conducted through Weibull analysis. Weibull analysis is mostly used in reliability engineering to model time-to-failure or cycles-to-failure data, as studied in different papers, as it can represent early failure that is deep cut or FOD, random, and wear-out failures.

Weibull analysis is a mostly used reliability methods for modeling the life and failure patterns of components. we have used the failure interval cycle just to identify the pattern of failure in nose wheel so we used the shape parameter (β) to indicate failure behavior values less than 1 suggest early (infant mortality) failures, around 1 indicate random failures, and greater than 1 show wear-out failures and the scale parameter (η) to represent the characteristic life, where approximately 63% of components are expected to fail. By analyzing failure data with the Weibull distribution, engineers can assess reliability, predict failures, and optimize maintenance schedules based on the observed failure trends.

4.6 Data-Driven Analysis

The ANOVA results indicate that the effect of wheel assembly type, NWA and MWA, on the failure interval (in FC) is statistically insignificant. Similarly, the positional variation within the assemblies also demonstrates a negligible influence on the failure behavior. These findings suggest that other unobserved or external factors may contribute more significantly to premature failures.

4.6.1 ARIMA Model

To predict nose wheel failures, an ARIMA (Auto-Regressive Integrated Moving Average) model was applied using the failure interval cycles as the main variable, while installation date, removal date, type of wheel, and wheel position served as nominal variables. The ARIMA model is a time-series forecasting model that captures cumulative frequency, trends, auto-correlations, and patterns in sequential data, making it suitable for predicting future failures based on historical cycles. In this study, only the nose wheel was analyzed, and the failure interval between installations was used to model and forecast the expected life of the nose wheel. In the ARIMA model, we have used the (2, 1, 2) where P=2 (Autoregressive used the past 2 values), d=1(differencing by 2), and q=2 (2 point Moving average for the last 2 errors). So, this model used the last 2 values, removed the trend once, and corrected using the last 2 errors. This method is suitable when the data is moderate and has short-term dependency.

Table 4.13: ARIMA Model Sample data

Metric	AKW Pos1	AKW Pos2	AKX Pos1	AKX Pos2
Total Events	28	29	28	29
Mean Interval Cycle	239.1	243.1	255	234.7
Std. Deviation	75.9	70.1	71.1	69.1
CV (%)	31.8	28.8	27.9	29.4
Min Cycle	51	106	72	73
Max Cycle	373	360	384	397
Median Cycle	255.5	232	250.5	241
Mean in Days	72.9	74.1	77.7	71.6
ARIMA Next Pred (FC)	323	243	206	142

In Table 4.14, we have forecasted the upcoming five failures in NWA and MWA.

Table 4.14: ARIMA for NWA and MWA

Failure Number	NWA Forecast(FC)	MWA Forecast(FC)
1	260.21	380.53
2	236	378.66
3	242.28	378.33
4	250.24	378.27
5	230.85	378.26

In the Arima Model, initially, the sample data was analyzed with aircraft position only that 1^{st} position and the 2^{nd} position of NWA. After that, we studied the output of the analysis, and we found that the 2^{nd} position has a high risk zone from that result, as shown in Appendix B. So we have modified the sample date in terms of aircraft as well as position-wise, so we get the following result, as shown in Appendix B. We have used the actual failure data of NWA of 2025 and calculated the error percentage from predicted data and actual data. We got the following result. We have used the actual failure data of NWA of 2025 and calculated the error percentage from predicted data and actual data. We got the following result, as shown in Table 4.15.

Table 4.15: ARIMA Model Results

Fleet	Position	Prediction(FC)	Actual(FC)	E (%)
AKW	1	323	327	1.22
AKW	1	328	306	7.2
AKW	2	243	207	17.4
AKW	2	273	32	-
AKW	2	266	67	-
AKW	2	259	102	-
AKW	2	271	336	19.3
AKX	1	206	182	13.2
AKX	1	221	304	27.3
AKX	1	217	282	23.1
AKX	1	228	307	25.7
AKX	2	142	109	30.3
AKX	2	197	324	39.2
AKX	2	175	299	41.5
AKX	2	208	258	19.4

4.6.2 Moving Average Method

The Moving Average Method is one of the simplest, easiest, and most useful techniques for trend analysis and forecasting. We have aircraft component failure intervals data, so we have to use the simple moving average method. It is also divided into 3-Period Moving Average, 5-Period Moving Average, 7-Period Moving Average, and so on. In the 3 Point Moving Average method, we have to use the average of the previous 3 values to predict the next value. Similarly, we have used the average of 5 and 7 values in the 5-Period Moving Average and the 7-Period Moving Average.

4.6.3 Exponential Moving Average Method

The Exponential Moving Average is a time series forecasting method that applies weighted averaging with exponential decay to historical observations. The EMA is a Forecasting technique that is nearly similar to a moving average, but in this method, we have given more weight to recent values and less weight to older ones. It is widely used in time series analysis and predictive maintenance. In recent observations, we have given higher priority to the old ones.

EMA equation

$$EMA_t = \alpha x_t + (1 - \alpha) EMA_{t-1}$$

Where, x_t = current data point, EMA_{t-1} = previous EMA

α = smoothing factor (between 0 and 1) = 2/(n+1)

Where n is the number of periods. If n is very small, then it is more sensitive, and if n is very large, it is less sensitive or a smoother curve.

Similarly, for the LWEMA

$$EMA_t . w_t = \alpha x_t . w_t + (1 - \alpha) EMA_{t-1} . w_t$$

Where w_t be the weighted factor in EMA, 25FC be equal to 0.1.

Based on this conclusion, the study focuses solely on the failure interval (cycle-based data) as the primary variable for predictive modeling. Several time-series forecasting techniques were employed, including MA (3), EMA with smoothing constants $\alpha = 0.3$ and $\alpha = 0.6$, and LWEMA with $\alpha = 0.8$.

The performance of these time series models was separately evaluated and compared to identify the most suitable method for predicting failure intervals. This comparative approach enables a more robust understanding of predictive accuracy and model suitability for maintenance forecasting applications.

CHAPTER 5: RESULTS AND DISCUSSION

5.1 Results

From the analysis of the utilization pattern of A320 aircraft, there is an average utilization hours per day of 9 FH, average utilization cycle per day of 3.28FC, average utilization cycle per year of 954 FC, average hours per cycle of 3.03 FH, and average utilization days per year of 290 days. After that, there is an analysis of the premature fault from the different sources, so it is observed that the premature fault rate is higher in the ATA chapter 22(Landing gear). Therefore, further analysis is done in this ATA chapter, where it is found that there is a main fault in the NWA, MWA, and carbon brake assembly, and the main reason for failure is mentioned in the 5-why analysis and Fishbone analysis in the methodology section.

From the sources, there is a high variation in the collection of data, as shown in the figure.

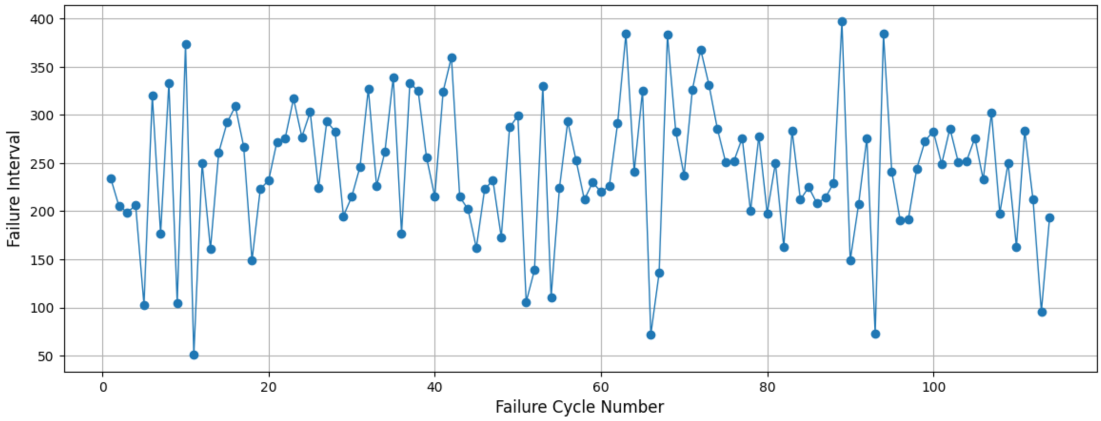

Figure 5.1: Distribution of Data

So it is observed that data is normally distributed from the KDE analysis, kurtosis p-value, and skewness p-value.

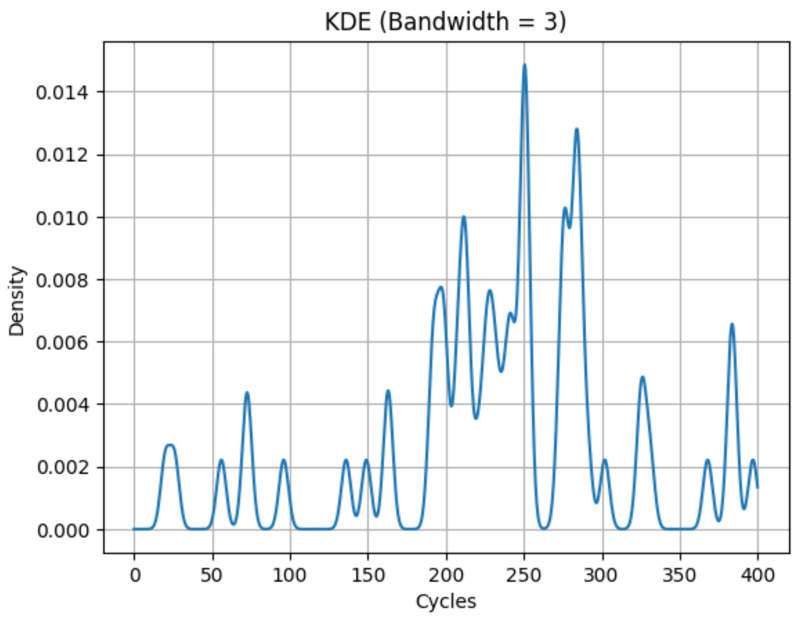

Figure 5.2: KDE Diagram

Here, there is analysis of data with the varying bandwidth as shown in diagram. There is a normally distributed of selected data.

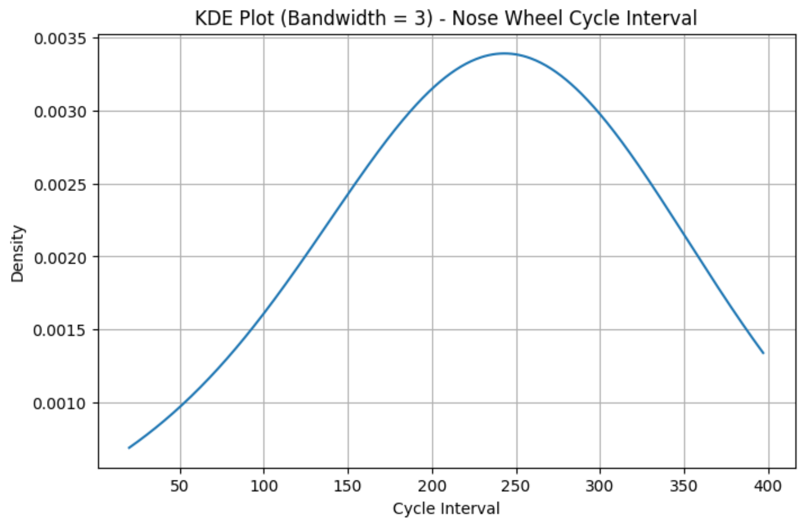

Figure 5.3: KDE Diagram with Bandwidth 90

The same data used in Figures 3.6 and 3.7 shows the examples of two KDE representations with different bandwidths. It is found that the bandwidth is a smoothness factor. Also, there is a representation of a histogram with KDE as shown in the figure.

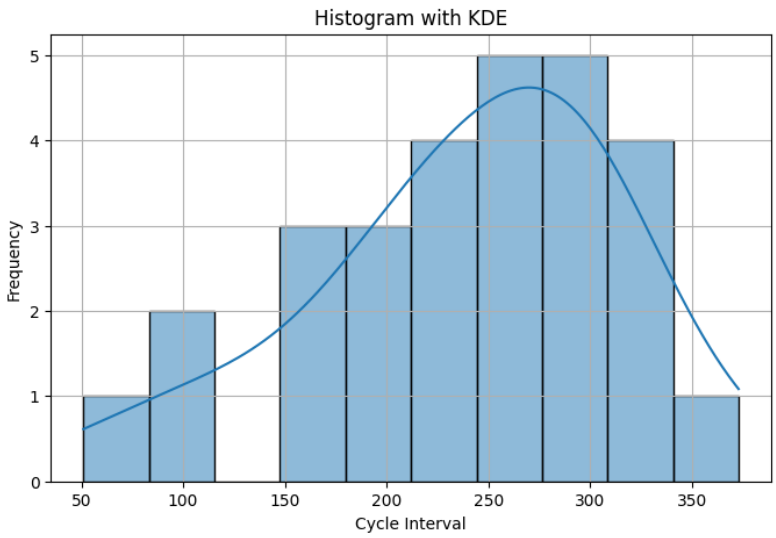

Figure 5.4: Histogram Diagram with KDE for position-1 in AKW

As concluded from the ANOVA analysis reveals a statistically significant difference between nose wheel and main wheel types, indicating that wheel type is a critical factor influencing the prediction of wheel failure.

5.1.1 Weibull Analysis

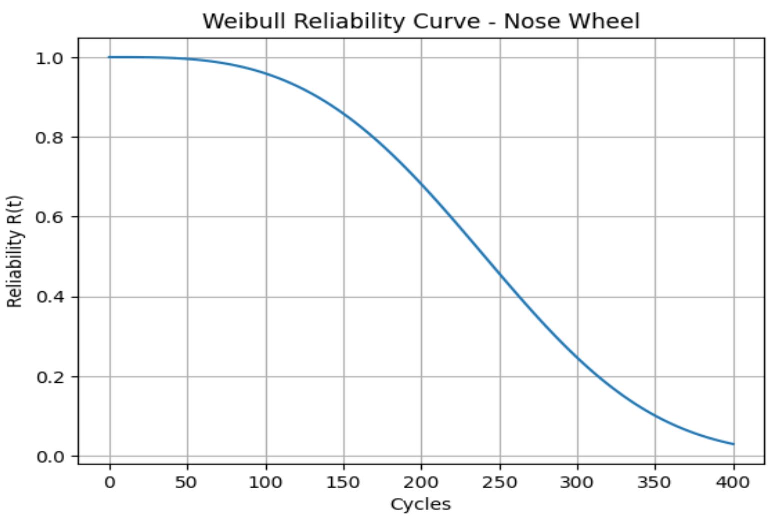

Figure 5.5: Weibull Reliability Curve of NWA

In Weibull Analysis (Figure 5.4), the result showed that early inspection should be done in 120 to 140 FC, Pre-failure or wear-out inspection should be carried out in 280 to 300 FC, and the replacement threshold should be 320 to 350 FC. We get the shape parameter (β) to be nearly equal to 1.85, so it indicates the wear-out dominant. At 150 FC, it shows high reliability, 275 FC only 37% survive, and 350 FC has very low reliability. So, most failures cluster around the 200 to 300 FC. Optimal preventive replacement is 280 to

320 FC at normal conditions. Similarly, the shape parameter (β) is nearly equal to 2.8, and the shape parameter (η) is 420FC for MWA. So, it indicates that early inspection should be carried out at 150 to 200 FC, normal operation should be carried out at the range of 200 to 380 FC, and wear out zone should be at 400 FC. Most of the data are clustered around 350 to 450 FC. Optimal preventive replacement 400 to 450 FC at normal conditions.

5.1.2 Data-Driven Analysis

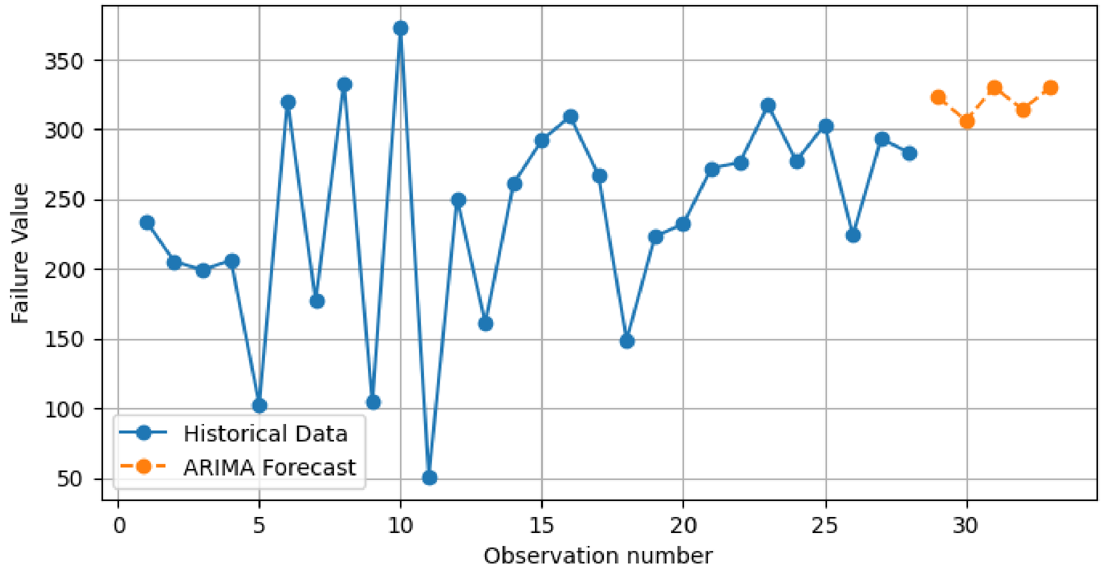

Figure 5.6: ARIMA Model of AKW-1

In the ARIMA Model (Figure 5.5), the sample data is analyzed with aircraft position only that 1st position and the 2nd position of NWA. After that, we studied the output of the analysis, and we found that the 2nd position has a high-risk zone from that result, as shown in Appendix B. So we have modified the sample date in terms of aircraft as well as position-wise, so we get the following result, as shown in Table 5-1. We have used the actual failure data of NWA of 2025 and calculated the error percentage from predicted data and actual data. We got the following result.

Table 5.1: Results of Different Methods

S.N.	MAE(FC)	RMSE(FC)	R^2
MA (3)	50	64	0.16
EMA(α=0.3)	41	53	0.415
EMA(α=0.6)	26	34	0.758
LWEMA	44.4	56.8	0.304

The comparative performance of the applied forecasting and time series models is summarized using MAE, RMSE, and the coefficient of determination (R^2). Among all models, the Exponential Moving Average with smoothing factor α = 0.6 demonstrates the best predictive performance, yielding the lowest MAE (26) and RMSE (34), along with the highest R^2 value (0.758). This indicates a strong capability to capture the underlying trend in the failure interval data while minimizing prediction error. We have predicted the next failure through the EMA, and we got this result, as shown in Table 5.4.

The MA model with window size 3 shows the worst performance with relatively high MAE (50) and RMSE (64) and low R2 (0.16) indicating its limited ability to model the variability in the dataset. The LWEMA also has a R^2 value of 0.304, indicating that the variance in the failure intervals can only be partially explained.

The EMA with α = 0.3 performs better than the simple MA and LWEMA but lower to the α = 0.6 model. This suggests that a higher smoothing factor is more appropriate for the given dataset, but allowing the model to respond more effectively to recent changes in failure behavior.

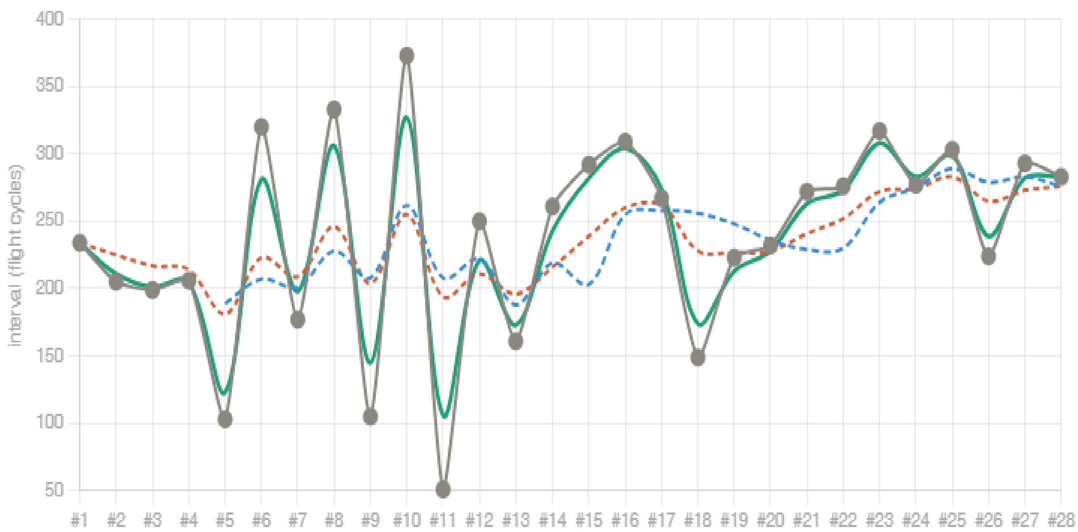

Figure 5.7: Actual vs MA vs EMA graph

Where Gray color is the actual intervals, blue color is the 5 period MA, dark red or maroon color is the EMA (α=0.3), and dark green is the EMA (α =0.8), which is the analysis of the 1st position of the one aircraft.

The EMA model with α=0.6 provides a baseline forecasting capability with more accuracy among other method. While not optimal for exact predictions of next failure cycle due to various factor also affect the wheel assembly, here it is mainly used to identify trends and provides useful information for failure prediction and their material planning. The high inconsistent in failure intervals FC data suggests the need for additional predictive features for improved accuracy. We have also shown the best prediction value and the worst prediction value in Appendix B.

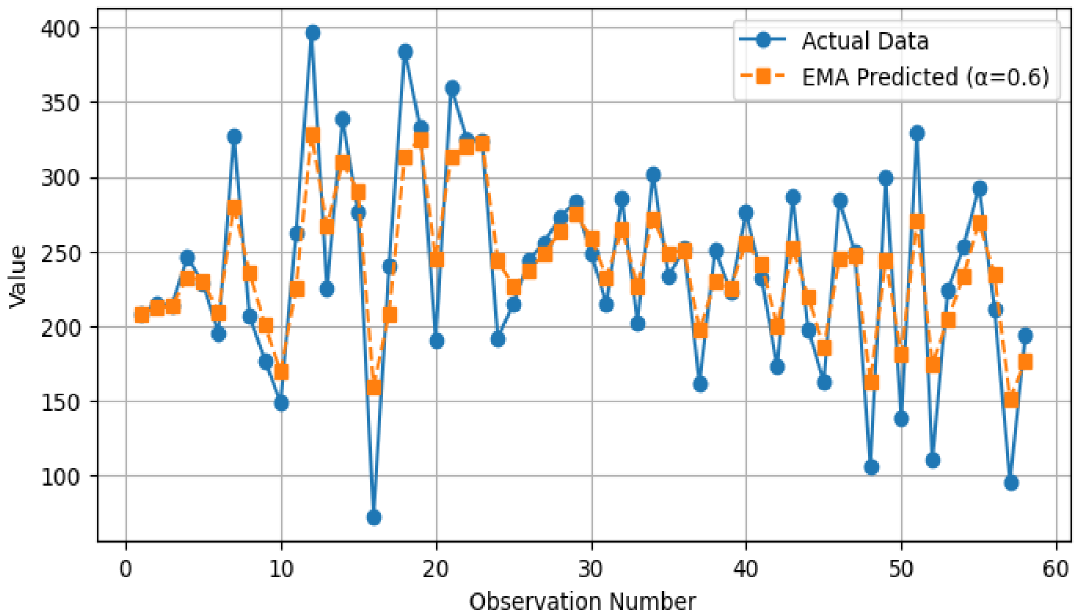

Figure 5.8: Position 2 predicted vs Actual

In Figure 5.7, we have plotted a graph between the position 2 sample data vs the prediction value of position 2. We have used the EMA and ARIMA models for the prediction of the next failure in the NWA. We got a result as shown in Table 5.2:

Table 5.2: Result of EMA and ARIMA

Position of the aircraft	EMA Error (%)	ARIMA Error (%)
AKW-1	14.37	1.22
AKW-2	30.43	17.4
AKX-1	34.76	13.2
AKX-2	30.3	30.3

A comparison between the predicted and actual failure cycle intervals shows that the prediction value error ranges from 1% to 40%, indicating variability between the forecasted and real fault data. This variation reflects the influence of changing operational conditions, environmental factors, and uncertainties in the failure behavior of the nose wheel assembly. We have taken the best method for a small sample size, EMA $\alpha = 0.6$. On the basis of this result, we have to predict the NWA and MWA failures on an annual basis. Finally, it is studied and analyzed, and the different method and analyzed in different positions as well as on different aircraft. It is found that there are a total of 971 FC and 914 FC for the 4th failure in EMA and ARIMA prediction, as shown in Table 5.3. In both method there is error range is also 30% to 40%, and the average utilization of A320 aircraft is 954FC annually and 3.28 FC per day. Therefore, from this, it is possible to have nearly 4 NWA failures in a 1000FC.

Table 5.3: EMA and ARIMA Prediction

S.N	EMA Prediction(FC)	ARIMA prediction(FC)
1	280	323
2	270	243
3	279	206
4	142	142
Total	971	914

Finally, it is concluded that there are 16 NWA and 21 MWA replaced annually in A320 aircraft due to variation in error percentage. So, compare the actual results of wheel assembly failure of NWA and MWA, which are 15 and 20, respectively, in the year 2025. We got the error of 6.67% and 5%, respectively.

5.2 Discussions

When we have done a detailed study of the other literature review, there is used of different method to predict the failure, and a large sample size is used. There is the use of advanced technology, which includes sensors, software, other equipment, and so on. In our cases, we have the original data with a small sample size that includes several instances of noise in the data. In a small sample size, there is a statistical method to predict the failure (Okoro, O. C., Zaliskyi, M., Serhii, D., & Abule, I., 2023). Based on this paper review, the prediction of the most premature fault occurring component, such as NWA and MWA. According to the study presented in “A320 Family Maintenance Analysis and Budget”, a typical aircraft in the A320 family operates with an average ratio of approximately 1.5 FH per FC, accumulating around 2,800 FH annually. In recent years, airlines such as AirAsia, JetBlue, EasyJet, and Frontier Airlines have achieved higher utilization rates, approaching 10 FH per day, with aircraft frequently operating on routes with flight durations of 2–3 hours per flight. Based on this benchmark, the standard operational assumption includes an annual utilization of 2,800 FH and 1,850 FC, approximately 355 operating days per year, accounting for around 10 days of downtime due to base maintenance and other checks, and An average daily utilization of 5.3 Flight Cycles per day (FC/day) and 8.0 Flight Hours per day (FH/day) (family, 2006). In comparison with the NAC utilization pattern, it was completely different from the review paper, which strongly impacts the performance of aircraft and increases the economic burden on the NAC. So, within a certain time period, it would initiate the different data-driven technologies to enhance the growth and performance of reliability.

CHAPTER 6: CONCLUSION AND RECOMMENDATION

6.1 Conclusions

The main purpose of this work is to analyze the utilization of A320 aircraft and component failures that would fail repetitively in a study period. This paper would help make enhancements to be made at a maintenance management level, which make easy for decision making, mainly focusing on employee, spare part, and time constraint.

Currently, there is analyzed the root cause of the wheel assembly and the failure in the A320 aircraft is being analyzed. This evaluation is used to assist the decision on the number of materials required for a wheel assembly to be requested at the supplier by the Engineering Store and Supply Division (rotatable components management section).

However, the current maintenance strategies at the management level can be upgraded and optimized in order to maintain regular schedules for tasks that require fewer adjustments. The occurrence of downtime of aircraft, emergency orders of wheel assembly and their materials imply high costs, which is more expensive and a peak stress on technicians and planning engineers that should be removed or completely avoided. A prediction time series method that is mainly ARIMA and EMA would improve the effectiveness of the tire and other materials required for the inventory management and decrease these occurrences.

To create the plan of develop the prediction of failure, an ANOVA was performed to determine which variables had the most impact on the number of cycles an assembly lasted. From this study, it was found that the only variable that significantly affected the number of cycles was the aircraft position where the wheel assembly was installed. So we have to analyze the NWA and MWA separately through the different time series models.

In conclusion, the proposed methodology provides a practical and efficient approach for failure prediction in aircraft wheel systems for a small sample size. We have given most failure components in a related study period.

6.2 Recommendations

This study is based on a sample size collected from operational records, where we can find fewer sample data; therefore, further work should focus on expanding the dataset to improve the robustness and accuracy of the analysis. Future research on the performance of landing system could be further improved with the integrations of more operational factors, such as takeoff weight, landing weight and their speed, ambient environmental temperature, brake temperature, taxing time, stopping distance, and so on, to better find out the failure patterns of the wheel assembly and their effect on other systems. Future research can also investigate the interaction between different ATA chapters, such as the interaction of pneumatic system, air conditioning system, and anti-icing system, and how they affect the overall performance of aircraft and engine. This approach would offer a broader view of system reliability and ensure more sophisticated predictive maintenance approaches, and also enhanced safety. There is a possibility of advanced machine learning techniques to analyze the data.

REFERENCES

Allen, W. (. (2015). Preventative maintenance and root cause analysis for critical process conveying equipment. *Cement Industry Conference, AUMUND Corporation.*

Castilho, I. X. (2015). *Fault Prediction in Aircraft Tires Using Bayesian Networks.*

Çetin, F. S., Üngör, U., Koyuncu, E., & Özkol, İ. (2026). Data-driven predictive maintenance for aircraft components through sparse event logs. *Aerospace, 13(1), 110.*

Chandola, D. C., Chandola, P., Verma, S., & Kamal. (2023). An exploratory study to evaluate the significance of maintenance planning in reducing aircraft maintenance turnaround time within the airline industry. *In Proceedings of the 2023 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), Amity University Dubai, UAE. IEEE.*

family, A. (2006). *A320 Family Maintenance cost and budget Analysis.* Retrieved from Aircraft Commerce.

I. Dagal, B. Erol, W. Fendzi Mbasso, A. Harrison, A. Demirci and U. Cali,. (2025). A Data-Driven Approach to Aircraft Engine MRO Using Enhanced ANNs Based on FMECA,. *in IEEE Access, vol. 13, pp. 124710-124733*.

Kafalı, H. (2024). Assessing the environmental impact of aircraft maintenance. *Journal of Aviation, 8(1), 7–14*.

Kessel, V., Freeman, & Santos. (2023).

Lee, W.-K. (2006). Risk assessment modeling in aviation safety management. *Journal of Air Transport Management, 12(5), 267–273.*

M. Ward, N. McDonald, R. Morrison, D. Gaynor, and T. Nugent. (2010). A performance improvement case study in aircraft maintenance and its implications for hazard identification,. *Ergonomics, vol. 53, no. 2, pp. 247–267*.

Marevac, E., Kadušić, E., Živić, N., Hamzić, D., & Hadžajlić, N. (2025). Data-Driven Predictive Analytics for Dynamic Aviation Systems: Optimising Fleet

Maintenance and Flight Operations Through Machine Learning. *Future Internet, 17(11), 508.*

Nicchiotti, G., & Rüegg, J. (2018). Data-driven prediction of unscheduled maintenance replacements in a fleet of commercial aircrafts. *PHM Society European Conference, 4(1.*

Nicchiotti, G., & Rüegg, J. (2018). Data-driven prediction of unscheduled maintenance replacements in a fleet of commercial aircrafts. *PHM Society European Conference, 4(1).*

Okoro, O. C., Zaliskyi, M., Serhii, D., & Abule, I. (2023). An approach to reliability analysis of aircraft systems for a small dataset. *Scientific Journal of Silesian University of Technology. Series Transport, 118, 207–217.*

P. Korvesis, S. Besseau and M. Vazirgiannis. (2018). "Predictive Maintenance in Aviation: Failure Prediction from Post-Flight Reports," . *IEEE 34th International Conference on Data Engineering (ICDE), Paris, France, 2018, pp. 1414-1422.*

Peysson, F., Boubezoul, A., Ouladsine, M., & Outbib, R. (2009). A data-driven prognostic methodology without a priori knowledge. *IFAC Proceedings Volumes, 42(8), 1462–146.*

Ramamurthy, P., & Sundaramurthy, A. (2019). Aircraft landing performance assessment through post-flight data analytics. *INCOSE International Symposium, 29(Suppl. 1), 346–342.*

S.A.S., A. (2023). *Aircraft Characteristics: Airport and Maintenance Planning – A320 Family.* Airbus.

Skormin, V. A., Gorodetski, V. I., & Popyack, L. J. (2002). Data mining technology for failure prognostic of avionics. *IEEE Transactions on Aerospace and Electronic Systems, 38(2), 388–403.*

Ugnenko, Evgeniya and Perova, Elena and Voronova, Yelizaveta and Viselga, Gintas. (2017). Improvement of the mathematical model for determining the length of the runway at the stage of aircraft landing. *Procedia Engineering*, 733--741.

van Kessel, P. J., Freeman, F. C., & Santos, B. F. (2023). Airline maintenance task rescheduling in a disruptive environment. *European Journal of Operational Research, 308(2), 605–621.*

Xu, G., Liu, M., Wang, J., Ma, Y., Wang, J., Li, F., & Shen, W. . (2019, August). Data-driven fault diagnostics and prognostics for predictive maintenance: A brief overview. *In 2019 IEEE 15th international conference on automation science and engineering (CASE) (pp. 103-108). IEEE.*

Yang, X. (2020). Reliability growth method and application based on operation fault analysis. *n Proceedings of the 2020 Global Reliability and Prognostics and Health Management (PHM-Shanghai), 333–336. IEEE.*

APPENDIX A

Table 8.1: ATA chapter-wise component failure

ATA Chapter	Component	Part Number	No. of fault	Fault Frequency(%)	Impact	Priority
ATA 21	Temperature Sensor	9105A00502	11	27.50%	Affects system performance	High
ATA 21	Valve skin air outlet/inlet	VFT300B00	10	25%	Affects system performance	High
ATA 26	Smoke detector	ppc1100-00	44	86.27%	Affects system performance	High
ATA 28	Fuel quantity tank probe	20145-0101	13	38.23%	Affects system performance	High
ATA 30	Anti-ice Valve	326975	6	50%	Affects system performance	High
ATA 35	Smoke hood	15-40F-80	5	6.94%	No airworthiness impact	Low
ATA 35	portable oxygen Cylinder	3552AADAC XCD	13	18.05%	No airworthiness impact	Low
ATA 35	Crew oxygen cylinder	89794077	43	59.72%	No airworthiness impact	Low
ATA 74	Ignition Plug	CH31964-1	-	46.16%	Affects system performance	High
ATA 74	Lead Ignition	512090-1	-	38.46%	Affects system performance	High
ATA 78	Hydraulic Control Unit	TY1540-24	13	76.47%	Affects system performance	High

ATA Chapter	Component	Part Number	No. of fault	Fault Frequency(%)	Impact	Priority
ATA 25	Steam oven	4323100-016622	-	-	No airworthiness impact	Low
ATA 25	Life vest	66601-101	-	-	No airworthiness impact	Low
ATA 25	Water heater	4360004-8000-18	-	-	No airworthiness impact	Low
ATA 25	Soap Dispenser	DCIN-152052	-	-	No airworthiness impact	Low
ATA 31	Display Unit	C19755BA01	-	-	Affects system performance	High
ATA 33	Landing Light	727-1213-01	-	-	Affects system performance	High
ATA 33	Fluorescent tube	F30WT8-840	Maximum	-	Affects system performance	High
ATA 38	Vaccum Generator	14330-375	Average	-	No airworthiness impact	Low
ATA 47	Air Separation Module	2060017-103	3	37.50%	Affects system performance	High
ATA 80	Pneumatic Starter valve	790424-4	5	83.33%	Affects system performance	High

APPENDIX B

Result of the ARIMA model for the next five failures.

Table 9.1: Prediction of the ARIMA model in terms of FC

Failure	AKW-1	AKW-2	AKX-1	AKX-2
F1	323	243	206	142
F2	306	273	221	197
F3	330	266	217	175
F4	314	259	228	208
F5	330	271	230	202

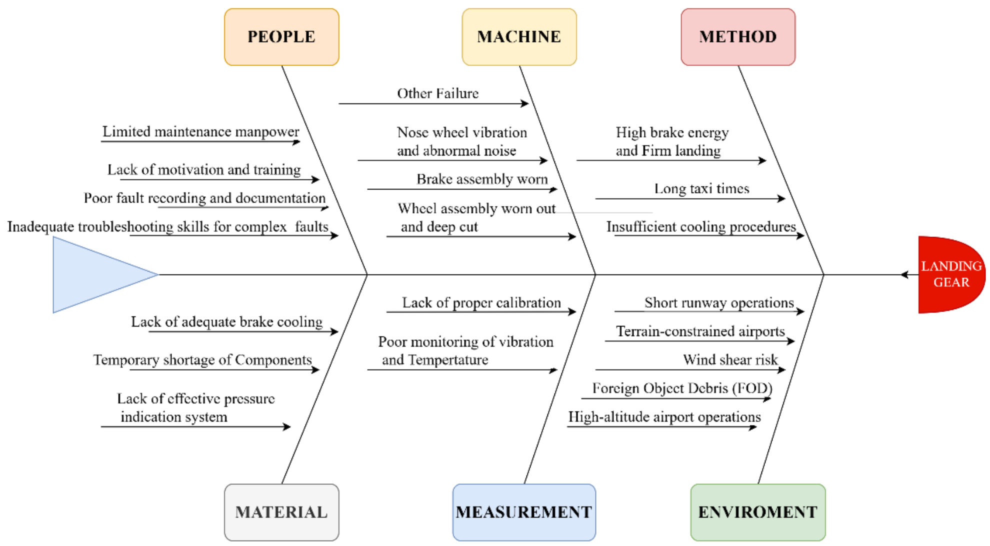

Figure 9.1: Fishbone Diagram for Landing Gear System Faults (ATA 32)

Table 9.2: Prediction of the ARIMA model in terms of days

Failure	AKW-1	AKW-2	AKX-1	AKX-2
F1	98	74	63	43
F2	93	83	67	60
F3	101	81	66	53
F4	96	79	70	64
F5	100	83	70	61

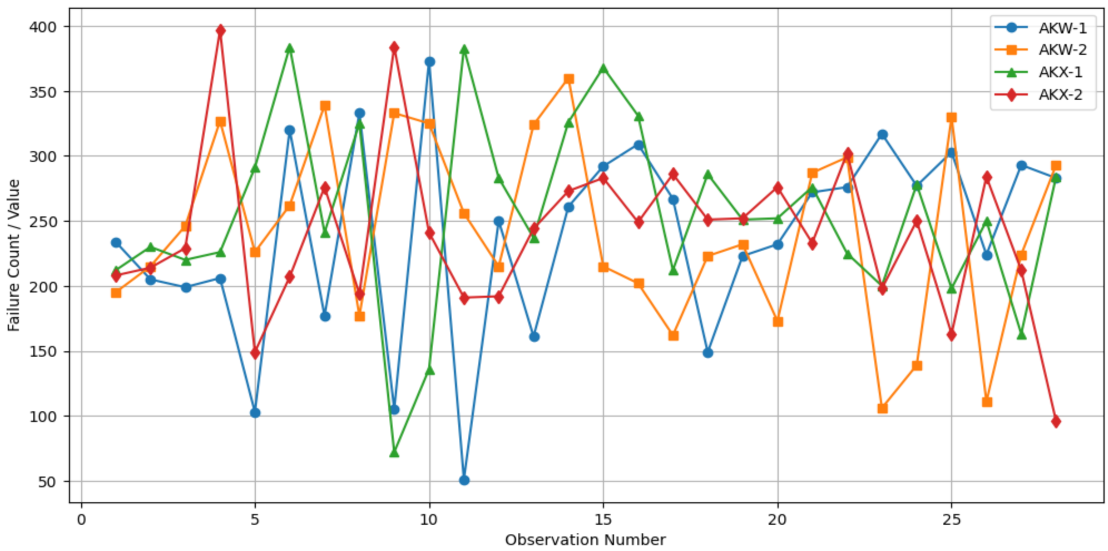

Figure 9.2: Variations in Data of NWA

Table 9.3: ARIMA prediction for position-wise

Future	Pred. Position-1(FC)	Pred. Position-2(FC)
F1	198	127
F2	208	169
F3	194	144
F4	199	158
F5	192	151
F6	193	154
F7	188	153
F8	188	154
F9	184	153
F10	183	154

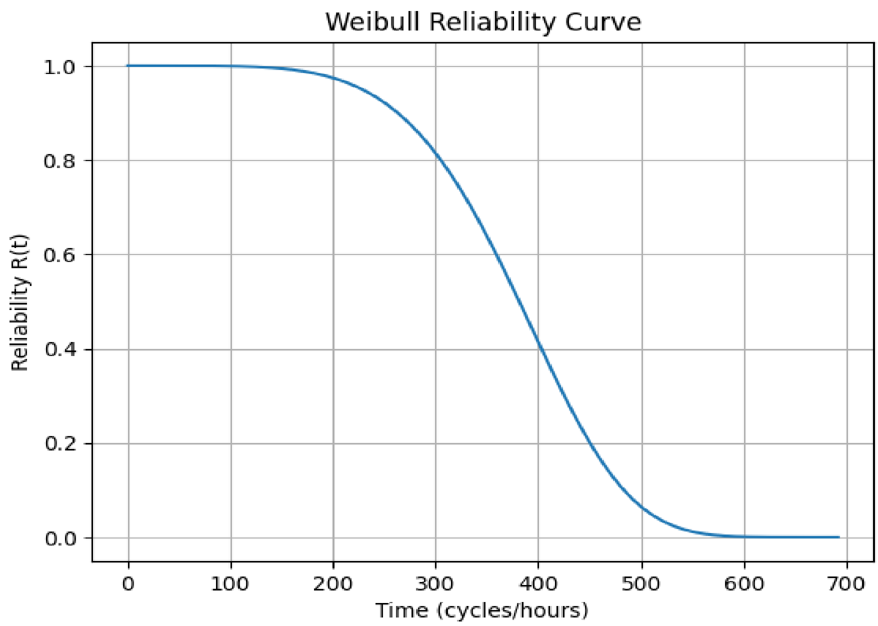

Figure 9.3: Reliability curve for MWA

Table 9.4: Best Prediction of EMA

S.N	Aircraft	Actual(FC)	Predicted(FC)	Error %
1	AKW-1	234	234	0
2	AKW-1	206	206	0
3	AKX-1	230	229	1
4	AKX-2	214	215	1
5	AKX-1	225	226	1

Table 9.5: Worst Prediction of EMA in FC

S.N	Aircraft	Actual(FC)	Predicted(FC)	Error %
1	AKW-1	51	294	243
2	AKX-2	384	144	240
3	AKX-1	383	147	235
4	AKX-1	72	306	234
5	AKW-1	373	175	197

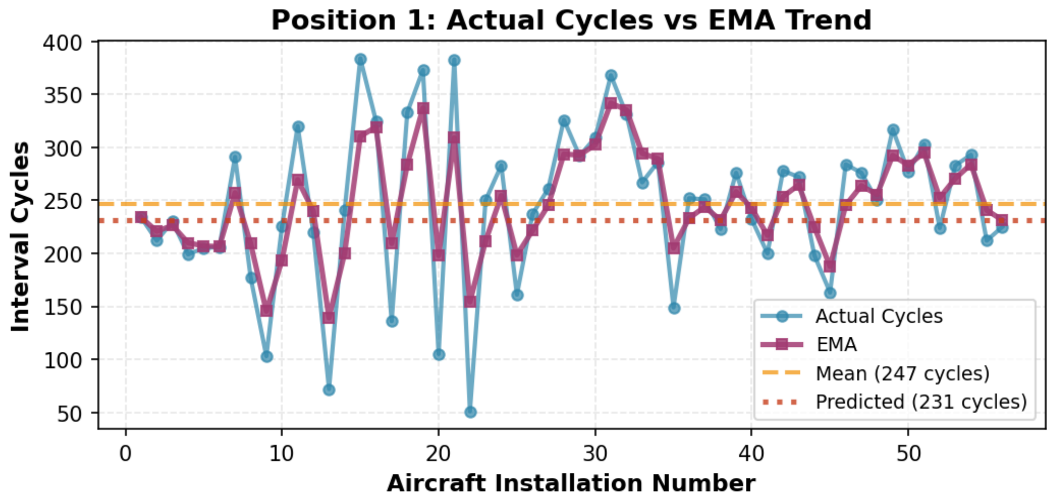

Figure 9.4: Graph of Actual and EMA trend in Position-1

Used Python Codes in Google Colab

```
#KDE Diagram Program with histogram
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import skew, kurtosis

# my dataset
data = np.array([
    234, 205, 199, 206, 103, 320, 177, 333, 105, 373,
    51, 250, 161, 261, 292, 309, 267, 149, 223, 232,
    272, 276, 317, 277, 303, 224, 293, 283
])

skewness = skew(data)
kurt = kurtosis(data)

plt.figure(figsize=(8,5))
sns.histplot(data, kde=True, bins=10)
plt.title("Histogram with KDE")
plt.xlabel("Cycle Interval")
plt.ylabel("Frequency")
plt.grid(True)
plt.show()
```

#Weibull plot programme

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import weibull_min

#my dataset
data = np.array([
371,337,408,365,472,348,469,509,378,437,491,412,372,345,173,187,4
36,493,482,375,
291,336,165,291,310,361,385,487,480,535,377,391,443,484,312,435,3
81,392,179,458,
407,456,395,336,368,379,425,492,171,463,692,371,336,440,390,387,3
18,263,399,424,
498,380,390,327,342,178,118,350,246,468,371,411,495,351,380,421,4
00,309,369,336,
373,434,389,406,241,244,369,246,331,336,432,188,446,371,358,391,3
44,433,473,418,
379,370,399,394,489,411,411,259,385,314,208,366,353,402,364,357,4
36,488,325,388,
423,424,398,374,315,378,405,393,384,388,329,350,98,483,454,426,43
8,313,322,383,
427,356,447,386,384,134,423,418,392,497,371,370,415,308,167,394,3
84,457,475,456,
517,360,405,398,458,410,392,364,430,419,395,237,391
])

shape, loc, scale = weibull_min.fit(data, floc=0)

t = np.linspace(0, max(data), 200)


R = np.exp(-(t/scale)**shape)

plt.figure()
plt.plot(t, R)
plt.xlabel("Time (cycles/hours)")
plt.ylabel("Reliability R(t)")
plt.title("Weibull Reliability Curve")
plt.grid()
plt.show()
print("Shape parameter (beta):", shape)
print("Scale parameter (eta):", scale)

# KDE Plot of position-1 with bandwidth=90
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import gaussian_kde
```

```python
# Your dataset
data =
np.array([20,26,56,72,73,96,136,149,163,163,191,192,194,198,198,2
00, 207,208,212,212,212,214,220,225,226,229,230,233,237,241,241,
244,249,250,250,251,251,252,252,273,276,276,276,278,283,283,
284,284,286,286,291,302,325,326,331,368,383,384,384,397])
kde = gaussian_kde(data)
kde.set_bandwidth(bw_method=90 / np.std(data))
# X range for plotting
x = np.linspace(min(data), max(data), 500)
y = kde(x)
plt.figure(figsize=(8,5))
plt.plot(x, y)
plt.title("KDE Plot (Bandwidth = 90) - Nose Wheel Cycle
Interval")
plt.xlabel("Cycle Interval")
plt.ylabel("Density")
plt.grid(True)
plt.show()
```

Sagar Neupane

Sagar_Neupane_Final_thesis.docx

Tribhuvan University

Document Details

Submission ID

trn:oid:::3117:587921195

Submission Date

May 8, 2026, 3:51 PM GMT+5:45

Download Date

May 8, 2026, 3:59 PM GMT+5:45

File Name

Sagar_Neupane_Final_thesis.docx

File Size

1.4 MB

73 Pages

15,852 Words

87,717 Characters

6% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

Filtered from the Report

- Bibliography
- Quoted Text
- Cited Text
- Small Matches (less than 8 words)

Exclusions

- 30 Excluded Matches

Custom Section Exclusions

{titlesCount} Section Titles, {keywordsCount} Keywords

Section title	No. of Section Starters	Section Starters
"Acknowledgements"	4	Acknowledgements, Acknowledgement, Acknowledgment, Acknowledgments

Match Groups

- **80** Not Cited or Quoted 6%
  Matches with neither in-text citation nor quotation marks
- **0** Missing Quotations 0%
  Matches that are still very similar to source material
- **0** Missing Citation 0%
  Matches that have quotation marks, but no in-text citation
- **0** Cited and Quoted 0%
  Matches with in-text citation present, but no quotation marks

Top Sources

- 5% Internet sources
- 2% Publications
- 0% Submitted works (Student Papers)

Integrity Flags

0 Integrity Flags for Review

No suspicious text manipulations found.

Our system's algorithms look deeply at a document for any inconsistencies that would set it apart from a normal submission. If we notice something strange, we flag it for you to review.

A Flag is not necessarily an indicator of a problem. However, we'd recommend you focus your attention there for further review.

Match Groups

- **80 Not Cited or Quoted 6%**
  Matches with neither in-text citation nor quotation marks
- **0 Missing Quotations 0%**
  Matches that are still very similar to source material
- **0 Missing Citation 0%**
  Matches that have quotation marks, but no in-text citation
- **0 Cited and Quoted 0%**
  Matches with in-text citation present, but no quotation marks

Top Sources

5% Internet sources
2% Publications
0% Submitted works (Student Papers)

Top Sources

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

1	Internet	fenix.tecnico.ulisboa.pt	1%
2	Internet	www.coursehero.com	<1%
3	Internet	www.mdpi.com	<1%
4	Internet	text.123docz.net	<1%
5	Internet	etrr.springeropen.com	<1%
6	Internet	mafiadoc.com	<1%
7	Internet	www.tdx.cat	<1%
8	Internet	repository.tudelft.nl	<1%
9	Internet	laganvalleydup.co.uk	<1%
10	Internet	www.diva-portal.se	<1%

त्रिभुवन विश्वविद्यालय
TRIBHUVAN UNIVERSITY
इन्जिनियरिङ्ग अध्ययन संस्थान
INSTITUTE OF ENGINEERING
पुल्चोक क्याम्पस
PULCHOWK CAMPUS

redited by University Grants
nmission (UGC) Nepal 2020

5-521260
5-521611
5-522104
5-522809

पुल्चोक, ललितपुर ।
Pulchowk, Lalitpur

Date: May 9, 2026

To Whom It May Concern:

This is to certify that the paper titled "*Data-Driven Reliability Assessment and Maintenance Planning of A320 Aircraft Using Operational Records in Nepal Airlines Corporation*" (Submission ID #957), with **Sagar Neupane** as the first author, was accepted through the peer-review process and has been presented at the 18th IOE Graduate Conference, organized at Pulchowk Campus, Lalitpur, Nepal, from May 7 to 9, 2026.

Please note that inclusion of the accepted manuscript in the conference proceedings is contingent upon timely compliance with any further editorial requirements during the publication process.

Prof. Sangeeta Singh
Convener
18th IOE Graduate Conference