Reliability Analysis of Boeing's Dreamlifter Large Cargo Freighter

by

So Young (Michelle) Park
B.S., Chemical Engineering, MIT (2015)

Submitted to the MIT Sloan School of Management
MIT Department of Mechanical Engineering
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Author . . . .
MIT Sloan School of Management
MIT Department of Mechanical Engineering
May 14, 2021

Certified by . . . .
Dr. Arnold I. Barnett
George Eastman Professor of Management Science
Thesis Supervisor

Certified by . . . .
Dr. Daniel Frey
Professor of Mechanical Engineering
Thesis Supervisor

Accepted by . . . .
Maura Herson
Assistant Dean, MBA Program, MIT Sloan School of Management

Accepted by . . . .
Nicolas Hadjiconstantinou
Chair, Mechanical Engineering Committee on Graduate Students

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Abstract

Proper maintenance is critical to keep aircraft flying through their designated service life. And once an aircraft reaches the end of its operational life, or if maintenance and repair costs exceed the cost of flying a new aircraft, it is typically replaced, retired, and dismantled. The typical operational lifespan of commercial aircraft is around 30 years. Boeing's Dreamlifter fleet, the primary air transportation method for several 787/767 major production articles and the topic of this thesis, is an anomaly in that the 30-year-old fleet is far from facing retirement. The unique custom design makes the Dreamlifters an irreplaceable asset, and thus it is critical that the fleet remains operational throughout the lifetime of 787 production, or the limit of validity of the Dreamlifters.

This thesis analytically breaks down the Dreamlifters' highly complex systems through exploration of various data elements relevant to reliability. Employing reliability-centered maintenance (RCM) concepts, Monte Carlo simulations and historical failure data, we propose an obsolescence management framework that provides a probabilistic mitigation timeline for a component with limited supply. This simulation approach can be expanded to other aircraft components even with relatively small data sets, provide insight into optimal replacement intervals, and help prioritize risk management targets. We also share recommendations for successful project continuity.

Thesis Supervisor: Dr. Arnold I. Barnett
Title: George Eastman Professor of Management Science

Thesis Supervisor: Dr. Daniel Frey
Title: Professor of Mechanical Engineering

Acknowledgments

"But our citizenship is in heaven. And we eagerly await a Savior from there, the Lord Jesus Christ, who, by the power that enables him to bring everything under his control, will transform our lowly bodies so that they will be like his glorious body."

— Philippians 3:20-21

God has guided my way to LGO, where I met lifelong friends and made critical relationships. I've gone through both spiritual growths and falls during my time, but nonetheless God has never failed to be present and provide.

Mom and dad: your unconditional support, your trust in me, and the interest-free student loan you have graciously offered were of paramount importance throughout my LGO journey and internship.

Prof. Barnett and Prof. Frey: thank you for all the support and guidance you have provided throughout my internship - I am sorry we weren't able to host you in Charleston, but it was such an honor working with both of you!

Kyle and Ty: thank you for welcoming me to the Dreamlifter Ops team and for connecting me to all the touch points and stakeholders that enabled me to successfully complete my internship. COVID was an unpleasant surprise but I sincerely appreciate all that you did to help me make the most out of it!

LGO zoomies (iykyk): who would've known that a seemingly failed reunion in Charleston would lead to an even stronger friendship? Our weekly calls during the pandemic definitely helped keep me sane, and highlighted the true value of the LGO community.

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Chapter 1

Introduction

As time passes, our bodies age. So do aircraft, and proper maintenance is critical to keep aircraft flying through their designated service life. The average retirement age of commercial aircraft ranges from 26 to 33 years (for passenger and freighter aircraft, respectively), driven by macroeconomic factors, introduction of new aircraft, components demand and other factors [1]. Figure 1-1 captures this distribution well.

Boeing's Dreamlifter fleet, the topic of this thesis, is an anomaly in that the 30-year-old fleet is far from facing retirement. The Dreamlifters make up a cargo airline fleet unique to Boeing. The fleet consists of four aircraft, extensively modified from retired passenger 747-400s. As the apt name gives away, the Dreamlifters are the primary transportation method of the 787 Dreamliner assemblies from global suppliers to final assembly.

The Dreamlifters are also one of the oldest 747-400 fleets flying today, at a fleet average age of 30 years. Most commercial aircraft have already retired at this age. Instead, the Dreamlifters are anticipated to operate for several more decades to carry out their core mission of supporting the final assembly of 787s and other in-production models. As such, the ambition to operate the Dreamlifters to the limit of validity will place the fleet in uncharted territory of commercial aircraft operations.

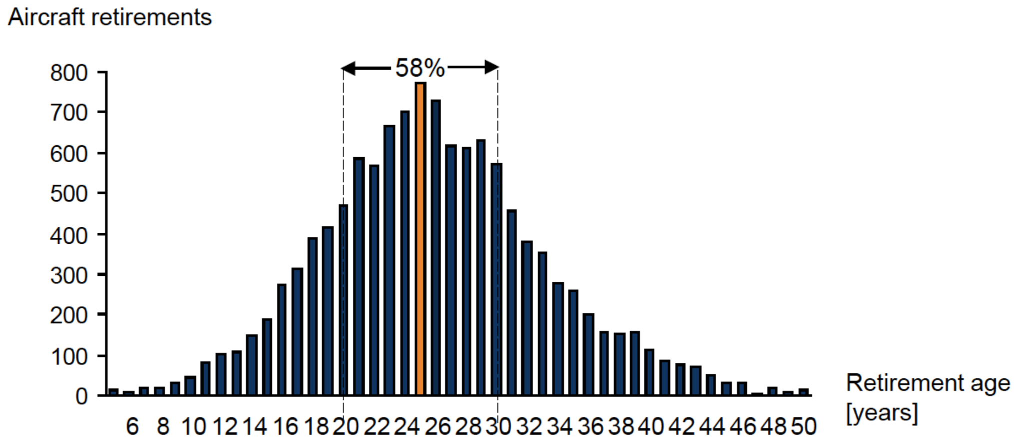

Figure 3: Aircraft retirement age distribution (1980-2017) [4]

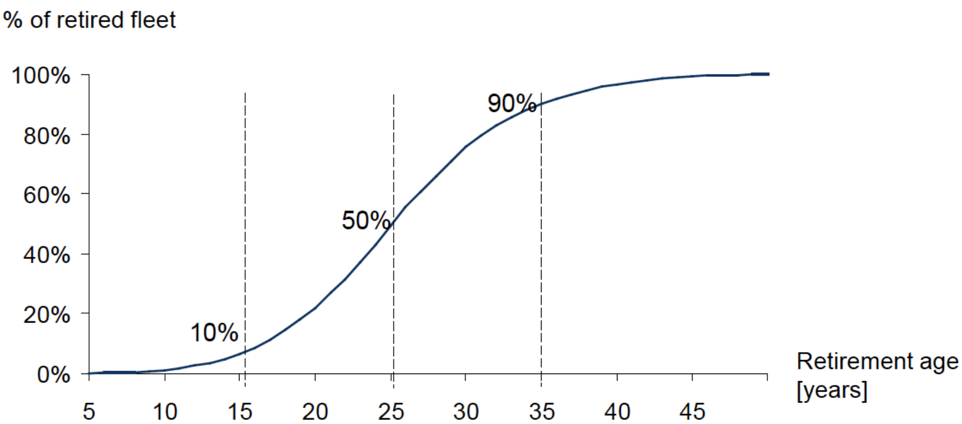

Figure 4: Percentage of retired fleet by age (1980-2017) [5]

Figure 1-1: Aircraft retirement age distribution covering aircraft retirements from 1980-2017 indicate a median retirement age of 25 years, and only 10% of the retirements occur past 35 years.
Source: IATA Best Industry Practices for Aircraft Decommissioning Manual, 1st edition (Note: Figures 3 and 4 are the figure numbers in the source document)

1.1 Project Motivation

The development of the Dreamlifter fleet was executed on an aggressive timeline. The team was allowed no more than 24 months for the design, modification, and certification of the Dreamlifters. This accelerated timeline required swift decision making, and overall a conservative approach was taken to reduce potential risks and maximize the likelihood of FAA certification.

The FAA-designated limit of validity (LOV) of the Dreamlifters is 165,000 flight hours or 35,000 flight cycles, whichever occurs first. Less clearly defined, however, are the various challenges associated with operating the Dreamlifters to those limits. Is the current maintenance plan adequate for the longevity of the Dreamlifter to prevent against potential extensive downtime? What can or cannot be bench-marked from other aging fleets? How should parts obsolescence be managed when only four aircraft demand certain parts?

In essence, the Dreamlifters are aging freighters tasked with a mission that will likely place the fleet in uncharted territory of technical operational life. Any aging aircraft operates with challenges - both controllable and uncontrollable - and the need to establish a better understanding of the implied risk of the Dreamlifters' longevity plan motivated this project. Through this thesis, I aim to present a risk management framework that can serve as a strategic building block for the fleet's longevity and provide direction for project continuity.

1.2 Background

1.2.1 History of the Dreamlifters

The Dreamlifter's uniquely bulging fuselage and its capacity to hold 80 Mini Coopers (or 8 million 12-ounce cans of the beverage of your choice) never fail to grab the attention of the public (Figures 1-2, 1-3). As Boeing prepared to introduce the 787 Dreamliners, its global production system called for a viable, efficient, and competitive transportation method. A scenario analysis involving rail, existing commercial and military transport aircrafts concluded that the only feasible design that satisfies all transportation requirements was to convert retired passenger 747-400s into large cargo freighters (LCF). This would reduce delivery times to as little as one day from as many as 30 days. Four retired passenger 747-400s were acquired from the following airlines to carry out the modification: one from Air China, two from China Airlines, and one from Malaysia Airlines. Modifications of the first Dreamlifter began in 2005, and by 2007 the program was granted FAA type certification and approval for return to service [2].

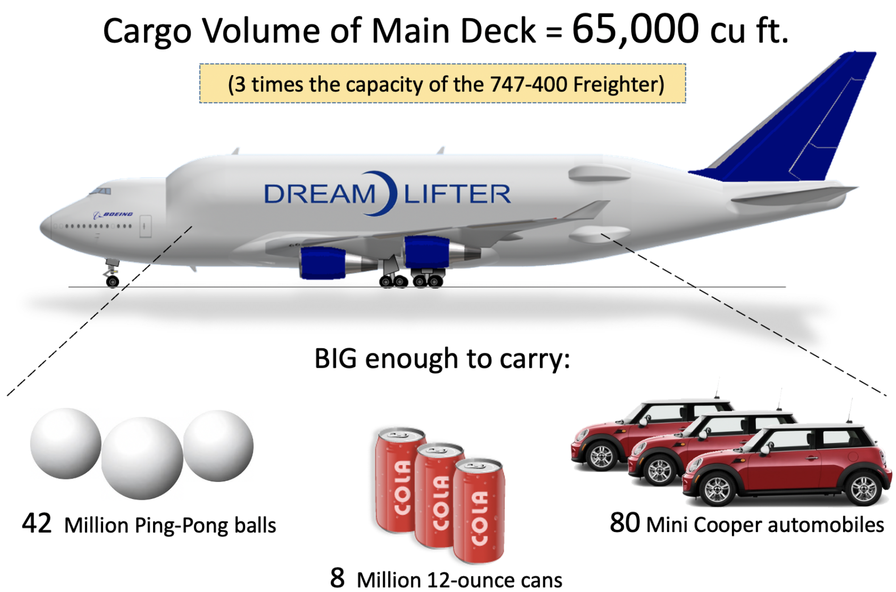

Figure 1-2: The Dreamlifter's main deck cargo volume illustrated at various scales. Source: Dreamlifter Operations team

Figure 1-3: The bulging fuselage is a unique design feature of the Dreamlifters. Source: Boeing Media

Planning the design work the Dreamlifters was like no other. A quote from Kurt Kraft, the Chief Project Engineer at the time, nicely summarizes how this project was unique compared to traditional programs:

> "He notes the engineering design on a program involving three (correction: four) modification airplanes is much different than design on a traditional program that may involve hundreds of airplanes going through the factory. Programs with a large production run may emphasize reducing weight or improving performance. But the focus on the LCF is to find optimal solutions very quickly and to greatly limit nonrecurring costs wherever we can to avoid designs that will require hard tooling, for example, Kraft says. We are focused on providing a safe and reliable airplane that will meet all of the requirements of its mission." [3]

The terms LCF (Large Cargo Freighter) and the Dreamlifter are used interchangeably throughout this thesis.

1.2.2 Unique Design Features

An enormous amount of engineering work went into designing the Dreamlifters. Crudely put, the top of the retired passenger aircraft was sawed at waterline 200, just above the passenger floor, to build a taller structure for larger payloads (e.g. wings and mid-body) while retaining areas that did not need to be modified. The list of LCF-unique design aspects is long, but the following three features are important to note for this research work:

1. **Pressurization**: The only part of the airplane that is pressurized is the flight deck area. The pressure bulkhead, which has a waffle design and was manufactured from 75,000 pounds of raw aluminum stock, separates the pressurized flight deck from the unpressurized cargo area. The fact that the bulk of LCF's volume is unpressurized is important for the aircraft's overall wear and tear as the (de)pressurization cycles generally drive aircraft fatigue.

2. **Swing Tail**: Perhaps the most visually unique feature (and also was a critical design challenge) of the Dreamlifters is its swing tail design. Upon landing, the entire tail section swings open horizontally to load and unload the large composite structures. A special ground support equipment called the Mobile Tail Support provides hydraulic power to slowly disengage the 21 latches that sit at the hinge of the tail. This specific pull-in, latch, and lock actuation control system is the only mechanism that can open and close the swing tail. In case one is wondering, the swinging portion of the Dreamlifter's tail weighs as much as a loaded World War II B-17 bomber [3].

   Once the tail is open, the 787 Dreamliner parts are loaded or unloaded from the Dreamlifters by the DBL-100 aircraft loader (longest in the world at the time of creation at 120 feet, nicknamed the "Darn Big Loader" and holds the Guinness World Record awarded in 2006) [4]. This custom-built loader employs a laser guiding system to raise the platform to a standardized height and slide the sub-assemblies into the hollow fuselage.

Figure 1-4: Cargo Loader docked on the open Swing Tail to load sub-assemblies

3. **Fire Suppression**: There are no smoke detectors on the Dreamlifters. Instead, a rigorous cargo review and approval process is strictly adhered to ensure all cargo carried is safe and posses no fire danger to the aircraft. Since the crew is separated from the cargo by a massive pressure bulkhead, an array of cameras in the cargo hold allows the crew to view the condition of the cargo at any time.

1.2.3 Aircraft Operator and Aircraft Owner

Evergreen International Airlines, a U.S. air freight operator based in McMinnville, Oregon, was the first operator of the Dreamlifter fleet. In March 2010, it was announced that operation of the Dreamlifter fleet would be transitioned to Atlas Air by September of that year. While Atlas is the FAR Part 121 operator of the fleet, Boeing retains aircraft ownership and operational oversight [5]. Boeing's Dreamlifter Operations team, who hosted this LGO internship, works very closely with Atlas Air to ensure the fleet is operated in a safe, reliable, and cost-effective manner.

The contractual details of the Atlas-Boeing partnership are nuanced and confidential. The limited data availability experienced in certain parts of the internship can be attributed to the nature of the aircraft operator-owner relationship, along with many other factors. The topic of data availability is covered in greater detail in Chapter 3.

1.2.4 Current Maintenance Practice and Metrics

The Dreamlifters largely follow the maintenance plan of the 747-400 family in terms of maintenance intervals, and have specific practices around areas unique to the Dreamlifters. The specifics get updated based on observations made during both line checks and heavy maintenance checks.

Two important metrics relevant to this project are flight hours and flight cycles. The following figures illustrate the current flight hours and cycles accumulated by the Dreamlifters in relation to their LOV (165,000 flight hours or 35,000 flight cycles, whichever occurs first).

Figure 1-5: Flight Hours and Flight Cycles accumulated by the four Dreamlifters. Note that the time in operation varies for each Dreamlifter as the modification dates were different. Axes values are intentionally removed.

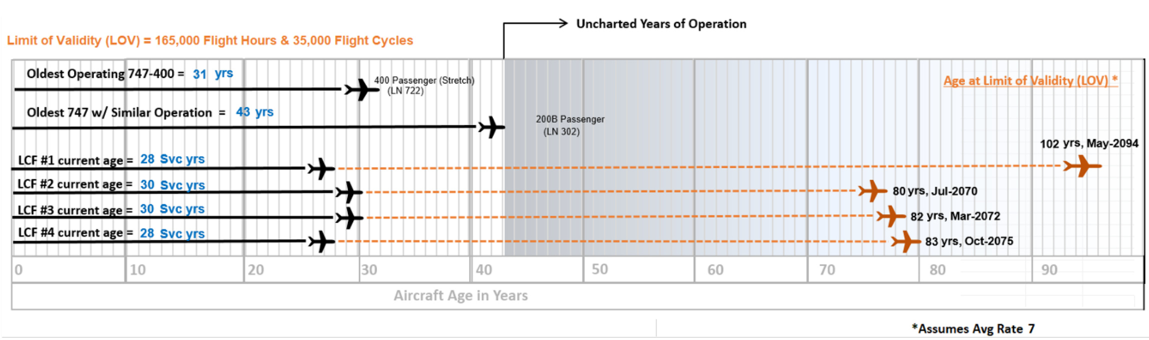

Figure 1-6: The Dreamlifters are reaching the age of the oldest operating 747-400 in service years, and will reach 80-102 years of service at their limit of validity based on 787 production rates as of Q2 of 2020.

1.3 Methodology and Hypotheses

This thesis aims to answer the following questions:

1. Is the Dreamlifters' standard maintenance program sufficient to meet the operational needs of the aging fleet? How do you break down and analyze a highly complex system?

2. While the Dreamlifters may be unique in design, they are not the only aging aircraft that exist. How are other aging Boeing fleets - both commercial and military - tackling similar challenges, and how can the Dreamlifter Operations team leverage some of the lessons learned?

3. How can you identify obsolescence issues and properly manage them for a custom-designed fleet of four aircraft?

The hypotheses of this project are that (1) reliability of components, systems, and structures decreases with time and aircraft utilization, and (2) parts obsolescence will present a growing operational and financial risk for the out-of-production Dreamlifter fleet. Both of these statements may appear intuitive and perhaps even not needing to be tested against. However, in order to provide actionable recommendations, it was critical to comb through available data and quantify the risk of "not doing anything".

The first phase of the project involved extensive stakeholder interviews, and understanding how the Dreamlifter maintenance program evolved to the current version. The Dreamlifter stakeholder map is fairly complex with numerous touch points. Internal stakeholders were primarily located in Charleston, SC, Everett, WA, and Southern California while external stakeholders had global presence.

Next, the focus was on data collection, gap analysis, and synthesis. Information pertaining to the Dreamlifter fleet exists in various forms and locations, including the following (from easiest to most difficult to obtain): queryable Boeing databases, Boeing's intranet, files on the team's shared network, and information owned by Atlas Air. After identifying what information is obtainable and what is not, the research scope was determined.

By consulting a data analytics team at Boeing, I built a preliminary framework for predictive maintenance that, when further matured, would be an analytical guide that recommends reliability actions. To demonstrate the applicability of this framework, I constructed a Monte Carlo simulation for component X (a phased out component that is key to operating the LCF) as an obsolescence case study. Using historical failure records to estimate the remaining time until inventory depletion. The intended use of this type of simulation is risk mitigation - i.e. inform the Dreamlifter Operations team at what point all remaining available component Xs are projected to be consumed, and allow the team to build out a rigorous supply chain strategy that eliminates the risk of operational disruption due to shortage of component X. Data inputs and results are generalized in order to protect proprietary information.

Simulation-based analysis can be extremely powerful, but not feasible for all elements of the Dreamlifters. In the case where data availability is limited, or when dealing with interconnected systems, it is difficult to identify the root cause and assign a fix or replacement action. Electric wiring interconnect system (EWIS) is a great example - EWIS degradation is a function of several variables including (but not limited to) aging, physical properties, installation, environment, and maintenance (cleaning and repair) of the EWIS [6]. I briefly summarize benchmark interview notes from other aging Boeing programs. I then present findings on where the Dreamlifter team stands today in terms of EWIS data collection, and what improvements need to be achieved in order for various types of data analyses to be possible.

1.4 Thesis Structure

The thesis is organized as follows:

Chapter 1 - Introduction presented an overview of the Dreamlifter program, including its history and design attributes that make the fleet unique. The overall methodology and set of hypotheses are provided.

Chapter 2 - Literature Review goes over the academic articles that discuss aging aircraft studies. It also presents articles that pertain to aircraft reliability, an area that is closely relevant to the stated mission of the Dreamlifters. Further, articles detailing the principles behind Reliability-Centered Maintenance (RCM) are shared. In particular, a python library designed to perform data analysis involved with reliability engineering (such as finding failure patterns and using them to forecast future failures throughout the lifetime of repairable items) is covered in detail. This python library is used extensively in the Monte Carlo simulation.

Chapter 3 - Data Sources and Quality presents the different sources of data pertaining to the Dreamlifter fleet, forms of information storage, and the different types of data cleaning and organization methods employed for the different data sets. The purpose of this chapter is to demonstrate the varying levels of data availability, which depended both on (a) whether there is a well established data recording system and/or practice in place (i.e. is it clearly defined who should enter data where, and are the responsible parties adhering to the guidance?), and (b) how successful one navigates the complex stakeholder network for data not readily accessible through simple data query. This chapter also briefly covers key challenges encountered in the data collection process throughout the internship.

Chapter 4 - Descriptive Analysis and Exploring Predictive Maintenance presents how the information discussed in Chapter 3 was queried to attempt a top-down descriptive analysis, or holistic overview of the Dreamlifter maintenance data. Also introduced in this chapter is a preliminary data exploration exercise, using the principles of Reliability-Centered Maintenance (RCM), that was performed to assess the feasibility for empirical forecasts for the Dreamlifters.

Chapter 5 - Reliability Analysis: Obsolescence Management with Case Study continues the discussion of the RCM-based analysis, and confirms its value proposition by addressing a known supply obsolescence risk of component X via Monte Carlo simulation. RCM equations and assumptions are described in detail, as well as the actionable recommendation that was offered to the Dreamlifter team. The applicability of this simulation-based framework to other aircraft parts is discussed.

Chapter 6 - Reliability Analysis: EWIS Case Study presents the research work performed (and data challenges that followed) to test the hypothesis that the wiring systems on the Dreamlifters are degrading over time. High-level recommendations to enhance the practice around EWIS data collection is briefed.

Chapter 7 - Conclusions and Future Work summarizes the key findings of this thesis, and how it sets the stage for follow-on research work for the grander business problem. The chapter wraps up the project with suggestions of high priority follow on work, and recommendations for project continuity.

1.5 COVID-19 Impacts

The unfortunate reality is that COVID-19 has seeped so deeply through our lives that I can save the explanation. The term COVID-19 will bring back all sorts of memories to the readers, vivid or vague depending on how long it has been since the onset of the pandemic and how it has personally impacted the reader.

Only a month and a half into the internship, the coronavirus had become a large enough public health risk that the majority of the Dreamlifter team was instructed to *temporarily* work from home. At the time the team was cautiously optimistic that in a couple of months the team would be back on site, but that optimism never materialized. 75% of my internship was conducted virtually. What this meant was that a series of planned trips to visit key stakeholders were canceled, and that I had only one physical tour of the Dreamlifters. This contributed to various project challenges, especially that it took much longer than expected to obtain certain data from some groups. Fortunately the host company has a tight-knit network where 2-3 phone calls or emails allowed me to ultimately reach the individual closest to the needed information. Additional physical tours of the Dreamlifters and connecting with stakeholders in person would have facilitated many facets of the research; however, we had to work with what was feasible while abiding by the COVID-19 guidelines.

Chapter 2

Literature Review

Boeing certainly is not alone in operating aged aircraft; many aging aircraft studies have been conducted in both commercial and military aviation, though the goal or mission that drives the need for such studies varies quite significantly. In this section, some research articles that explore the relationship between aircraft age and safety as well as cost are discussed. Furthermore, publications that pertain to aircraft reliability, an area that is closely relevant to the stated mission of the Dreamlifters, are introduced. In particular, a handbook on structural reliability and risk analysis and a job aid for aircraft EWIS best practices, both published by the FAA, are discussed.

2.1 Aircraft age and Safety

Professor John Hansman's work published in 2014 on the impact of aircraft age and safety for air transport jet airplanes concludes that there is no correlation between the fatal accident rates and aircraft age up to 27 years of age (based on aircraft incidents that occurred between 1959 and 2012 for commercial jet transport aircraft with a maximum takeoff weight exceeding 60,000 lbs) [7]. A slight increase in the fatal accident rate was observed above the age of 27 years, but found to be not statistically significant due to the limited number of operational years for the older aircraft cohorts. For context, it is worth noting that the objective of this study was to " investigate if there is a valid basis for imposing operational or import restrictions on commercial air transport jet aircraft based on chronological age".

This conclusion may at first seem less relevant to the problem at hand knowing that the Dreamlifters' average fleet age is already beyond 27 years, but it is nonetheless meaningful to note that aircraft age and accident rates were not proportional within the given data set. For the 385 accidents of 20+ year old aircraft, the study finds that less than 30% were *aircraft related*, where aircraft related events include: fire/smoke (F-NI in the legend) and system/component failure malfunction (both non-powerplant SCF-NP and powerplant SCF-PP) as shown in Figure 2-1. Professor Hansman's study states that "since safety concerns regarding aircraft age such as widespread fatigue damage would manifest as aircraft related occurrences, the relatively low fraction of these occurrences in the accidents of 20+ year old aircraft indicates that aircraft age itself does not appear to be a key risk factor".

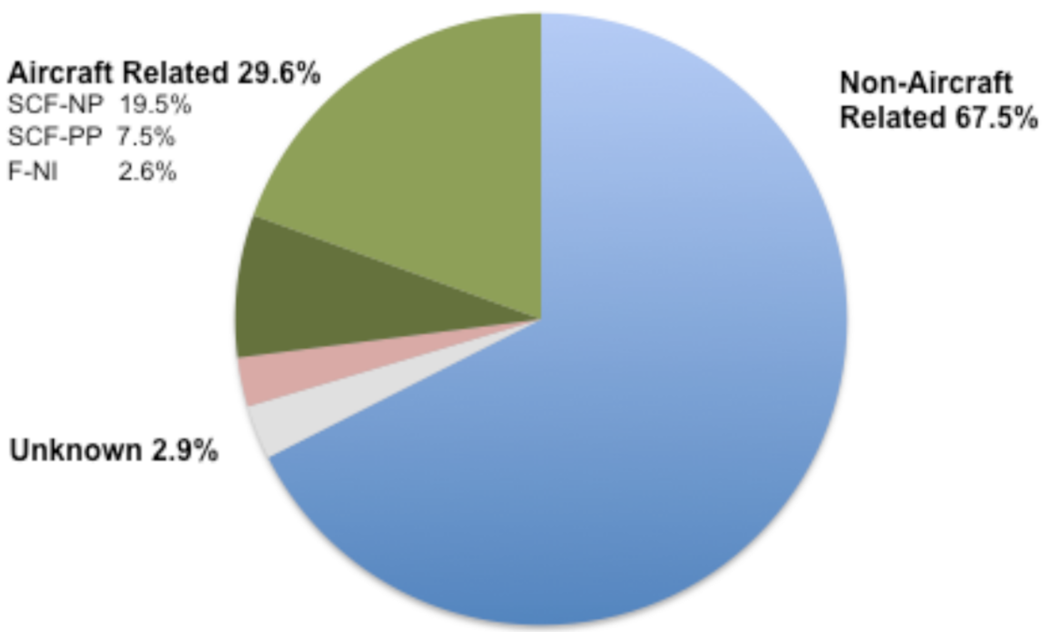

Figure 14: Occurrence categories for all 385 accidents of 20+ year old aircraft.

Figure 2-1: Less than 30% of the accidents of 20+ year old aircraft were aircraft related; roughly 68% of the accidents were non-aircraft related

2.2 Aircraft age and Cost

A question that might arise naturally with aging aircraft is whether maintenance costs increase with age, and if so, by how much. This information could help aircraft owners determine the optimal timing of fleet replacement, where applicable. Maintenance cost reduction was not the driving objective of this thesis work, but surely of high importance to Boeing's Dreamlifter team; in fact, the team constantly seeks process improvement projects that has the potential to reduce operational costs.

A 2006 report by published by RAND Project Air Force examined the "aging effects", i.e. how commercial aircraft maintenance costs change as aircraft grow older [8]. RAND Project Air Force, a division of the RAND Corporation, is the U.S. Air Force's federally funded research and development center for studies and analyses. Data used in this report are Form 41 data, which are reports that U.S. commercial airlines are required to file with the Department of Transportation indicating the airlines' maintenance costs and flying hours. Dating from 1965-2005, the aggregated data set included 1,003 observations covering nine U.S. airlines and 29 aircraft types spanning 38 years. Total maintenance costs comprised of engine and overhead costs in addition to cost for maintaining the airframe. Analysis approach was a log linear regression with the natural logarithm of maintenance cost per flying hour as the dependent variable and a number of independent variables including average fleet age. The RAND study team ran three separate log linear regressions, one each for the age range of 0-6 years old, 6-12 years old, and over 12 years old, and regression results are summarized in Figure 2-2. The study partly attributes the relatively sharp increase in the normalized total maintenance cost for aircraft of age 0-6 years to aircraft coming off warranty which tends to increase airline maintenance costs. For the older age ranges, average fleet age seems to become weaker in being able to explain the total cost; the study points out that for aircraft over 12 years of age, the age effect was 0.7% (with a standard error of also 0.7%), thus rejecting the assumption that aircraft maintenance costs grow rapidly as aircraft age.

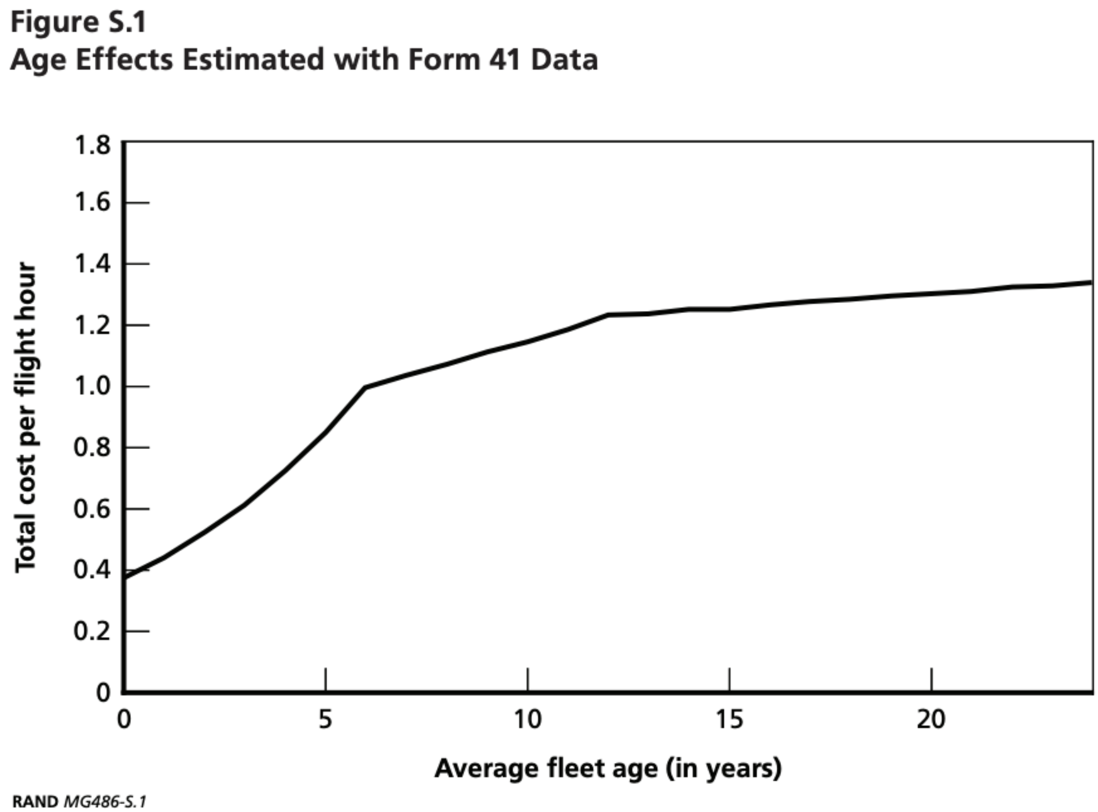

Figure 2-2: According to RAND's study team, age effects vary with fleet age, with steepest increase observed for younger aircraft of 0-6 years old, and close to zero increase for aircraft older than 12 years.

Source: [8]

2.3 Structural Reliability and Risk Analysis

The Structures Technology Branch within the Air Force Research Library published a reported titled *Aircraft Structural Reliability and Risk Analysis Handbook Volume 1: Basic Analysis Methods (Revised)*. While this handbook focuses on structural failures due to growth of fatigue cracks in metallic structure, the basic statistics, probability, and fundamental concepts of reliability techniques are relevant and applicable to non-structural failures as well, as will be discussed in the case study in Chapter 5. Following are some of the basic statistics terms and their definitions as described in the handbook [9]:

Reliability: the probability that a system or component will survive, i.e., function as intended, under designated operating or environmental conditions for a specific time period. Reliability is the complement to the probability of failure,

$$Reliability = 1 - FailureProbability$$

Lifetime Distribution: describes how a nonrepairable population fails over time. The lifetime distribution can be any probability density function (*pdf*), $f(t)$, gives the probability that a randomly selected unit will fail before time t.

Probability Density Function (*pdf*): The *pdf* of continuous random variable X, $f_X(y)$, illustrates the local behavior of X. $f_X(y)$ is not itself a probability; it must be multiplied by the length of a very small interval starting at y to yield the chance that X falls in that interval. The density at y times dy is the chance of X falling in the interval [y, y + dy]. Put in mathematical form [10]:

$$Pr(y \leq X \leq y + dy) \approx f_X(y)dy$$

A *pdf* must be non-negative and the total area under the *pdf* curve must be equal to one.

Cumulative Distribution Function (*CDF*): A *CDF*, $F_x(y)$, gives the probability that a continuous random variable, X, will take a value less than or equal to a specified value, x_1,

$$F_X(x_1) = Pr(X \leq x_1) = \int_{-\infty}^{x_1} f_X(y)\ dy$$

The value of the *CDF* must be greater than or equal to 0, and less than or equal to 1. The *CDF* is a non-decreasing function.

Hazard Rate Function:

The HRF is defined from the probability of failure of an item in the time interval t to $t+\Delta t$ with the condition that the item is functioning at time t, for small Δt. The probability that the failure time T is between t and $t+\Delta t$ with the condition that T is greater than t is given by

$$Pr(t < T \leq t + \Delta t | T > t) = \frac{f_T(t)}{1-F_T(t)} \Delta t$$

where $f_T(t)$ is the PDF and $F_T(t)$ is the CDF of the lifetime distribution for the item, respectively. The HRF, $h_T(t)$, is defined as

$$h_T(t) = \frac{f_T(t)}{1-F_T(t)}.$$

The HRF is also known as the failure rate function, the instantaneous failure rate, or force of mortality. The HRF is a measure of the proneness to failure as a function of age. The expected proportion of items of age t that fail in a short time Δt is equal to $\Delta t \cdot h_T(t)$.

The HRF is strictly not a probability. A cumulative hazard rate function, $H_T(t)$, can be defined as

$$H_T(t) = \int_0^t h_T(x) dx.$$

The relationship between $H_T(t)$ and the CDF of the lifetime distribution, $F_T(t)$, is

$$F_T(t) = 1 - e^{-H_T(t)}.$$

When t equals ∞, $F_T(\infty)$ equals 1 and $H_T(\infty)$ equals ∞. Therefore, the cumulative hazard rate function cannot be a CDF since it has values greater than 1, and $h_T(t)$ cannot be a PDF.

Figure 2-3: Hazard Rate Function definition
Source: [9]

2.4 Failure Data Analysis for Maintenance Planning

In this section, let us discuss how failure data analysis can help construct an optimal replacement and planning strategy by reviewing the work of researchers from the Aerospace Engineering Department of King Fahd University of Petroleum and Minerals [11]. This paper models the failure rate of Boeing 737 auxiliary power unit (APU) oil pumps obtained from a Turkish airline using the Weibull distribution. Through this Weibull failure forecasting, the authors were able to determine the age at which an operating part in an aircraft system should be replaced with a new part, and identify the optimum replacement age of the pumps for various cost ratios.

The Weibull distribution is commonly used in reliability applications involving aircraft and propulsion system service life, and is known to work well with extremely few data samples in identifying the failure characteristics of parts. The Weibull distribution can have two or three parameters, namely the shape (α), scale (β), and location (t_0) parameters. The magnitude of the shape parameter indicates the mortality characteristic, or whether the failure rate is decreasing, constant, or increasing over time. The CDF for the Weibull distribution is expressed and visually plotted as below:

$$F(t) = 1 - exp(-[(t - t_0)/\beta]^{\alpha})$$

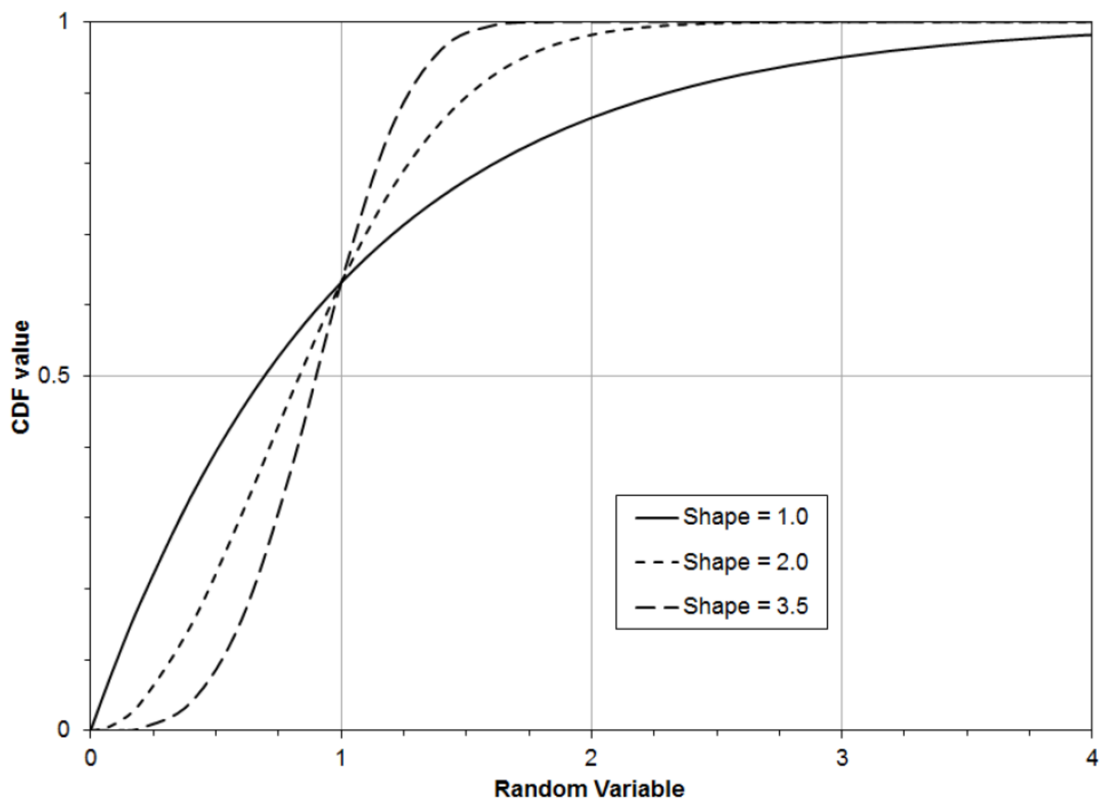

Figure 2-4: Weibull CDF function
Source: [9]

The study confirmed that the Weibull distribution fit the APU failure data set well, with a shape parameter greater than 1, reflecting pump failure rates were indeed increasing over time, displaying wear-out and thus suggesting that a planned replacement of pumps may be worthwhile. Predicted values were in close agreement with actual data, indicating model adequacy. With this information, the study calculated the optimal replacement age that minimizes the expected cost per period of operation for different ratios of C_f/C_p, where C_f = replacement cost of in-service failures and C_p = cost of planned replacements. This type of analysis gives a threshold cost ratio under which a planned replacement has no advantage and should operate to failure. In cases exceeding the threshold, the corresponding optimal replacement age should be used in setting the interval of planned replacements.

Chapter 3

Data Sources and Quality

As with any research study, identifying what data is available and where to find various data sets is an important first step. A significant amount of time was dedicated to this activity at the beginning of the internship, and this journey continued throughout the project as I continued to connect with stakeholders that held different data pieces. Since the ability to replicate analyses with the same set of data is crucial, the following breakdown is by data source, rather than data content or aircraft part.

1. Boeing database - this database is composed of multiple schemas, where "the term *schema* refers to the organization of data as a blueprint of how the database is constructed" [12]. Boeing relational database is divided into database tables, from which desired information was easily queried using the SQL language. A number of the datatables contained Dreamlifter data. Figure 3-1 illustrates an example SQL query command that was used to extract a piece of data. Note that pseudo aircraft IDs are shown to protect proprietary information.

The utilization of Boeing databases proved to be immensely helpful for collecting certain Dreamlifter information, and assisted with comparison with other 747 models where applicable. Example datatables that contained Dreamlifter data include Aircraft Reliability and Maintainability System (ARMS), Aircraft Complaint Logbook, Component Removal, Aircraft Condition Monitoring System, and Airplane Alert. Especially the ARMS database was useful to automatically pull data over time, such as the Dreamlifters' accumulated flight hours and flight cycles, two important *time* `database` : adw_views.part_quantity_by_aircraft

```
# connect to the database
conn = pyodbc.connect("DSN=        ; UID=(intentionally deleted); PWD=intentionally deleted")

query_parts = """
SELECT DATA_SOURCE_NM, PART_NBR, PART_NM, AIRCRAFT_ID,PART_QTY
FROM
where AIRCRAFT_ID in ('RT000', 'RT111', 'RT222', 'RT333')
"""

df_parts = pd.read_sql(query_parts, conn)
print('number of unique part numbers on LCF fleet: ', df_parts['PART_NBR'].nunique())
```

Figure 3-1: Sample SQL command that queries Dreamlifter parts information. Parts of the image are intentionally removed for confidentiality.

metrics for reliability analyses.

The one challenge with this data query approach was that of the countless datatables, identifying those that have data pertaining to the Dreamlifters required manual search of checking each datatable by LCF-specific aircraft identifiers. Further, if a whole pie represents the entire Dreamlifter data routinely collected through various equipment and groups, it was difficult to estimate how many slices were covered by the information I was able to collect through the Boeing database. Regardless, the benefits of this type of queryable data source far outweigh the challenges.

2. Heavy maintenance data - Dreamlifter's maintenance program outlines when maintenance checks should be conducted. These "checks" are continuous scheduled inspections that all commercial and civil aircraft need to follow. Each airline or operator's maintenance program must be approved by the appropriate airworthiness authority, and in the U.S. that is the FAA. An ABC check system is commonly used to indicate the extensiveness of the inspections - A check being the lightest, and D check the heaviest. C and D checks are extensive, with D checks essentially ripping apart the entire airplane for inspection and overhaul. As such, heavy check results provide extremely rich data and could reveal problem areas that rise with increased aircraft utilization that are otherwise not discovered in daily operations (e.g. non-routine events).

The LCF maintenance program is incredibly structured, but heavy maintenance visits (HMV) have variability. Both anticipated and unexpected findings may arise from heavy checks, hence making standardization of data collection difficult. Dreamlifters' HMV data are stored across various Boeing systems, in forms ranging from scanned handwritten maintenance logs to data entries in databases that can be queried. As an effort to consolidate HMV data, a continuous improvement project was developed between Atlas Air and Boeing's Dreamlifter team over the past few years - after each HMV, Atlas would consolidate the HMV results into a master Excel sheet and share with the Dreamlifter team. This big achievement, enabled by close partnership between Atlas Air and the Dreamlifter team, in effect presented a form of *centralized* HMV data.

To understand and leverage this data-set and further improve the data consolidation mechanism, a couple of points are worth noting: (1) Excel sheets are generally subject to transcription errors and dedicated version control is critical for data integrity, and (2) there is a 2-3 month time lag between the HMV completion and the data summary package made available to the Dreamlifter team. As noted above this was a relatively new initiative, and during the time of my internship consolidated data was available for the most recent 3-4 HMVs fleet-wide. Continuing this effort for upcoming HMVs were prioritized over retrofitting old HMV records given the complex and resource-intensive nature of this consolidation activity. As such, the scope of historical HMV analysis for this research was the most recent 3-4 HMVs.

3. Line-replaceable unit (LRU) report - a LRU is defined as an "essential support item which is removed and replaced at the field level to restore the end item to an operational ready condition" [13]. The terms LRU and component are often used interchangeably. Atlas manages LRU reports, and regularly shares the accumulated report with Boeing. This report include information such as aircraft ID, component position, part number, installation and removal timestamps, reason for removal, etc. This report added immense value to the reliability analysis of component X, as it presented the raw historical failure data that formed the basis of the Monte Carlo simulation.

Chapter 4

Descriptive Analysis and Exploring Predictive Maintenance

4.1 Heavy Maintenance Checks

In Chapter 3, we explored the key data sources as they pertain to this thesis. To address one of the questions this project aimed to answer, i.e. "The Dreamlifter maintenance program meets all regulatory requirements, but should it be expanded to meet the growing needs of the aging fleet?", the focus was placed on HMV data and specifically the non-routine findings. Non-routine tasks are additional maintenance needs found during maintenance checks but not included in the scheduled task requirements.

The consequences of severe non-routine tasks are quite heavy - when aircraft are put out of service for longer than the planned maintenance window, its reliability is at risk (i.e. aircraft can't return to service in time and can affect operational schedule) and financial harm is done. Non-routine tasks from the three most recent HMV checks were analyzed to find common (or discrepant) findings across Dreamlifters. Note that in this thesis, C and D checks fall under HMV, and in practice lighter checks are often bundled with heavy checks if the maintenance intervals align. Further, comparison with other 747 models was not feasible (data availability) and not considered necessary for the purpose of this research given the unique operations and design of the Dreamlifters.

The breakdown of non-routine cards by major aircraft areas for a C check that was conducted in early 2020 is illustrated in Figure 4-1, in decreasing order of material costs. Absolute cost and labor values are intentionally concealed. Over 400 non-routine tasks were performed, and three metrics are captured for each area: (1) capital fraction (of the total material cost of non-routines for this HMV, what fraction was spent for each area), (2) labor fraction (similar calculation, but of the total labor involved in this HMV non-routines in man-hours), and (3) allocation of non-routine cards across areas (as a pseudo-measure of maintenance complexity).

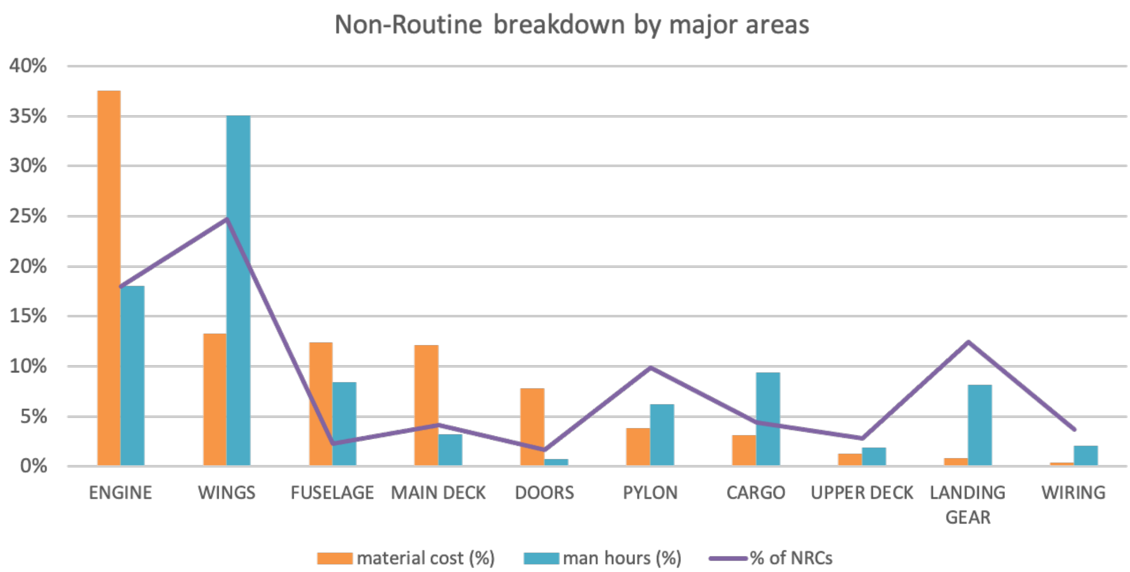

Figure 4-1: Breakdown of non-routine cards for an LCF C check conducted in 2020

Non-routine (NR) tasks alone accounted for roughly 50% of the total C check material costs, and 30% of total labor costs, arguably significant shares. An interesting observation from Figure 4-1 is that NR tasks for engines and wings *combined* made up over half of total NR material costs and half of total NR man-hours. The split is quite different, however; NRs on engines were costly but had relatively low labor requirements, whereas the opposite was true for NRs on the wings.

NR tasks on the wings were studied in further detail. In decreasing order of number of NR tasks, problem areas included flaps, fairings, hydraulics, pneumatics, and corrosion. Issue types were predominantly breaks, cracks, wear and other damages, but some leaks and functional failures were observed as well.

Just by the metrics, wiring-related NRs appear minimal. However, as the devil can be in the detail for complex interconnected systems such as wiring, the specifics will be covered in Chapter 6. Labor intensity – calculated as man hours spent per non-routine task, and a simple combined measure of metrics 2 and 3 described above – can be compared for two Dreamlifters as shown for LCF1 and LCF2 in Figure 4-2. The purpose of tracking labor intensity is to identify any outliers or anomalies, and whether preventative measures can be taken for subsequent heavy checks to minimize the overall HMV duration. Two thing to note for Figure 4-2 are:

1. LCF1 and LCF2 had accumulated different numbers of flight hours and flight cycles when this data was collected.

2. LCF1 heavy check was C2 and gear change, while the heavy check for LCF2 was D1C2A1 and strip/paint. For obvious reasons such comparison would be more insightful for similar (if not identical) heavy checks. Unfortunately this was not feasible with the data set available at the time of this internship, but should be a consideration for future analyses.

Information shared in this section merely provides a flavor for how HMV findings can be dissected. As the Dreamlifter team and Atlas Air continue efforts to consolidate HMV data for all previous and upcoming heavy checks, more detailed data analyses should be performed to address the key questions of this thesis. Follow up work could entail the following:

- Correlation analysis of non-routine man hours and flight hours or cycles (i.e. are unplanned maintenance tasks increasing with age)

- Are similar non-routine tasks conducted for more than one Dreamlifter, and if so, can they be shifted forward to lighter checks or order relevant parts ahead of time to reduce AOG time?

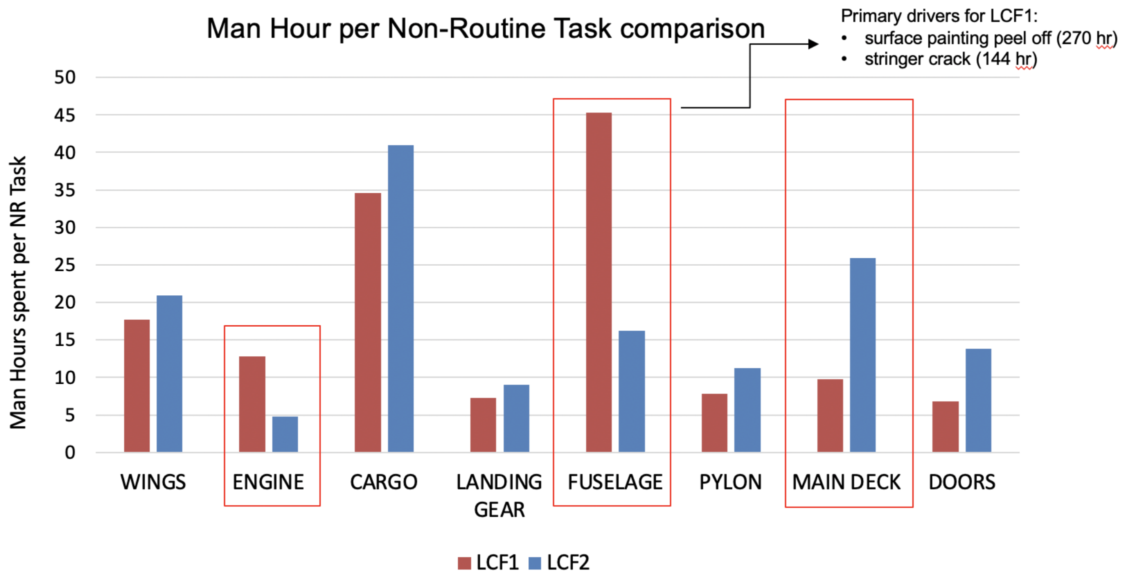

Figure 4-2: Labor intensity comparison for heavy check non-routines for two Dreamlifters. Red boxes indicate aircraft areas that demonstrated noticeable difference in labor intensity due to certain non-routine tasks that consumed large man hours.

4.2 Predictive Maintenance

Descriptive analysis presented in section 4.1 is static - it captures past maintenance activities, but does not inform us how the aircraft is likely to perform with additional flight hours and cycles. In the process of exploring ways to forecast reliability, an important connection was made to a data science and analytics team in the Boeing Global Services (BGS) organization. This team (which will be referred to as the BGS Data Analytics team for simplicity) builds analytics tools that have predictive maintenance capability, and primarily supports Boeing's defense portfolio that includes various aerial refueling tanker aircraft and strategic bombers. Through a brief engagement over a span of three weeks, preliminary analysis was conducted for fit assessment: is the Dreamlifter data package sufficient in volume and data quality to build predictive reliability tools?

There are two approaches to predictive maintenance that the BGS Analytics team employs: (1) reliability-centered maintenance (RCM), and (2) condition-based maintenance (CBM). SAE Standard JA1011, Evaluation Criteria for RCM Processes, defines RCM as a "specific process used to identify the policies that must be implemented to manage the failure modes that could cause the functional failure of any physical asset in a given operational context". In other words, it is an engineering framework that enables monitoring, assessment, prediction, and deep understanding of physical assets. First introduced to the commercial aviation industry, RCM was then adopted by the U.S. military beginning in the mid-1970s, and then by the U.S. commercial nuclear power industry in the 1980s. On the other hand, CBM is another maintenance optimizing strategy that generally uses non-intrusive technologies to inspect asset health with the intent to identify failures as early as possible to limit consequences.

Reliability is defined as the ability of a system or component to perform its required functions under stated conditions for a specified period of time [14]. In traditional RCM, a basic measure of a system's reliability is mean time between failure (MTBF): predicted elapsed time between inherent failures of a system during normal system operation. What MTBF is not, despite being a common misconception, is the expected number of operating hours before a system fails, or the "service life" [14]. For example, it is quite feasible that a product has extremely high reliability (MTBF on the order of 1 million hours) but a low expected service life. This can be explained by a key assumption of calculating MTBF: the product is in the phase of its "useful or normal life", and its failure rate is constant. In other words, this calculation ignores a product's period of early failure or wear out (reference Figure 4-4). Hence, one should not directly correlate a product's service life with its failure rate or MTBF [14]. How reliability is evaluated within the context of this research is further discussed in Chapter 5.

$$\text{Reliability} = e^{-\left(\frac{Time}{MTBF}\right)}$$

Figure 4-3: Reliablity as a function of MTBF (mean time between failure)
Source: [14]

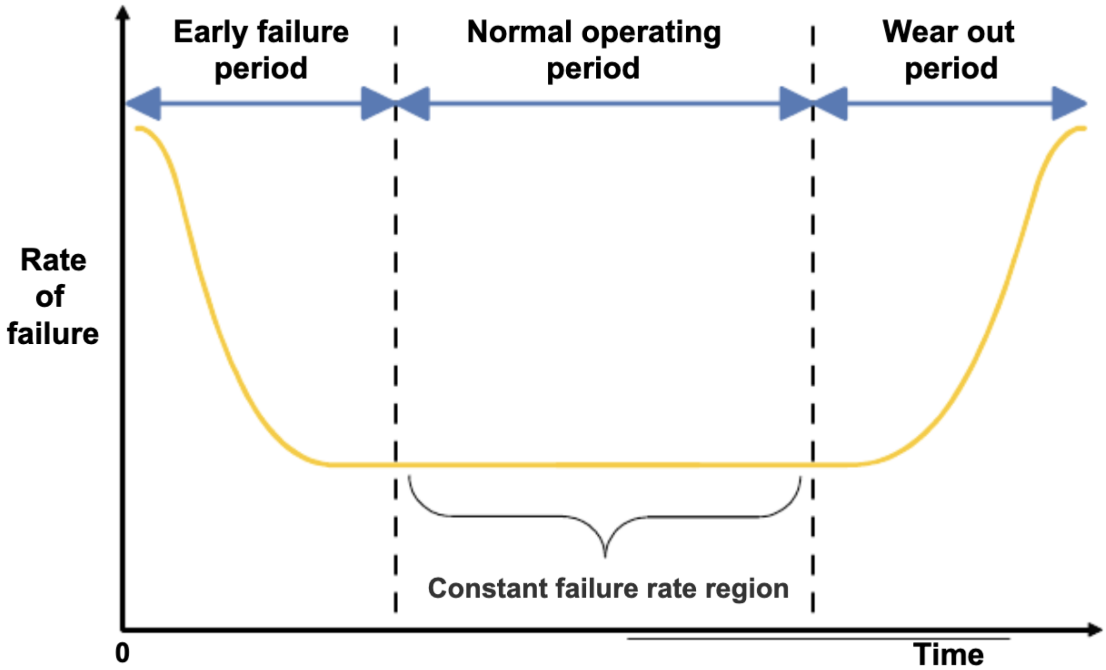

Figure 4-4: Failure rate "bathtub curve" illustrates that a product's failure rate cannot be assumed to be constant throughout the product lifecycle
Source: [14]

For practical application in the aircraft maintenance space, data requirements and goal of the two approaches differ as follows [15]:

- RCM relies on flight logbook records, and aims to predict long-term failure by finding features in the data that strongly correlate with failure probabilities and patterns;

- CBM relies on flight sensor data, and aims to predict short-term failure by finding features in the data that identify degraded or failure conditions

Logbook data for RCM was relatively easy to extract from the Boeing database, but acquiring sensor data to enable CBM-type analysis had roadblocks. Typically the aircraft operator, rather than the aircraft owner, possesses sensor data, and sharing data beyond aggregate trends with the Boeing team was not viable for various reasons. As such, the preliminary analysis for Dreamlifters was centered around RCM, not CBM.

To summarize the two-week preliminary logbook data exploration, it was concluded that there is potential for empirical forecasts for the Dreamlifter fleet. The volume and integrity of historical data was deemed sufficient to build various RCM-based forecast models for the Dreamlifters. Various use cases of such models would include [15]:

1. Maintenance strategy: When should old parts be replaced? Should they be used until failure?

2. Trend and change alerts: Are the parts failing or wearing out sooner than expected?

3. Part-driven actions: For a given part, which aircraft tails in the fleet are at most risk? What is the estimated number of parts needed?

4. Tail-driven actions: For a given tail, which parts are are at most risk? Should they be replaced now, deployed with spares, or wait until the next scheduled replacement?

Based on this information, a statement of work was documented together with the BGS Data Analytics team detailing resource and data needs, implementation schedule, etc. Unfortunately implementation was regarded infeasible during the time of the internship due to competing priorities of the business during the COVID-19 pandemic. Nonetheless, valuable RCM insights were drawn from this engagement, and guided the obsolescence management case study to follow in Chapter 5.

Chapter 5

Reliability Analysis: Obsolescence Management with Case Study

5.1 Overview of Obsolescence Management

Obsolescence management can be reactive or proactive - detecting and resolving obsolescence cases when they arise is considered reactive, whereas taking active measures to avoid or reduce the impact of obsolescence is proactive [16]. A 2015 technical report sponsored by the FAA writes:

> Proactive methods include, for example, identifying and ranking critical components according to their forecast risk of obsolescence prior to its occurrence or notification through predictive methods; quantitative methods for the selection of resolution options; and imposing quantitative obsolescence risk assessment rules and restrictions within the design processes [17].

In reality, the described techniques for proactive obsolescence management are not widely implemented and research finds that industries mature in this area are described as being at the top end of reactive at best. The aviation industry in particular lacks public guidance to assist companies in establishing obsolescence management processes. Usually a reactive process develops around a couple of key departments, and as awareness matures, more resources are devoted to activities that would grow to proactive management - e.g component life cycle monitoring to mitigate critical obsolescence situations.

It should be clear that with more time available to react to obsolescence, more cost effective and implementable solutions can be designed. However, this is often a luxury for the Dreamlifters. In-production airplane models with high demand may exercise leverage and influence suppliers to actively issue product or process change notices well in advance. Being the custom low volume out-of-production model they are, the Dreamlifters rarely have strong negotiating power in these conversations with suppliers. The consequence of obsolescence is disproportionately large: lack of available spares could lead to grounded aircraft (or AOG, aircraft on ground), preventing the Dreamlifters from flying and being on schedule for the next delivery.

The current obsolescence management practice for Boeing's 747-400 fleet (out-of-production model) is to identify obsolescence issues through supplier surveys. Survey results include information such as part number, keyword (e.g. wiring), supplier name, and supplier comments that often indicate estimated years of parts availability or remaining production plan, and replacement strategy if the part reaches end-of-life (EOL). This survey is sent out to suppliers every 3-4 years, which doesn't allow changes to be captured as they occur. In addition, this approach relies heavily on the parts manufacturers' proactive communication of obsolescence to Boeing, which again is a real challenge for custom low volume aircraft.

Causes of obsolescence vary from supply-chain caused sources to airspace-management and regulation-induced demand changes (Figure 5-1). The FAA-sponsored technical report writes that:

> The fundamental cause of the supply chain issue is that the aviation industry is not vertically integrated and depends on an extensive commercial off-the-shelf (COTS) supply base, which creates a gross technology life-cycle mismatch between the supply base and avionics manufacturing. The components supply chain is on a commercially focused technology cycle of approximately 2–7 years, whereas the life cycle of aircraft and avionics

is typically 20 years or more [17].

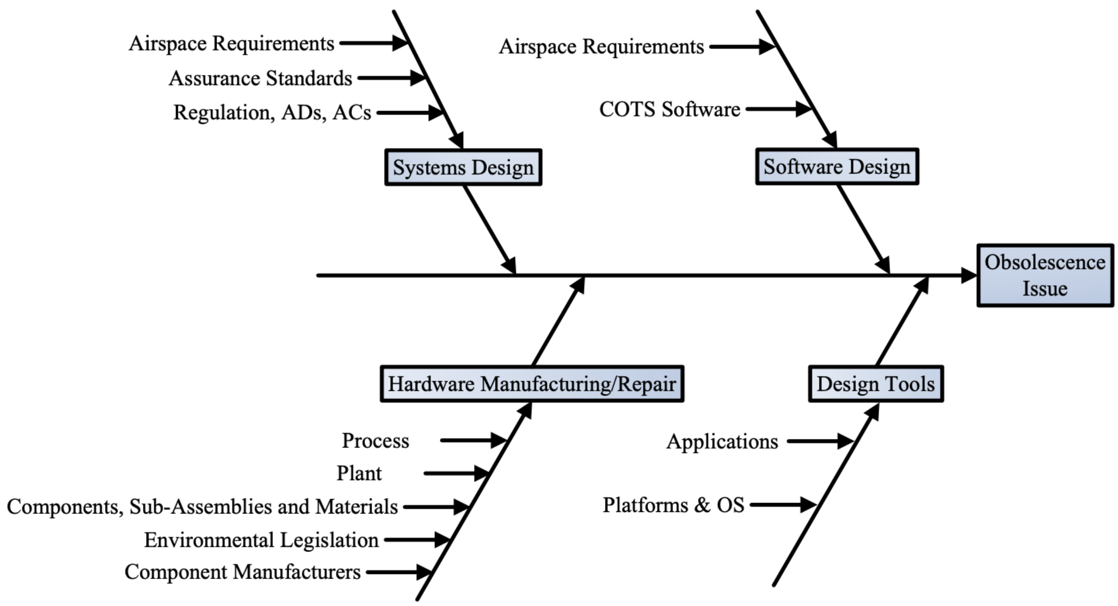

Figure 5-1: Various causes can lead to obsolescence issues
Source: [17]

The overriding goal of obsolescence management is to minimize life-cycle cost (LCC), i.e. build a cost-effective solution in terms of component costs, overhead, schedule impact, factory downtime labor consumption, and operations costs that satisfy customer needs [17]. The FAA technical report points out that the LCCs are borne by all the stakeholders (i.e. operators, aircraft manufactures, and suppliers), and it is not difficult to imagine situations where stakeholders have different views on how to achieve minimum LCCs. The report further claims that "participants must have access to all relevant information (e.g., the last time buy window; what second sources or equivalents can be found; what component stocks exist in distribution or can be sourced through brokers or aftermarket suppliers; and what the **demand forecast** is" [17]. It is this demand forecast that my research work aims to estimate, and ultimately become a capability that the Dreamlifter team possesses to advance from the current reactive process to a proactive state.

5.2 Obsolescence Case Study: Component X

Given that there are approximately 6 million parts on each Dreamlifter, it is impractical to evaluate the obsolescence risk for all parts. A case study approach was taken, powered by RCM analysis, for a component that has limited supply, operational impact, and safety implications for the Dreamlifter fleet. The manufacturer has communicated that repair capability of the current model is limited, and that they plan to introduce a replacement model. We will assign a code name for this component and refer to it as *component X*. The current and new models of component X may have similar functional requirements, but they cannot be simply swapped. The complication is that installing this new model on the Dreamlifters requires a series of process changes including a formal design change, a modification task, and regulatory certification. A known number of the current model (i.e. those currently installed on the aircraft) remain on the shelf available to Boeing for repair and replacement when needed. The Dreamlifter team knows that stock will ultimately be depleted, but unaware *when* that would occur. Knowing the timing of obsolescence is critical because the timeline of the aforementioned activities preceding the new model installation can be uncertain, and if not planned ahead precisely, Dreamlifter AOG is likely to occur (the Dreamlifters cannot fly with uncertified component X's).

5.2.1 Data Collection and Pre-Processing

The Dreamlifter LRU report distributed by Atlas Air was the basis of this case study. It covers the installation and removal track records of LRUs since 2010, which is when Atlas Air started operating the Dreamlifters. The LRU report data source was covered in brief in Chapter 3, paragraph 3. Records of component X were filtered by part number, and the physical location of the components on each Dreamlifter was extracted from the comments field where applicable.

Gross statistics:

1. An equal number of component Xs (n) are installed on each Dreamlifter, so at any given time there are 4n component Xs across the fleet.

2. Approximately 67% of the 4n component Xs never failed since 2010.

3. The remaining 33% failed at least once, and some of them failed more than once.

Pre-processing steps:

1. Convert timestamp of the record (e.g., July 11, 2020) to aircraft utilization (e.g., 85,300 flight hours and 16,300 flight cycles) using the flight logbook database.

2. Calculate time between failure (TBF) in flight hours and flight cycles.

   - Hypothetically assume a component was installed on LCF1 at 1000 flight hours, last failed at 2000 flight hours, and LCF1 has accumulated a total of T flight hours at the time of analysis. This component is then tagged with two TBF values: TBF1 = 2000 hours - 1000 hours = 1000 hours (uncensored, constant value); TBF2 = T - 2000 hours (right-censored value; see bullet point 3 below)

3. Label censored data:

   - Censoring refers to when the observation period ends and not all test units (in this case, component Xs) have failed. In the hypothetical calculation above, TBF2 is a censored data point whereas TBF1 is uncensored (i.e., we know the exact time between failure).
   - Censored data needs to be handled by appropriate statistical methods, such as the Kaplan-Meier approach, probability plotting, hazard plotting, and maximum likelihood estimation.
   - There are 4n censored data points in the data set, one for each operational component X.
   - Censored data are right-censored, as illustrated in Figure 5-2. Censored and uncensored TBF values were separated, and the list of censored values were passed to the function input called *right_censored* in the *Reliability* python package.

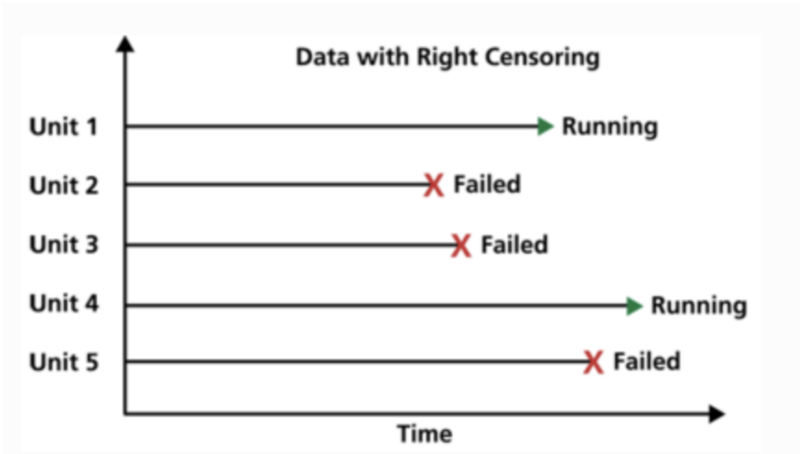

Figure 5-2: Illustration of right data censoring
Source: [18]

From the pre-processed data set, the time-in-service (TIS) value was calculated as shown in Equation 5.1. Component X is considered to be "in use" whenever the aircraft engine is on, so in addition to flight hours spent in the sky, utilization on the ground were also accounted for. On average, the Dreamlifters are powered on for 1.5 hours before taxi (for crew show time) and 1 hour after taxi for post-flight maintenance for each flight. Therefore, an average constant of 2.5 hours per flight are included in the total TIS for component X.

$$\begin{aligned} \text{Time In Service} = &\ \text{Time Between Failure (in flight hours)} \\ &+ 2.5 \times \text{Time Between Failure (in flight cycles)} \\ &+ \text{taxi time} \end{aligned} \tag{5.1}$$

It is worth listing the key assumptions made in the study design:

1. All faults that resulted in the removal and re-installation of any given component X are treated equally. *Rationale*: any root cause (whether product failure or external factors) that resulted in the removal of component X could occur again in the future.

2. When Atlas Air started operating the Dreamlifters in 2010, all component Xs were inspected and replaced (if found faulty). As such, component X prior to

2010 is not required for this analysis.

3. The combination of complete failure times (such as the example of TBF1 above) and incomplete, censored data (example TBF2) best represent the natural lifetime distribution of component X.

4. The position of component X on the aircraft (e.g. position 1, 2, ..., n) is not believed to be correlated with risk of component failure. Thus, each position is treated independently and considered equally likely to fail.

5. Replacement parts are as good as new.

6. Flight hours cannot be accumulated before the removal and installation of a given component. This is supported by the timestamps in the raw data set.

7. Time lag between the failure event and replacement activity is not significant. In other words, the data set is *not* considered readout or interval data. *Rationale*: per manual, the operator is required to address any component X failures within 10 consecutive days (i.e. 240 hours). Given the Dreamlifters' relatively low utilization, this 10-day window likely does not have a significant impact on the simulation results.

5.2.2 Methodology

A python library for reliability engineering called *Reliability* [18] was extensively used to construct a probability density function representing the time until depletion of the remaining component Xs. Readers who are curious about the technical backbone of this analysis are highly encouraged to visit the python library documentation for a list of supported distributions, probability plotting, and much more information. A scalar list of TIS values (computed as described in section 5.2.1) that collectively represents the entire failure history of component X was passed to this library as input data. The following steps were executed in sequential order:

1. Data fitting: Various probability distributions were fitted to the input data to identify the best fit. Distributions tested include Weibull, exponential, normal, lognormal, gamma, and beta distributions. To the degree supported by the python library, a combination of non-location shifted and location-shifted distributions were evaluated.

2. Distribution selection: All fitted distributions are evaluated by *goodness of fit* test results, and sorted by Bayesian information criterion (BIC). Also known as the Schwarz information criterion, BIC is a model selection criterion that measures the efficiency of the parametric model in predictive power. It penalizes the complexity of the model (i.e. number of parameters in the model) to mitigate overfitting. The model with the lowest BIC is preferred, and selected as the "best model".

3. Fit check: The model selection process is further confirmed with the following visual checks:

    - Histogram plot: probability density function (PDF) and cumulative distribution function (CDF) of each fitted distribution, along with the histogram of the failure data
    - Probability-Probability plot for each fitted distribution; compares parametric vs non-parametric fit
    - Probability plot of each fitted distribution to spot any obvious departures from theoretical distribution

4. Conditional probability: Conceptually, Bayes' Theorem is applied to construct a conditional probability density function that represents time until depletion of component X. Mathematical expression denoted in Figure 5-3. This concept is embedded in the simulation design.

Suppose that $f_t(y)$ is the probability density function of time to failure t, measured from time 0. What is the conditional density function for time until next failure, given that no failure has occurred up to time T? (time T is the accumulated FH as of July 3, 2020)

The answer is $f_t(y|T) = \begin{cases} f_t(y)/(1 - F_t(T)) & for\ y \geq T \\ 0\ for\ y < T \end{cases}$; reflects the use of Bayes' Theorem

Figure 5-3: Building a conditional probability density function appropriately handles censored data of component X

Source: [19]

5. Monte Carlo simulation: A total of 10,000 simulation rounds are run to establish a robust confidence interval. Let P(1) be the position of our first component X. As there are a total of 4n components on the entire fleet, the positions range from P(1) to P(4n). Each simulation round proceeds as follows:

   (a) For P(1), make a random pick from the distribution of our "best model"

      i. If the pick is smaller than T(1), where T(1) is the TIS value that corresponds to P(1), discard this pick. This pick is invalid because we know that component X in P(1) is functional today (i.e. has not failed).

      ii. Re-draw, and discard all outcomes below T(1)

      iii. The first pick that exceeds T(1) is our "eligible random pick" - keep this pick.

   (b) Repeat steps i-iii for all 4n component Xs. After this is done, one should have a list of 4n picks.

   (c) Sort this list in ascending order.

   (d) Select the R^th smallest value from the list, where R is the total number of component X's remaining in inventory for the current product model. The R^th smallest value represents time until the R^th failure in that round of simulation.

   (e) Repeat steps (a)-(d) 10,000 times. In effect, I have simulated the failure of all remaining available components 10,000 times.

(f) Summarize the simulation results by yielding a histogram that is the density function of the time until shelf depletion.

To learn more about the execution of this analysis, please see the programming script in Figure A-1.

5.2.3 Results

Of the various distribution types fitted to the failure data of component X, an exponential distribution with one parameter, λ, was selected as the best model with the smallest BIC (Figure 5-4). In other words, an exponential distribution with $\lambda = 1.48e - 05$ best represents our failure data. Numerical results including the model parameters and model selection criteria are listed in Figure 5-6. The lognormal distribution (both 2 parameters and 3 parameters) also fit the dataset in terms of BIC values. Depending on which model selection criterion one chooses to use (e.g. AIC vs BIC), the best-fit distribution may change. CDF of the best model is shown in Figure 5-5. Labeled in red are the failure data expressed in TIS (hours), and the blue band indicates the 95% confidence interval. As a refresher, equations for the PDF, CDF, survival function (SF) which is identical to the reliability function, hazard function (HF) and cumulative hazard function (CHF) are illustrated in Figure 5-7.

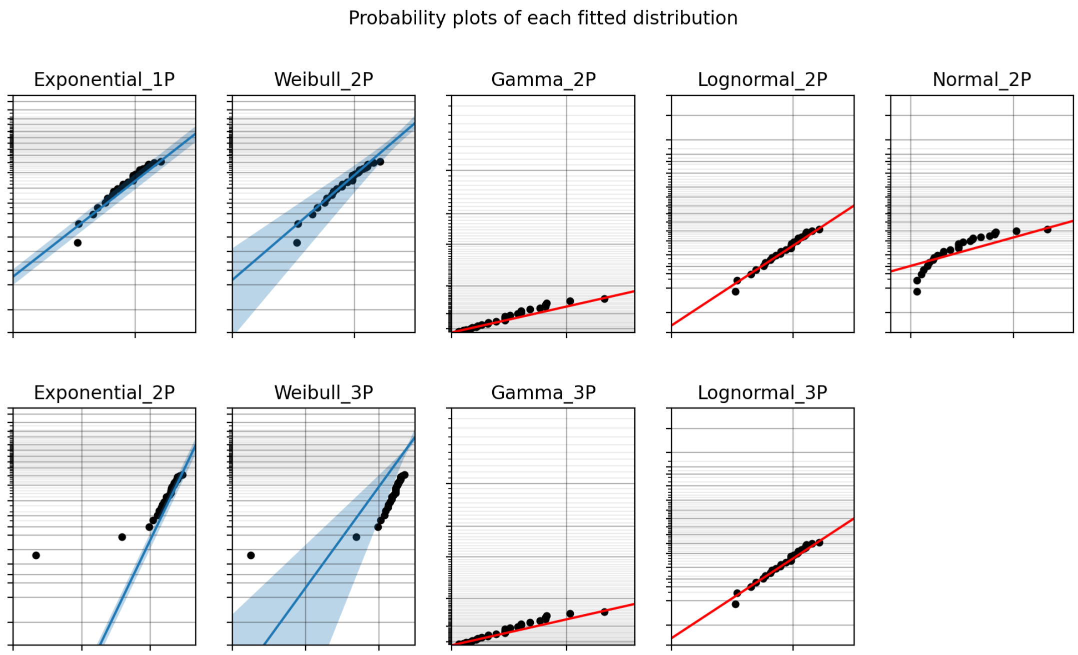

Figure 5-4: Historical failure data of component X fitted to various distributions. Exponential_1P (top left corner) is the best model with smallest BIC.

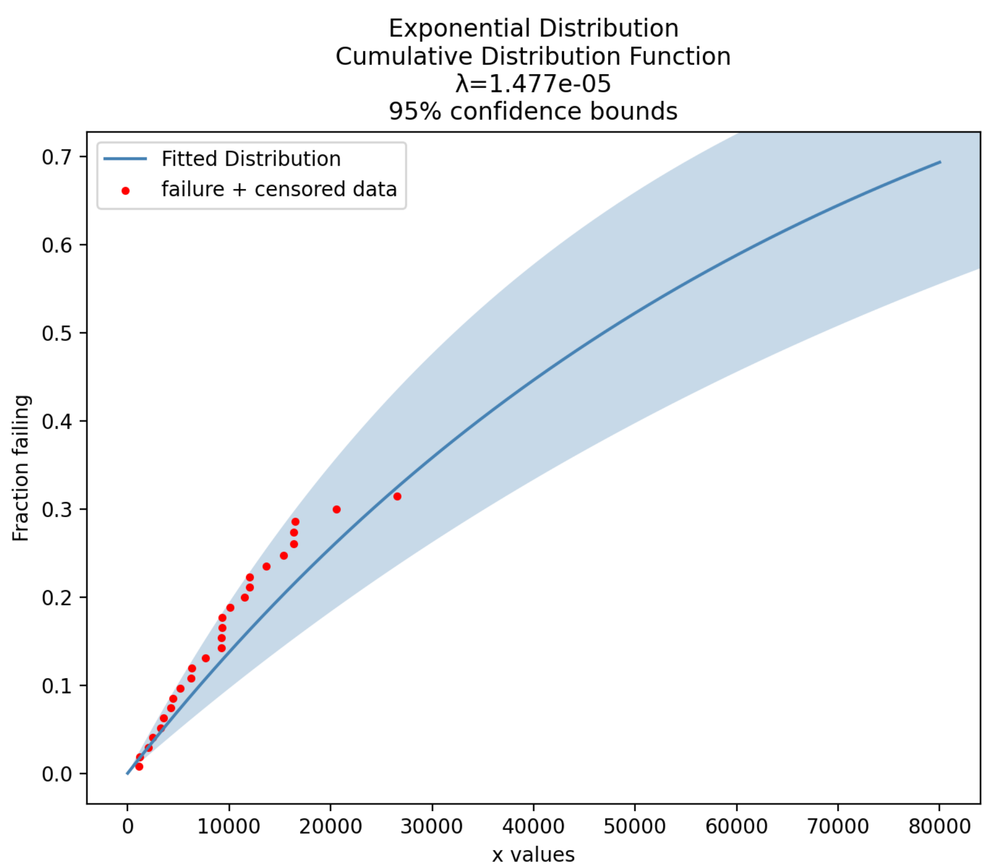

Figure 5-5: CDF of the best-fit model (exponential distribution with 1 parameter) with 95% confidence bounds; x-axis = time in hours.

Distribution	Alpha	Beta	Gamma	Mu	Sigma	Lambda	AICc	BIC
Exponential_1P						1.47734e-05	656.665384	659.131300
Lognormal_2P				11.0302	1.83228		654.740686	659.626042
Lognormal_3P			7.03815	11.0309	1.83443		656.860018	659.626042
Exponential_2P			1137.44			1.59171e-05	655.615324	660.500679
Gamma_2P	87643.1	0.877867					658.376117	663.261472
Gamma_3P	87648.2	0.877641	0.0154598				660.515565	667.772281
Weibull_2P	43934.4	1.09649					664.179563	669.064919
Normal_2P				36443	22375.5		684.296163	689.181518
Weibull_3P	20093.9	0.527197	1137.44				693.544948	700.801665

Figure 5-6: Numerical results of fitted distributions sorted by ascending BIC

Exponential Distribution

λ = scale parameter ($\lambda > 0$)

Limits ($t \geq 0$)

PDF: $f(t) = \lambda e^{-\lambda t}$

CDF: $F(t) = 1 - e^{-\lambda t}$

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

HF: $h(t) = \lambda$

CHF: $H(t) = \lambda t$

Note that some parametrizations of the Exponential distribution (such as the one in scipy.stats) use $\frac{1}{\lambda}$ in place of λ.

Figure 5-7: Key equations of an exponential function
Source: [18], Equations of supported distributions

As described in the methodology section, this exponential distribution was used to perform the random sampling simulation, and the results are shown in Figure 5-8. We then find the time corresponding to the 90th percentile of the simulation results by employing the *inversion method*. To do this, the simulation output (which is a list of 10,000 numerical values) was again fitted to various probability distributions to find the most representative. The actual 90th percentile value will not be disclosed, but how that information was used to provide an actionable recommendation is described below.

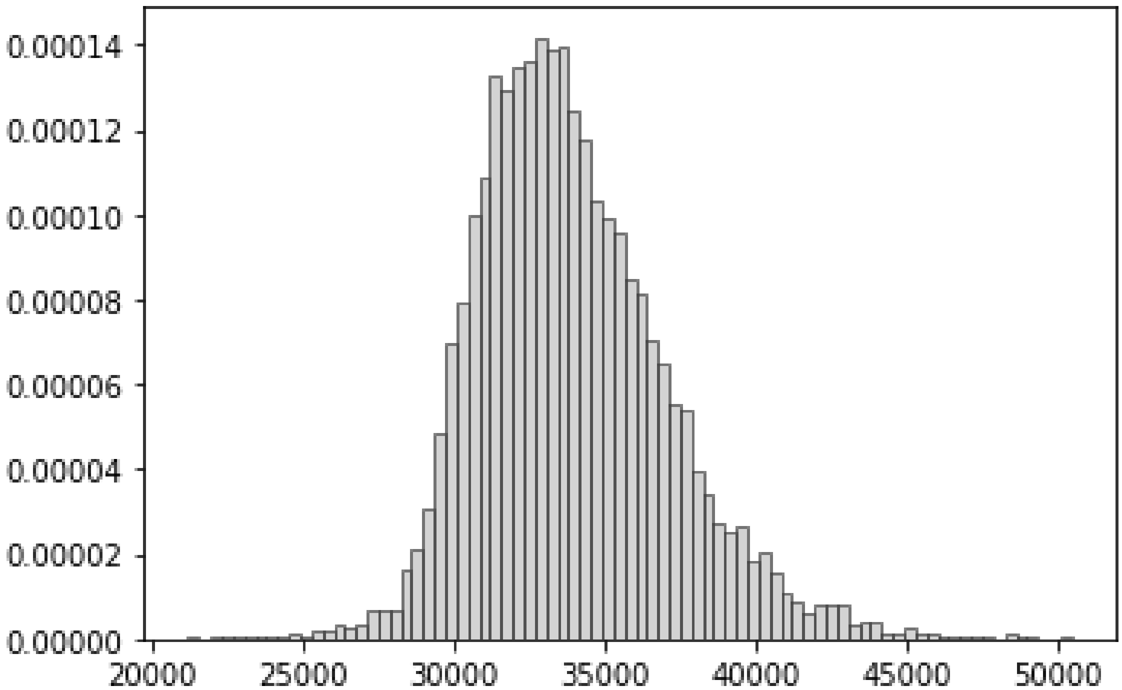

Figure 5-8: Output of the 10,000 simulation rounds illustrate the probability density function of the time until shelf depletion for component X

In essence, the 90th percentile value (let's call it L) is interpreted as such: there is a high likelihood (i.e. 90% chance) that after time L has passed from the time of analysis, the Dreamlifters will deplete the remaining R units of component X to replace failing component Xs. Different confidence levels can be easily calculated from the same distribution for more conservative projections as desired. The natural next question then is, when will time L occur? Translating L (in hours) to a projected occurrence date was done by referencing the Dreamlifters' utilization forecast. The utilization forecast was built based on Boeing's 787 production schedule announced during the internship, and involved different plausible scenarios based on the anticipated business landscape. Projections were made assuming 787 production rates of 10 per month for the remainder of 2020, 6 per month from 2021-2023, and 8 per month 2024 onwards. It is fully acknowledged that the 787 production rates are subject to change, and the time L should be converted accordingly as specific rates are realized by the Boeing company.

Knowing that today there is the possibility to *repair* Q units of component X (in addition to R units on the shelf that can be used for *replacement*), the analysis was expanded to account for this scenario, and delivered to the Dreamlifter team. It is important to note the risk associated with these Q units – it is uncertain that such repair capability will continue to be available by the supplier, and whether all failure modes are repairable. Assuming this repair capability is indeed realized, there is 50% chance that complete depletion will be reached by August 2025, and the likelihood increases to 90% by May 2026.

Chapter 6

Reliability Analysis: EWIS Case Study

From the beginning of the project, there was a question from the Dreamlifter management of whether electrical wires will pose a risk as the Dreamlifters continue to operate in the future. Unlike more visible signs such as corrosion, structural damage, or leakages, issues relating to the electrical wiring interconnect system (EWIS) are not as apparent. In addition, as the name illustrates, the *interconnected* nature of EWIS further complicates the maintenance strategy. The current Dreamlifter maintenance plan does include required tasks specific to EWIS, but it was not clear whether any enhancements should be made to prevent age-related issues that might surface as the fleet accumulates more operational time.

Two possible approaches to evaluate EWIS risk are to (a) gain insight from historical EWIS failure data records, and (b) conduct EWIS degradation studies. Approach (a) was attempted for this project, but as will be discussed below, the organization's current data collection practices are not quite sufficient to allow modeling and in-depth data analysis. Approach (b) is not currently suitable for the Dreamlifters as EWIS degradation studies not only require significant resources but may impact the aircraft availability. With three out of four Dreamlifters needed operational any given time, having the backup aircraft out of service is simply too costly. A technical report by the FAA on EWIS degradation evaluates the aging characteristics of three types of aircraft electric wire that are commonly used in commercial aircraft and high in reported incidents [20].

6.1 EWIS historical data

Identifying EWIS maintenance records was not a straightforward task, primarily due to the fact that records were stored in different data bases with varying levels of information. Because EWIS is present practically throughout most of the aircraft body, there was no clear mechanism to properly query EWIS-related records. Attempts such as searching the keywords "EWIS", "electrical", "wiring", "wire(s)" in various databases were made. With the plausible assumption that non-routine EWIS findings are more noteworthy compared to routine findings, non-routine records from line maintenance activities were extracted from the following databases: logbook, scheduled maintenance, non-routines. Please note that due to the challenges addressed above, it is likely that the Figure 6-1 does not represent *all* EWIS findings that occurred. Patterns appearing somewhat cyclical were observed for each aircraft, but it was inconclusive whether these were random behavior, related to the service life of wires, or related to the maintenance intervals.

Realizing that finding EWIS failure records for the Dreamlifters is a big challenge, the focus shifted to other 747-400 variants to seek any common patterns that may exist. Shown in Figure 6-2 are normalized wiring data (i.e. number of defects per aircraft) plotted against aircraft age at the time the defect was found (in years since aircraft delivery) for 747-400 passenger aircraft and 747-400F freighters. A more appropriate time metric would be accumulated flight hours; however, due to data unavailability differences in aircraft utilization could not be accounted for. Another caveat is that the sole data source for this figure was maintenance logbook records from the In-Service Data Program database due to the extremely high volume of query results. When a more robust data filtering mechanism is in place, it would be wise to augment the data set to include non-routine findings from scheduled maintenance activities. Just from the records pulled, there does not seem to be a positive

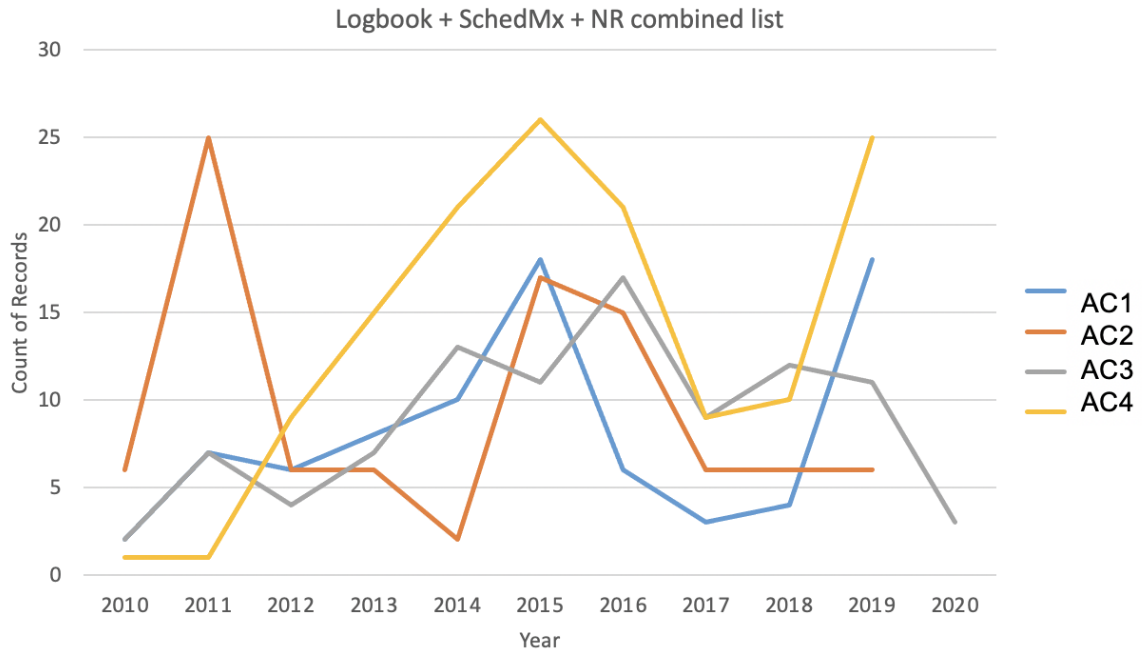

Figure 6-1: EWIS Non-routines record counts from line maintenance activities for the four Dreamlifters, by calendar year

correlation between number of defects per aircraft and aircraft age, and no obvious trend observed to believe similar aircraft models share similar EWIS defect profiles.

Line maintenance non-routine EWIS records were pulled from the same data sources as for Figure 6-1, but instead of organizing by calendar year records were ordered by ATA chapter in descending order. Over 60 records were associated with ATA 21 Air Conditioning, followed remotely by ATA 26 Fire Protection, ATA 33 Lights, and ATA 24 Electrical Power. Interestingly, the split of records among the four Dreamlifters varied significantly for each ATA, alluding to a complex underlying dynamic.

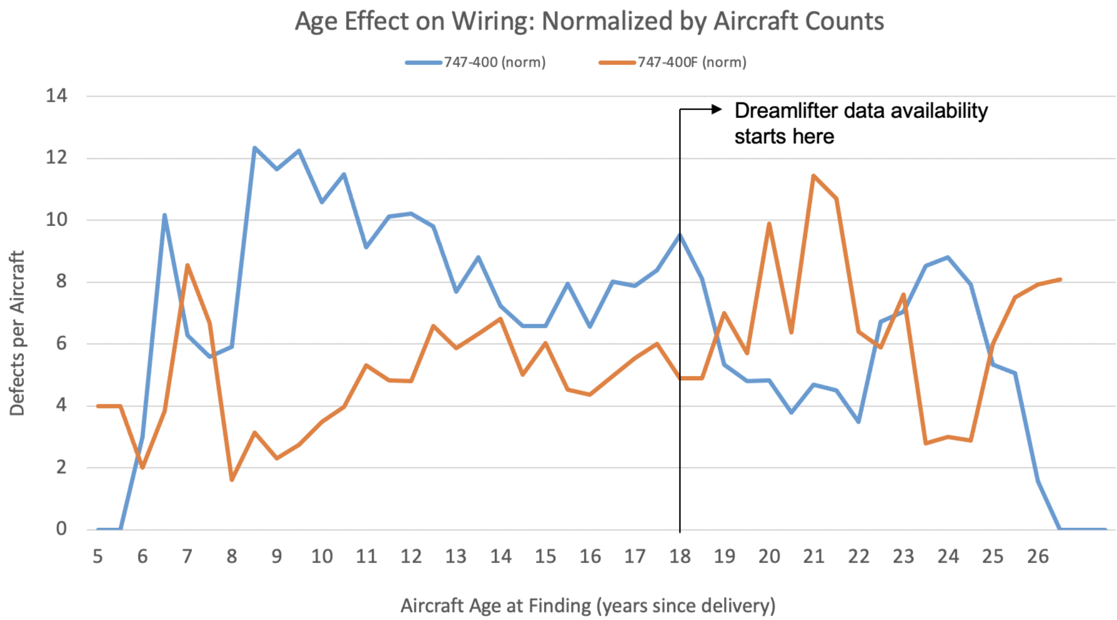

Figure 6-2: Number of EWIS defects per aircraft vs. aircraft age for 747-400 variants. Note the data limitations described above the figure.

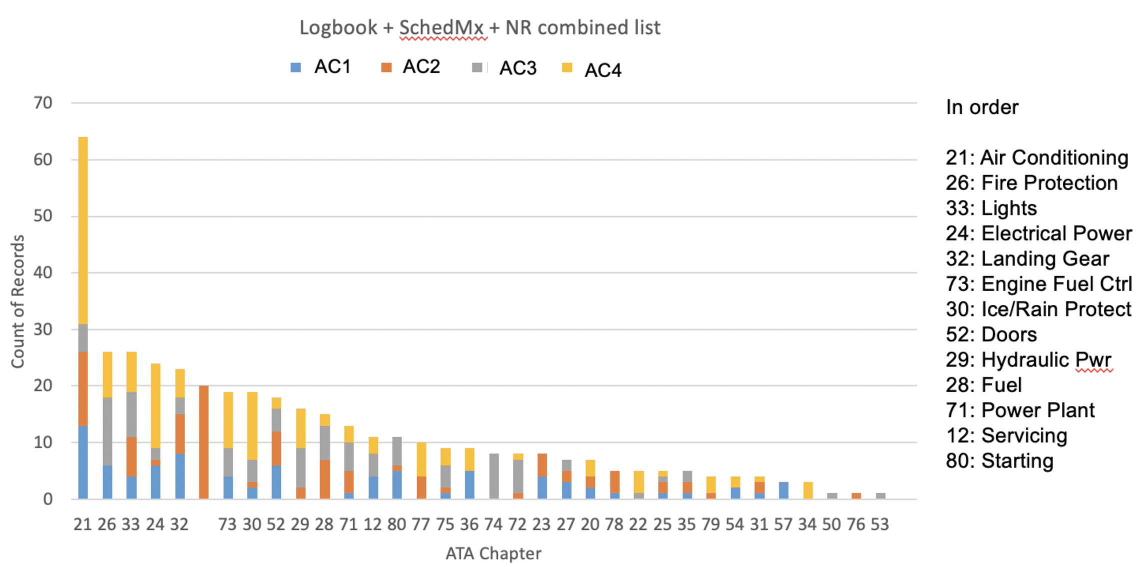

Figure 6-3: EWIS record counts by ATA chapter for the four Dreamlifters

Chapter 7

Discussion and Conclusion

This thesis research focuses on analytically breaking down a highly complex system, i.e. the Dreamlifter fleet, and identifying ways to address potential risks with operating an already mature aircraft fleet towards LOV. The following are the two important outcomes of this research work:

1. **Simplify and accelerate:** among all potential challenges of Dreamlifter operations, parts/component obsolescence is one bound to occur as suppliers transition to new product offerings and discontinue production due to low demand. The obsolescence management framework discussed in Chapter 5 is not limited to component X, but the approach has wide applicability for any aircraft components that have accurate historical failure data. The use case for component X delivered a practical mitigation timeline by mapping the *probabilistic time until component depletion* to calendar months by which the Dreamlifter team should take certain actions in coordination with the parts supplier. For other use cases where remaining inventory is not as limited, this same methodology could model component failure rates and provide insight into optimal replacement intervals as well as help prioritize risk management targets.

2. **Data collection is a competitive strategy:** it is often compelling to dive straight into data analyses, but confirming data availability and data quality is a necessary prerequisite that cannot be overlooked. Due to the complex nature of aircraft and their intricate supply chain, it is unrealistic to expect centralized data manage-

ment and seamless data integration. This research has uncovered that particularly for areas concerning EWIS, data sources are largely fragmented and lack a common identifier that can tie the various data sources together. This challenge must be first overcome in order to allow for insightful analyses.

7.1 Future Work

To best leverage the research findings presented in this thesis and promote successful project continuity, the following recommendations are made:

1. Start to communicate the component X case study results with the supplier, and use it as an input to forecasting demand for the newer model of component X

2. Allocate resources to construct a relational database specifically for Dreamlifter's EWIS records; in the long run this would allow rich data analyses and modeling to take place

3. Adopt an obsolescence identification process to ensure maximum utilization of already established efforts within the larger Boeing network:

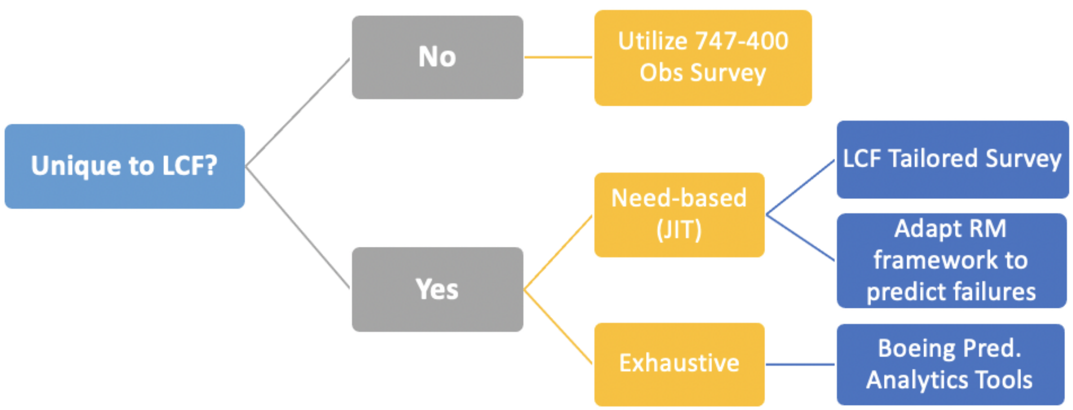

Figure 7-1: Example decision tree to navigate the obsolescence management process

Appendix A

Python Script for Reliability Analysis

Figure A-1 illustrates the programming script written in the Python programming language that was used to find the best-fit probability distribution for the component X use case, and to perform the Monte Carlo simulations described in Chapter 5. Note that this figure only presents the overall framework, and raw data points are intentionally removed.

```
"""
Created on Mon Jun 29, 2020
Last modifid on Mon Apr 19, 2021
@author: michellepark
"""

from scipy import stats
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd


#%% new dataset: accounting for taxi & aircraft power on time
data=    [A1,A2,A3, ...]
censored=[C1,C2,C3, ...]

data.sort()
censored.sort()

df=pd.DataFrame(data, columns=['Failure Time (hrs)'])

#%% Fit failure data to various distributions
# objective: find distribution that best fits Dreamlifter data

from reliability.Distributions import *
from reliability.Fitters import *
from reliability.Probability_plotting import plot_points

results=Fit_Everything(failures=data,
                       right_censored=censored,
                       show_probability_plot=False
                       )

print('The best fitting distribution was',results.best_distribution_name,
      'which had parameters',results.best_distribution.parameters)

# alpha = scale, beta = shape, gamma = offset param
alpha= results.best_distribution.parameters[0]
beta=  results.best_distribution.parameters[1]

#%% output fitted parameters & standard errors, goodness of fit stats,
#   probability plot (how well is my data modelled by a dist?)
```

```
fit_exp1 = Fit_Expon_1P(failures=data,
                        right_censored=censored
                        )
plt.show()
#%%
# from fitted distribution, plot
# SF: survival function (SF = 1-CDF = Reliability)
# CDF: cumulative distribution function (CDF = failure)

fit_exp1.distribution.CDF(label='Fitted Distribution',
                          color='steelblue',
                          xmin=0, xmax=80000)
plot_points(failures=data, color='red',
            right_censored=censored,
            func='CDF',label='failure + censored data')
plt.legend()
plt.show()

#%% conditional density & simulation
# X: time since last failure (FH, continuous random variable)
# X_n: X data from Aircraft n

from random import sample
#random.seed(64)
#random_seed = random.sample(range(100000000), 100000)
#generates same 10k random numbers every time


X_1 = [insert data points for aircraft 1]
X_2 = [insert data points for aircraft 2]
X_3 = [insert data points for aircraft 3]
X_4 = [insert data points for aircraft 4]
X_fleet = X_1+X_2+X_3+X_4

# monte carlo simulation
sim_list=[]

for j in range(10000): #10k simulation rounds
    rand_picks = []
    for i in range(0, len(X_fleet)):
        while True: #keep running w/o condition
            pick = fit_exp1.distribution.random_samples(1)[0]
            if pick < X_fleet[i]:
```

```
                #print(pick, i, 'disgarded', pick-X_1[i])
                continue

            else:
                #print(pick, i, 'keep')
                rand_picks.append(pick)
                break
    rand_picks.sort()
    print(rand_picks)

    select = rand_picks[R-1]
    sim_list.append(select)


#%%
# plot simulation histogram
from reliability.Other_functions import histogram
from plotly.offline import plot
import plotly.graph_objs as go

#%matplotlib qt
histogram(sim_list)

fig = go.Figure()
fig.add_trace(go.Histogram(
    x=sim_list,
))
fig.update_layout(
    title_text='Histogram of R^th lowest number for 10,000 simulation',
    barmode='overlay'
)

fig.show()
#plot(fig, auto_open=True)

#%% inversion method

sim_results=Fit_Everything(failures=sim_list)

print('Best fitting simulation dist. was',sim_results.best_distribution_nar
      'which had parameters',sim_results.best_distribution.parameters)

sim_dist = sim_results.best_distribution
sim_dist.quantile(0.95)
```

Figure A-1: Programming script that (1) identifies the best-fit probability distribution for component X and (2) performs the Monte Carlo simulations.

Bibliography

[1] IATA. *Best Industry Practices for Aircraft Decommissioning Manual*, 1st edition edition, November 2018.

[2] Boeing 747 Dreamlifter Fact Sheet. Accessed: 2020-12-25.

[3] Tom Koehler. The 747-400 will be transformed into an even larger freighter to save significant time and costs in transporting 787 assemblies. *Boeing Frontiers*, June 2005.

[4] Cargo history. DBL - The Longest Aircraft Loader In The World. https://dsl-ua.com/en/2020/05/15/ru-gruzovaya-istoriya-dbl-samyiy-dlinnyiy-aviatsionnyiy-pogruzchik-v-mire/. Accessed: 2020-12-27.

[5] Jon Ostrower. Atlas to assume Dreamlifter control in September. *FlightGlobal*, March 2010.

[6] FAA. *Aircraft Electrical Wiring Interconnect System (EWIS) Best Practices Job Aid*, 2.0 edition.

[7] RJ Hansman. Analysis of impact of aircraft age on safety for air transport jet airplanes. *International Center for Air Transportation (ICAT), Massachusetts Institute of Technology: Cambridge, MA, USA*, 2014.

[8] Matthew C Dixon. *The maintenance costs of aging aircraft: insights from commercial aviation*, volume 486. Rand Corporation, 2006.

[9] Eric J Tuegel, Robert P Bell, Alan P Berens, Thomas Brussat, Joseph W Cardinal, Joseph P Gallagher, and James Rudd. Aircraft structural reliability and risk analysis handbook, volume 1: Basic analysis methods (revised). Technical report, Structures Technology Branch (AFRL/RQVS), Aerospace Vehicles Division Wright . . . , 2018.

[10] Arnold I. Barnett. *Applied Probability: Models and Intuition.* 2015. Chapter 3: Continuous Random Variables.

[11] Mueyyet Tozan, Ahmed Z Al-Garni, Abdullah M Al-Garni, and Ahmad Jamal. Failure data analysis for aircraft maintenance planning. 2004.

[12] Database schema. Database schema — Wikipedia, the free encyclopedia. Accessed: 2021-01-03.

[13] DOD. Database performance specification: Logistics management information, January 2005. Notice 1.

[14] Wendy Torell and Victor Avelar. Mean time between failure: Explanation and standards. 01 2004.

[15] Alexander Bellemare-Davis. Enhanced reliability & logbook-based predictive maintenance, March 2020. Presented at the Advanced Visualization and Data Analytics Technologies Symposium / Modeling & Simulation Summit 2020.

[16] P. Sandborn. Strategic management of dmsms in systems. *DSP Journal*, pages 24–30, April/June 2008.

[17] Chris Wilkinson. Obsolescence and life cycle management for avionics. Technical report, 2015. report no. DOT/FAA/TC-15/33.

[18] Matthew Reid. Reliability – a python library for reliability engineering (version 0.5.1). Available from: https://pypi.org/project/reliability/.

[19] Arnold I. Barnett. Defining conditional density for time until failure. Prof. Barnett is one of the academic supervisors for this thesis.

[20] Joseph Kurek, Robert Bernstein, Mike Etheridge, Gary LaSalle, Roy McMahon, Jim Meiner, Noel Turner, Michael Walz, and Cesar Gomez. Aircraft wiring degradation study. Technical report, Raytheon Technical Services Company, Federal Aviation Administration, 2008.