3-2022

Examining Failures of KC-135s using Survival Analysis

Vanessa I. R. Unseth

EXAMINING FAILURES OF KC-135s USING SURVIVAL ANALYSIS

THESIS

Vanessa I.R. Unseth, Captain, USAF

AFIT-ENS-MS-22-M-173

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

AFIT-ENS-MS-22-M-173

EXAMINING FAILURES OF KC-135s USING SURVIVAL ANALYSIS

THESIS

Presented to the Faculty

Department of Operational Sciences

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Logistics & Supply Chain Management

Vanessa I.R. Unseth, BS

Captain, USAF

March 2022

AFIT-ENS-MS-22-M-173

EXAMINING FAILURES OF KC-135s USING SURVIVAL ANALYSIS

Vanessa I.R. Unseth, BS
Captain, USAF

Committee Membership:

Seong-Jong Joo, Lt Col (Retired), PhD
Chair

Adam Reiman, Col (Retired), PhD
Member

AFIT-ENS-MS-22-M-173

Abstract

The United States Air Force manages an inventory of 396 KC-135 Stratotanker aircraft. It is crucial to our national defense that the 64-year-old aircraft continue to provide aerial refueling, which enables our military to accomplish a core mission of global reach. With mission capability rates falling and total non-mission capability supply rates increasing, it is necessary to take a deeper look at recurrent failures of KC-135. This study applies non-parametric and semi-parametric survival models to a dataset retrieved from the Air Force's Logistics, Installations, and Mission Support-Enterprise View (LIMS-EV) to look at time until the subsequent failure for the KC-135. Results of non-parametric models show cumulative hazard rates against sorties or flight hours, which may help mission planners, maintainers, and logisticians prepare their tasks. In addition, semi-parametric models or Cox proportional hazards models with frailty confirm that airbases are not associated with recurrent failures.

AFIT-ENS-MS-22-M-173

Acknowledgments

I want to take a moment to thank my advisor, Dr. Seong-Jong Joo, for all his advisement and patience over the last year towards completing my thesis. Thank you, Dr. Adam Reiman, for your class on writing a thesis, being my reader, and providing great feedback. I am also grateful to AFMC/A4P for sponsoring this study. Lastly, I want to thank my friends, classmates, and family for their support through this journey.

Vanessa I.R. Unseth

Table of Contents

Page

Abstract iv

Acknowledgments v

Table of Contents vi

List of Figures viii

List of Tables ix

List of Equations x

I. Introduction 1

Background and Problem Statement 1
Research Objectives/Questions 3
Methodology 3
Assumptions/Limitations 4
Implications 4

II. Literature Review 5

Chapter Overview 5
Air Force Forecasting Methods 5
CBM Analysis 6
CBM+ Analysis 8
Gap in the Literature 11
Summary 11

III. Methodology 12

Chapter Overview 12
Data Source 12
Survival Analysis 13
Kaplan-Meier Model 13
Cox Regression Model with Shared Frailty 14
Statistical Programs 16
Summary 17

IV. Analysis and Results 18

Chapter Overview 18
Descriptive Statistics 18

Kaplan-Meier Model 20
Nelson Estimator by Location *22*
Cox Regression Model with Shared Frailty 24
Results 27

V. Conclusions and Recommendations 29

Chapter Overview and Summary 29
Contributions 29
Limitations 30
Recommendations for Future Research 30

Bibliography 31

List of Figures

Page
Figure 1. Mission Capable and Total Non-Mission Capable Rates (LIMS-EV) 2

Figure 2. Cumulative Hazards Plot: Hours Flown 21

Figure 3. Cumulative Hazards Plot: Sorties Flown 22

Figure 4. Cumulative Hazards Plot: Hours Flown per location 23

Figure 5. Cumulative Hazards Plot: Sorties Flown per location 24

List of Tables

Page
Table 1. Survival Descriptive Statistics 18

Table 2: Survival Descriptive Statistics: Hours Flown Between Failure 18

Table 3: Survival Descriptive Statistics: Sorties Flown Between Failure 19

Table 4: Frailty Using Hours Flown and Location 24

Table 5: Frailty Using Number of Sorties and Location 25

List of Equations

Page

1: Kaplan-Meier Estimator 13

2: Survival Function.. 14

3: Cox Proportional-Hazard.. 15

4: Shared Frailty Model 16

EXAMINING FAILURES OF KC-135s USING SURVIVAL ANALYSIS

I. Introduction

Background and Problem Statement

In 1957, The KC-135 Stratotanker entered the United States Air Force (USAF) inventory and became operational. The 64-year-old aircraft continue to provide aerial refueling, enabling our military to accomplish a core mission of global reach. Air Mobility Command manages an inventory of 396 aircraft and relies on the Stratotanker to remain agile and resilient for at least the next 30 years (Air Mobility Command, 2018). In 2002, the Deputy Under Secretary of Defense for Logistics and Materiel Readiness charged the military to research and develop Condition Based Maintenance Plus (CBM+). CBM is "a set of maintenance processes and capabilities derived from a real-time assessment of weapon system conditions obtained from embedded sensors or external test and measurement using portable equipment" (Smith, 2003). "Plus" added on the end of CBM connotates the US military's strategy to integrate technology and processes and improve system effectiveness.

Currently, the Air Force inherits a reactive approach to maintenance, and CBM implementation can shift the paradigm to a proactive approach. For example, in April 2018, a KC-135 was down for maintenance in Rota, Spain, from a failed hydraulic pump. Without predicting the failure and no spares readily available, the military lost five days of mission capability, waiting for the repairs. The same pump failed two dozen times in other aircraft over four years, costing the Air Force an estimated $6.6 million (Serbu, 2019). Instead of waiting for parts to fail to replace them, CBM+ presents a proactive solution to get ahead of problems and create a sustainable force. The mission capability rate and total non-mission capable supply rates are two lagging indicators the United States Air Force tracks to measure the health of the fleet. The mission capability rate is the percentage of possessed hours for an aircraft that is fully mission capable or partially mission capable. Therefore, a low rate indicates the unit is experiencing issues. The total non-mission capable supply (TNMCS) rates are the ratio or percent between aircraft possessed time and aircraft downtime due to supply (HQ ACC/A4M, 2018). From the fiscal year 2012 to the fiscal year 2019, the KC-135 mission capability rates declined, and the TNMCS rates for parts supportability worsened, as shown in Figure 1.

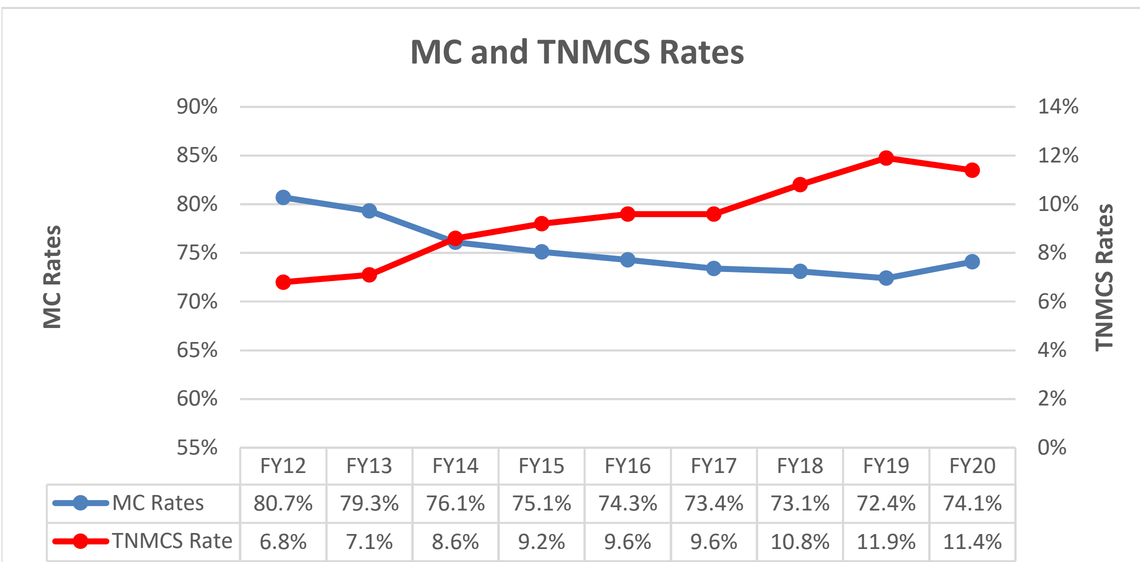

Figure 1. Mission Capable and Total Non-Mission Capable Rates (LIMS-EV)

Research Objectives/Questions

This study aims to find a way to help decision-makers identify how often the KC-135 will experience failures and prepare a proactive approach for maintaining the aircraft in the CBM+ perspective. This study collects historical flight data on the KC-135 and analyzes data using survival analysis. This study attempts to answer the following questions:

1. Can survival analysis be used to predict KC-135 failures?
2. Do aircraft failures vary based on location?

This study argues that the Air Force needs to take an incremental approach to implement CBM+ into the logistics community due to the large infrastructure requirement. The incremental approach with survival analysis will enhance KC-135 availability and readiness and improve part supportability.

Methodology

Currently, the Air Force relies heavily on eight and four-quarter moving average methods for forecasting spare part demands. Using data retrieved from the Air Force's Logistics, Installations, and Mission Support-Enterprise View (LIMS-EV) database, survival analysis is the selected method to analyze the data using the R program (R Core Team, 2021). Non-parametric and semi-parametric methods analysis of survival time.

Assumptions/Limitations

Due to the complexity of analyzing large numbers of aircraft, the scope of this research is limited to the KC-135 Stratotanker at three Air Force Active-Duty Bases by excluding those in the Air Force Reserve. Condition-based maintenance consists of three main steps: data acquisition, data processing, and maintenance decision-making under the umbrella of diagnostics and prognostics (Jardine et al., 2005). This study will focus on the prognostics factor, which deals with fault predictions and estimating how soon or likely another fault will occur. The data utilized for this research was retrieved from the Air Force's Logistics, Installations, and Mission Support-Enterprise View (LIMS-EV) and included the available variables recorded in the system. Additionally, if a failure occurred when an aircraft flew more than one sortie a day, the time of failure is assigned to the last sortie on the day. The documented failures did not identify the reason for failure. An assumption for semi-parametric models employed in this study is that covariates follow proportional hazards.

Implications

This study attempts to predict failures of KC-135, which may help maintenance crew and mission planners take proactive action against the failures. Results of this study also can be used for enhancing the CBM+ program.

II. Literature Review

Chapter Overview

The purpose of chapter II is to review the current Air Force forecasting methods and the accuracy of those techniques. This chapter discusses how the civilian sector applies condition-based maintenance into its operations. Additionally, this section analyzes literature on the status of CBM+ in the military. Lastly, this literature review includes applications of survival analysis studies across many career fields.

Air Force Forecasting Methods

Slay & Sherbrooke (1997) conducted a study dating back to the early 1990s and found that the Air Force's *War and Mobilization Plan* (WMP) had significant discrepancies in how demand for spare parts is forecasted. The study found the problem is rooted in the assumption that parts fail on a per-flying-hour basis, and therefore a two-hour sortie requires twice as many parts as a sortie that flies one hour. The research conclusion found that a two-hour sortie only requires about ten percent more parts than a one-hour sortie and coined the method decelerated demand forecasting. The Air Force incorporated the method and prevented an overestimate of over a billion dollars in gross war reserve requirements. In another study, Sherbrooke (1997) examined if the demand for parts is more closely related to sorties flown or flying hours.

The Air Force Materiel Command Manual 23-101 is the central guidance and instruction for forecasting and computing *Secondary Items* using the Secondary Item Requirements System (SIRS). In 2015, The Department of Defense (DOD) managed more than five million secondary inventory items valued at approximately $98 billion

(US Government Accountability 13 Office, 2015). *Secondary Items* are recoverable and consumable items (designated D200A) "installed in a higher assembly such as an aircraft, vehicle, piece of equipment, or another recoverable secondary item" (Air Force Materiel Command, 2011). SIRS uses historical failures, replacement, condemnation, and other reliability rates to compute and determine failure rates for a future program. The Equipment Specialist (ES) has five available forecasting methods in SIRS to compute future requirements. The five methods include eight quarter moving average (24 months), a four-quarter moving average (12 months), PREGLOG, exponential smoothing, and estimates. The eight-quarter and four-quarter moving average make up about 95 percent of the base-level forecast methods used (Air Force Materiel Command, 2011). In 2011, $9.2 billion worth of on-hand excess inventory was due to changes in requirements. In 2013, The US Government Accountability Office (GAO) found ineffective and inefficient inventory management practices. The inaccuracy of forecasting for spare parts resulted in the mismatch of inventory levels and requirements. (US. Government Accountability 13 Office, 2013). However, with moderate progress to minimize waste, inventory management remained on the High-Risk List for several years (US Government Accountability 13 Office, 2015).

CBM Analysis

The military airframes' programs differ from the civilian sector primarily due to the age of the fleet and the limited number and quality of sensors. Due to these differences, Air Mobility Command determined that about 80 percent of the CBM program will rely on Enhanced Reliability Center Maintenance (eRCM). The other 20 percent will rely on sensor data that meet a separate line of effort of CBM+ called Predictive Algorithm Development (PAD). Rather than fronting the high dollars to input sensors on the older airframes, the focus shifts to building algorithms that sift through historical data to determine ideal times to replace or repair parts (Serbu, 2019). Reviewing the civilian sector provides a foundation of analysis on successfully implementing CBM+.

Degradation modeling, such as continuous and discrete-state models, is one of the most common methods for predicting the remaining life of a product (Li et al., 2020). In one study, researchers apply Bayesian failure prognostics to an Airplane Condition Monitoring System dataset to have updated results with the evidence of new data. The study applies a dynamic linear model (DLM) and Bayesian inference formulas on five commercial aircraft Air Condition Systems (ACS) to describe the degradation process (Sun et al., 2020). The researchers extract data using the ACMS report to characterize the ACS's performance and track the system's overall health. The failure times were obtained based on pre-defined failure thresholds. The result of the study is a low error for failure time predictions of systems entering degradation warning stages of less than eight percent (Sun et al., 2020).

Brigadier General Steven Bleymaier, AMC’s director of logistics, engineering, and force protection, uses Delta Airlines as the benchmark to endorse the promotion of the CBM+ program to the Air Force. Delta Airlines removed $500 million from their supply inventory by implementing condition-based maintenance. Delta is the first major U.S carrier to invest in the open-data platform with a 95 percent reliability success rate.

From 2013 to 2017, Delta TechOps went from 169 to 324 cancel-free days. (Simmons, n.d.). Additionally, researchers applied a cost analysis on the Boeing 737-300 fuselage, comparing CBM to scheduled maintenance. They found that CBM provides better reliability and fewer maintenance trips because scheduled maintenance implements repairs that might threaten safety, while CBM only identifies components that grew to threaten safety (Dong, 2020). The challenge the Air Force faces is the increased complication of gathering accurate data on the health of the systems (Traskos, 2018).

CBM+ Analysis

A study conducted at Air Force Research Laboratory (AFRL) presented a strategy to develop and implement CBM+ technology under an Enterprise Predictive Analysis Environment (EPAE) concept. EPAE has two goals: to integrate and exploit data and allow for rapid standard verification and prototyping of different techniques. Implementation has three phases: the first phase tackles the challenge of data integration and appropriate infrastructure across various programs to support CBM+. The second phase aims to integrate engine domains into a standard data structure implemented in the Global Combat Support System-Data Service (GCSS). Lastly, the final phase focuses on the longevity of the EPAE program into production capability and integrating into the Air Force logistics programs (i.e., Commander Dashboards) for quick health assessments (Navarra et al., 2007).

Logistics, Installation, and Mission Support-Enterprise View (LIMS-EV) is an extensive IT infrastructure to access data universally. The goal is for LIMS-EV to be the central logistics node and leverage necessary data across other IT systems to build CBM+

predictive algorithms. AFRL identified raw data from sensors on the aircraft to provide the highest level of accuracy. Current Air Force CBM+ policy and guidance are sparse, but CBM+ is in the beginning phases for legacy systems, such as the KC-135, and reflected in the plans for the F-35 Joint Strike Fighter. (US Air Force, n.d.).

Survival Analysis

Survival Analysis typically focuses on studying the time until a failure. Survival Analysis is common in the medical field for analyzing patients' mortality with progressive diseases such as cancer. However, survival analysis is in many other areas, such as machine failures and certain events in social sciences.

In the last couple of years, COVID-19 has consumed our lives: scientists and analysts have attempted to understand and provide solutions to combat the virus rapidly. Narain et al. (2020) applied comparative survival analysis to determine what combination of care is associated with the lowest hospital mortality for patients with COVID-19 cytokine storm. The study includes 3,098 patients, divided into six groups based on demographic variables, comorbidities, and baseline lab values. Using a Cox regression model and adjusting for covariates, a patient's survival was compared between treatment groups to calculate survival rates. The study's conclusion found that corticosteroid and tocilizumab used in combination or corticosteroid used alone were associated with the lowest hospital mortality rates.

Ebden et al. (2010) published a study that applied a survival analysis model on 325 jet engines to estimate when the total engine risk falls below a 95 percent confidence interval. The study uses a mixed Weibull distribution to represent the combined density function across failure times of individual components. The model incorporates the configuration of the engine, the life usage of the components, the time-to-failure of each component, and engine health as the independent variables (Ebden et al., 2010). The study's conclusion provides a method to minimize premature inspections by calculating the time after a hazard function that lies below a certain threshold and deems unsafe.

Costa et al. (2020) conducted research using a Cox proportional-hazard model to analyze the best maintenance policy that saves the most money for Portuguese railway wheelsets. The study derives the survival probability given its diameter and determined that as tread diameter increases, so does the length of survival. The hazard function presents a range of probabilities that help decision-makers find an optimal point of renewal. The result of the study proposes that train operating companies could potentially decrease their long-run average cost by about one percent by implementing degradation and recovery modeling into their maintenance policies.

Similarly, Chen et al. (2015) implemented a study to evaluate rehabilitation pavement design approaches by comparing four factors: mill and fill, overlay, heater scarification, and rubblization, which affect composite pavement performance. The study uses a parametric survival model to compare three pavement performance indicators to determine the best rehabilitation method. The analysis concluded that rubblization has a more significant impact on cracking development in composite pavement compared to the other three methods. Additionally, mill and fill treatment outperform the overlay method in terms of reflective crack mitigation. The findings in their research were beneficial to show which rehabilitation methods had the desired longevity for survival that could save time and money.

Gap in the Literature

There is a bountiful amount of research using survival analysis. However, this research intends to fill the gap in the literature on applying survival analysis to recurrent failures for the Air Force's KC-135 Stratotanker.

Summary

The literature review supports the importance of this research on predicting failures on the KC-135. The government has identified the high risk of our current inventory management program and the need for a better process to get after lowering our costs. The medical field and civilian sector provided success stories on applying survival analysis to USAF maintenance programs. The military faces the challenges of finding a method to maintain a healthy fleet for an additional 30 years.

III. Methodology

Chapter Overview

Chapter III will explain survival analysis to estimate the cumulative hazard rates using non-parametric models and hazard ratios for covariates using semi-parametric models or Cox proportional hazards model. Survival analysis is also applied to determine if the locations of the KC-135 have an impact on failure. The two types of survival analysis models applied in this research include a non-parametric Kaplan-Meier model and a semi-parametric Cox regression model with shared frailty. These models will be applied to the KC-135 Stratotanker at McConnell, MacDill, and Mildenhall Air Force Bases, to simulate the need for condition-based maintenance in the Air Force. The available maintenance data is from the Air Force Logistics, Installations, and Mission Support-Enterprise View (LIMS-EV) system.

Data Source

LIMS-EV is the Air Force Headquarters A4/7 Business Intelligence gateway to provide a single one-stop-shop for standardized data exploitation for reporting and analytics delivery. The mission is to provide quick access to current and historical enterprise information and view enterprise interoperability to meet the high operational tempo in today's military environment. Within LIMS-EV, an enhanced Fleet Asset Status (FAS) capability displays near real-time maintenance and supply data per aircraft tail number (Air Force Headquarters A4PA, 2019). Additionally, LIMS-EV provides the ability to track data based on a stock number, National Item Identification Number (NIINs), serial numbers, so on.

Survival Analysis

Survival Analysis uses statistical models to examine the relationship of timing and the duration until the occurrence of an event. Additionally, it analyzes the conditional probability that an event occurs at a particular time, known as the hazard rate or dependent variable. Furthermore, survival analysis models can assess the relationship between specific characteristics and covariates or independent variables on the hazard rate. (Mills, 2011: 1-2). The advantage of survival analysis is its ability to apply the model to varying events such as medical, political, and, in the case of this research, aeronautical. Another advantage that distinguishes survival and event history models is that they take censoring into account. Right censored data, which is used in this research, "occurs when the event under study is not experienced by the last observation" (Mills, 2011: 5). This research will apply the R program's statistical computations (R Core Team, 2021).

Kaplan-Meier Model

The Kaplan-Meier (KM) model is a non-parametric model. The advantages of this model are its ability to analyze large datasets when event times are not precisely measured and provide useful visual plots of the cumulative survivor or hazard function (Mills, 2011: 62-63). The Kaplan-Meier estimator is expressed by:

$$\hat{S}(t_j) = \hat{S}(t_{j-1}) \times \Pr(T > t_j \,|\, T \geq t_j)$$

1: Kaplan-Meier Estimator

Where:

$\hat{S}(t_j)$ is the probability that the survival time for subject that is an airplane j is greater than t

t is the time when at least one event happened

T is the random variable of survival time ($T \geq 0$)

Kaplan-Meier estimates are beneficial for analyzing single events. However, this research has recurrent events and needs to estimate cumulative hazard rates using the Nelson estimate (Nelson, 1969; 1972). The cumulative hazard function estimates the expected number of failures for a given amount of time (Therneau, 2020). The hazard function focuses on experiencing the event, such as failures, while the survivor function focuses on not experiencing the event. The survival function is the exponential of the negative of the cumulative hazard function (Allignol et al., 2016), which is defined as follows:

$$\hat{S}(t_j) = exp(-H(t)) = exp\left(\int_0^t \lambda(u)du\right)$$

2: Survival Function

Where:

$\hat{S}(t_j)$ is the probability that the survival time for subject that is an airplane j is greater than t

$H(t)$ is the cumulative hazard function

Cox Regression Model with Shared Frailty

The Cox proportional-hazard (PH) model is a multiple linear regression model to evaluate simultaneously the effect of several factors on survival and a predominant model used in survival analysis. The advantage of the Cox PH model over the non-parametric model is the ability to include multiple covariates. It makes no assumptions about the shape of the hazard function (Mills, 2011:12). The Cox PH model is used in this research to identify a relationship with fixed covariates on the hazard function. Due to the limitations of available data, the scope of this research will focus on measuring the effect of the location of military bases. The Cox proportional-hazard model with fixed covariates is (Mills, 2011: 87):

$$h_j(t) = h_0(t)\exp\{\beta_1 x_{i1} + \cdots + \beta_k x_{jk}\}$$

3: Cox Proportional-Hazard

Where:

$h_j(t)$ is the hazard for a subject that is an airplane j at time t;

$h_0(t)$ is the hazard function for a subject whose covariates all have the value of zero;

$\beta_1 x_{j1}$ is the calculated beta coefficient for the fixed covariate;

β_k is the coefficient of the kth covariate

The shared frailty component analyzes when recurrent event times for clustered subjects repeat. A recurrent event is an observation of the same type of event in a single subject over the observation period, in this case, aircraft failures (Mills, 2011: 166). Shared frailty examines the two types of correlation: heterogeneity across subjects and event dependence. Heterogeneity across subjects means there may be reasons that are difficult or impossible to explain why the KC-

135s might be more prone to experience an event, such as factors that influence the occurrence of an event. Event dependence means the occurrence of the first event makes other events more or less likely to happen (Mills, 2011: 167). The shared frailty model is (Mills, 2011: 168):

$$\left(h_j(t)\middle|(\beta' x_{ij}, v_i)\right) = h_0(t) v_i \exp(\beta' x_{ij})$$

4: Shared Frailty Model

Where:

$h_j(t)$ is the hazard for each subject that is an airplane j at time t;

x_{ij} is the covariate vector that is associated with β, i is a subgroup coded as "ID";

β corresponding vector of regression parameters;

v_i is the shared frailty (random effects);

$h_0(t)$ is the hazard function for a subject whose covariates all have the value of zero

Statistical Programs

This research uses R, a statistical program to analyze KC-135 data. The R program is a language that provides integrated software for data manipulation, statistical computing, and displaying graphics (R Core Team, 2019). The advantage of R is the access to extended packages that help make computations and analysis easier. The study utilized the *survival package.* The non-parametric models used the *survfit* (Surv) function to compute cumulative hazard rates for recurrent events within the survival package (Therneau, 2020). Additionally, within the survival package, the semi-parametric models were obtained using the *Cox proportional hazards regression fit (coxph)* function to measure the effect of fixed covariates on the hazard function.

Summary

Survival analysis is common in the medical field, and a small amount of research uses this method on machines. Using the statistical program R, these models present different applications of survival analysis that will measure recurrent failures for KC-135s in the United States Air Force.

IV. Analysis and Results

Chapter Overview

Chapter IV will present the survival analysis results on KC-135 aircraft from Mildenhall, McConnell, and MacDill Air Force bases using the non-parametric and semi-parametric models. The study analyzes data for three years, from October 2018 to September 2021. The results of the models will address the two proposed research questions.

Descriptive Statistics

Before any analysis, the dataset pulled from LIMS-EV was sorted and formatted for survival analysis. Table 1 provides an overview of the descriptive statistics.

Table 1. Survival Descriptive Statistics

	Location of the KC-135s			
	MILD	MCCON	MACD	TOTAL
Number of KC-135	38	38	24	100
0 (Censored)	2,167	3,787	1,723	7,677
1 (Failures)	1,385	2,827	1,322	5,534
Observations	3,552	6,614	3,045	13,211
Failure Percentage	39%	42.7%	43.4%	41.9%

The dataset includes 100 KC-135 Stratotankers with 38 from Mildenhall AFB, England (MILD), 38 from McConnell AFB, Kansas (MCCON), and 24 from MacDill AFB, Florida (MACD). The dataset is broken down by days with at least one sortie flown. There were 13,211 observations that included5,534 failures, or 41.9 percent of the total observations. KC-135 Stratotankers failed 39 percent of the total observations at

Mildenhall Air Force Base (AFB), 42.7 percent at McConnell AFB, and 43.3 percent at MacDill AFB. There are 7,677 censored observations.

Table 2. Survival Descriptive Statistics: Hours Flown Between Failure

	MILD	MCCON	MACD	ALL
Events	1,385	2,827	1,322	5,534
Min.	0.500	0.200	0.300	0.200
Mean	13.527	15.611	14.119	13.494
Median	9.7	10.0	9.8	8.8
Max.	134.3	139.3	100.1	134.3
Std. Dev.	12.126	15.375	12.380	13.035

For this study, the location of the KC-135s is the only fixed-covariate in the recurrent events dataset. The time interval is the Hours Flown Between Failure (HFBF). Table 2 breaks down the statistics of hours flown between failures for each location. Of the three locations, McConnell AFB has the highest median of HFBF at 10, indicating the aircraft there are more reliable than Mildenhall and MacDill Air Force Bases. Overall, the median of hours flown between failure is 8.8.

Table 3. Survival Descriptive Statistics: Sorties Flown Between Failure

	MILD	MCCON	MACD	ALL
Events	1,385	2,827	1,322	5,534
Min.	1	1	1	1
Mean	2.78	3.03	2.70	2.68
Median	2	2	2	2
Max.	17	28	15	24
Std. Dev.	2.18	2.78	2.06	2.31

Table 3 provides the descriptive statistics of the sorties flown between failure (SFBF) broken down by location. Each location of the KC-135s represents the fixed-covariates, and the time indicator is the number of sorties flown until a failure. The median values across all three bases are two sorties flown until a failure indicating the aircraft fail about the same regardless of location.

Kaplan-Meier Model

The non-parametric Kaplan-Meier model uses the *survival (Surv)* function in R. Hours Flown is the time indicator, separated by *HStart* and *HStop*. The event indicator is represented as one for *Failure* or zero otherwise. If an airplane does not fail at the end of the observation period, it is censored (Failure=0). The Kaplan-Meier estimates single events in survival analysis; therefore, recurrent events use the Nelson estimator to capture the cumulative hazard rate to understand and graphically represent failures of the KC-135 (Nelson, 1969; 1972).

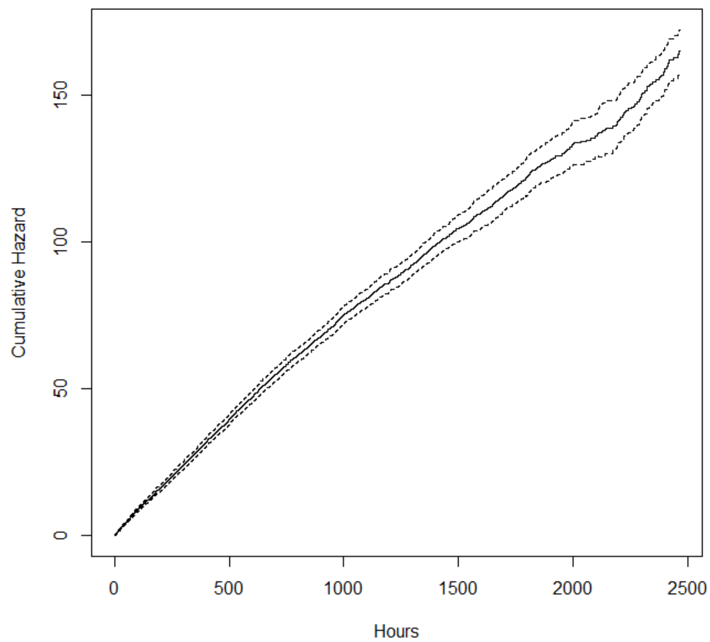

Figure 2. Cumulative Hazards Plot: Hours Flown

Figure 2 represents the hours flown on the x-axis and the cumulative hazard rates or the cumulative occurrence of events, in this case, failures, for the aircraft on the y-axis. At 500 hours flown on the x-axis, the aircraft is estimated to experience approximately 40 cumulative failures on the y-axis, which continue to increase over time.

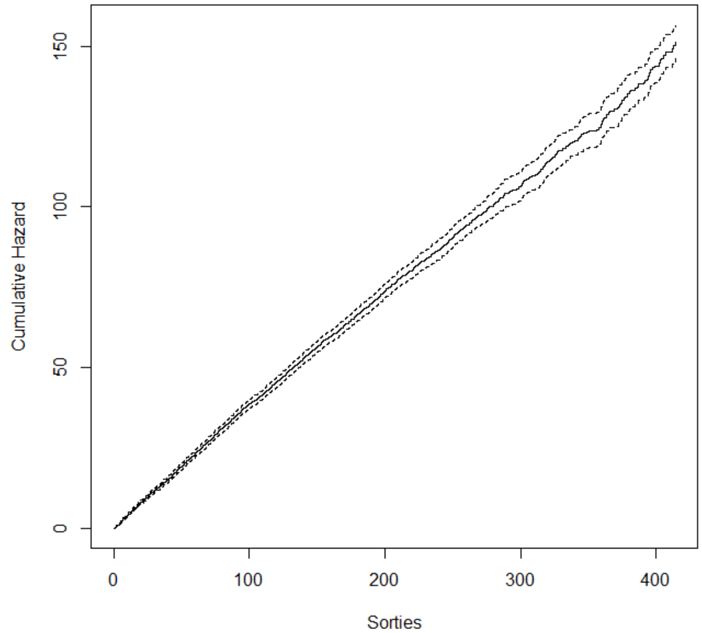

Figure 3. Cumulative Hazards Plot: Sorties Flown

Similarly, Figure 3 shows the cumulative sorties flown on the x-axis and the cumulative hazards on the y-axis. There is a positive relationship between the number of sorties and the cumulative hazard rates. As the number of sorties increases, so do the cumulative failures. At 100 sorties, the aircraft is likely to experience approximately 30 failures, which continue to increase over time.

Nelson Estimator by Location

This section calculates the Nelson estimator to compare the relationship of the KC-135s at each location using hours as the time indicator. The hours flown and the number of sorties flown are the time indicators, separated by *HStart* and *HStop* or *SStart* and *SStop*; the event indicator is *Failure*=1 and the locations (MILD=1, Else=0) and (MCCON=1, Else=0) and (MACD=1, Else=0) as the fixed covariates.

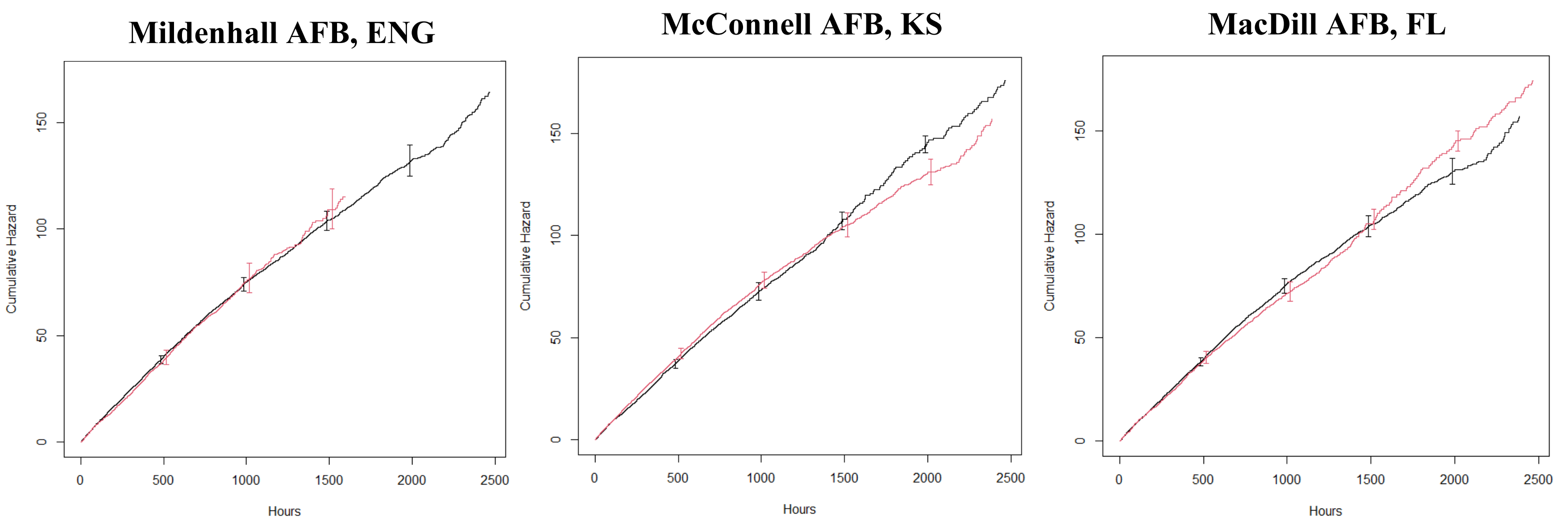

Figure 4. Cumulative Hazards Plot: Hours Flown per location

Figure 4 shows three separate plots of the cumulative hours flown on the x-axis and the cumulative hazard function on the y-axis, for each base from left to right: Mildenhall AFB, McConnell AFB, MacDill AFB. The red line in each plot represents the location indicated in the title above the plot, and the black line represents the other two bases for easy comparison. Overall, the results indicate that failures of KC-135s are about the same at each location as the cumulative hours flown increase over time.

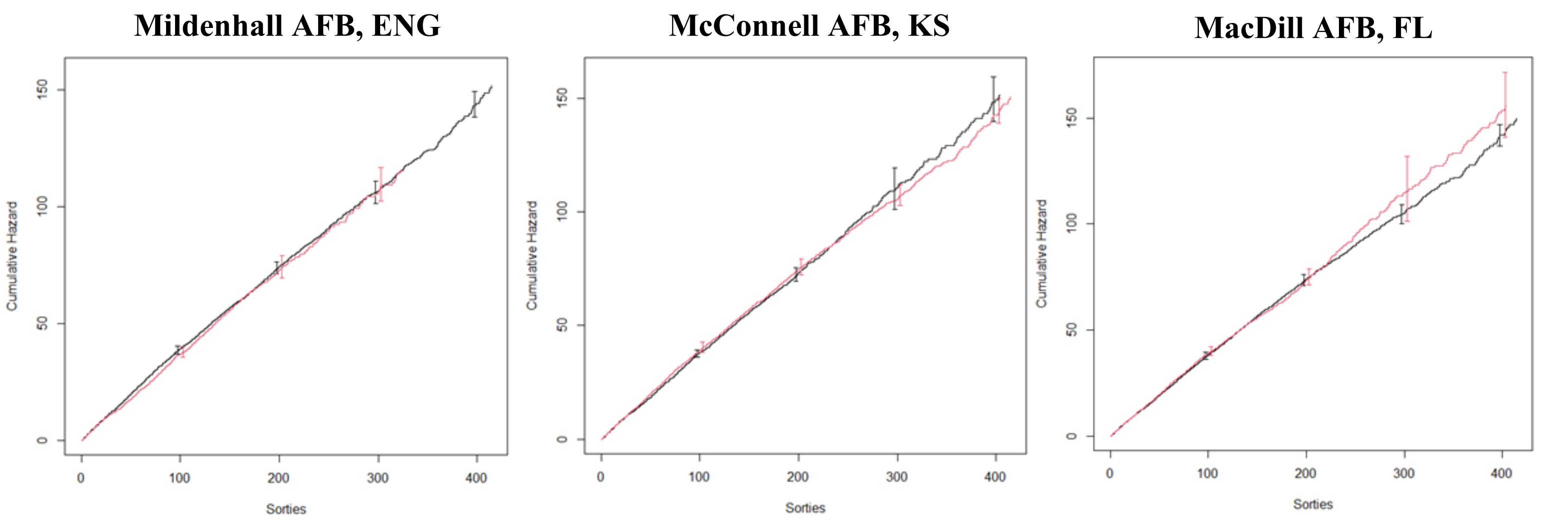

Figure 5. Cumulative Hazards Plot: Sorties Flown per location

Figure 5 shows three separate plots with the cumulative sorties flown on the x-axis and the cumulative hazard function on the y-axis, for each base from left to right: Mildenhall AFB, McConnell AFB, MacDill AFB. The red line in each plot represents the location indicated in the title above the plot, and the black line represents the other two bases for easy comparison. Overall, the results indicate that failures of KC-135s are about the same at each location as the cumulative number of sorties flown increases over time.

Cox Regression Model with Shared Frailty

Subjects often experience the same type of event more than once, defined as a recurrent event. The frailty model is an unobserved random proportionality factor that modifies the hazard function and looks for correlations of event times with the event among similar groups (Mills, 2011: 164-165). Since some aircraft might be more 'frail' than others, they would be more likely to experience an event. Therefore, in this study, the model aims to describe the excess risk by location and individual KC-135s, represented as Frailty(ID), experiencing recurrent events.

Table 4. Frailty Using Hours Flown and Location

	MILD	Frailty (ID)	MCCON	Frailty (ID)	MACD	Frailty (ID)
Coef.	0.009537		-0.08098		0.9173	
Se(Coef)	0.09477		0.08635		0.0932	
Exp(Coef)	1.01		0.9222		1.096	
Lower .95	0.8384		0.7786		0.9131	
Upper .95	1.216		1.092		1.316	
p-value	9.2e-01	3.5e-43	3.5e-01	7.4e-41	3.2e-01	4.0e-44
DF	1	72.42	1	72.54	1	70.87
Chisq	0.01	379.59	0.88	366.63	0.97	381.69
Theta		0.1247		0.1257		0.1080

Table 4 represents the output of the frailty model using hours flown and each location. The 'Coef.' row shows the beta coefficient estimates (β) for each location that is now conditional on frailty. The beta coefficient is the degree of change in the dependent variable for each additional change in the predictor variable. For example, Mildenhall has a beta coefficient of 0.009537; therefore, every one unit increase in hours flown at MILD will increase failure by 0.009537. The same interpretation follows for MCCON and MACD; however, since McConnell has a negative value, it is an inverse relationship. The next row, 'Se(Coef)', is the stand error of the coefficient and measures how precisely the model estimates the coefficient's unknown value. The smaller the standard error, the more precise the estimate. The 'Exp(Coef') is the exponentiated coefficient, representing the hazard's multiplicative effects. For MILD and MACD, values greater than one indicate that the covariate is associated with an increased risk of failure. MCCON's exponentiated coefficient is less than one, meaning the covariate has a decreased risk of failure. An exponentiated coefficient of one indicates no association between covariate and hazard. Since all three locations have values very close to one, there is more caution in believing there is an associated hazard with the location. With an alpha = 0.05, all the p-values are above the alpha. Therefore we can conclude that we fail to reject the null hypothesis that all of the beta coefficients are zero and state that we cannot be 95 percent confident that the covariate affects the hazard. The 'Chisq' is the chi-square statistic and is another method that tests the significance of the entire model and supports our p-value conclusion. The variance of random effect, labeled Theta, is the estimated frailty variance. The variance of random effect is 0.1247 at MILD, 0.1257 at MCCON, and 0.1080 at MACD. The p-values for all the Frailty(ID)'s are less than the alpha=0.05; therefore, we conclude a significant within-group correlation.

Table 5. Frailty Using Number of Sorties and Location

	MILD	Frailty (ID)	MCCON	Frailty (ID)	MACD	Frailty (ID)
Coef.	-0.0333		-0.0609		0.1108	
Se(Coef)	0.0873		0.0792		0.8763	
Exp(Coef)	0.9673		0.9409		1.117	
Lower .95	0.8151		0.8056		0.9409	
Upper .95	1.148		1.099		1.326	
p-value	7e-01	2e-37	4.4e-01	1.2e-36	2.1e-01	6.5e-37
DF	1	70.82	1	71.35	1	1
Chisq	0.15	343.52	0.59	340.09	1.6	339.5
Theta		0.1039		0.1081		0.0986

Table 5 represents the output of the frailty model using the number of sorties flown and each location. All the same interpretations apply for each row as Table 3. All three locations had p-values above the alpha=0.05; therefore, we can conclude that we fail to reject the null hypothesis that all beta coefficients are zero and state that we cannot be 95 percent confident that the covariate has any effect on the hazard. The variance of random effect, labeled Theta, is the estimated frailty variance. The variance of random effect is 0.1039 at MILD, 0.1081 at MCCON, and 0.0986 at MACD. If the variance of random effect were zero, that indicates there is no evidence of frailty among the aircraft. The p-values for all the Frailty(ID)'s are less than the alpha=0.05. Theta's at all three locations is greater than zero; therefore, we conclude a significant within-group correlation, and frailty does exist.

Results

The analysis allows us to answer the investigative research questions. The first question asks if survival analysis can predict KC-135 failures. Using the Nelson model, Figures 2 and 3 show the overall cumulative failure rates increase as sorties and flight hours increase, and Figures 4 and 5 show the same result based on each location. These results can help mission planners, maintainers, and logisticians prepare their tasks.

The second question explores if aircraft failures vary based on location. Tables 4 and 5 outputs show, with an alpha = 0.05, all locations had p-values greater than 0.05. Therefore, we fail to reject the null hypothesis and conclude that we cannot be 95 percent confident that the location affects recurrent failures. Additionally, frailty was applied to each aircraft (ID) to determine differences among the aircraft in Tables 4 and 5. The variance of random effect is 0.1039 at MILD, 0.1081 at MCCON, and 0.0986 at MACD. The p-values for all the Frailty(ID)'s are less than the alpha=0.05. Theta's at all three locations is greater than zero; therefore, we conclude a significant within-group correlation, and frailty does exist. This conclusion indicates that other factors may capture the cause of failures.

V. Conclusions and Recommendations

Chapter Overview and Summary

This study applied survival analysis to recurrent events or failures of the United States Air Force KC-135 Stratotanker retrieved from the United States Air Force's Logistics, Installations and Mission Support-Enterprise View (LIMS-EV). The data consists of hours flown, the number of sorties flown, failures from three active-duty bases: Mildenhall Air Force Base, England, McConnell Air Force Base, Kansas, and MacDill Air Force Base, Florida. This study examined the data set for three years from October 2018 to September 2021, which contained observations for 100 aircraft. Of the 13,211 observations, there were 5,534 documented failures. Using non-parametric and semi-parametric models on the KC-135 dataset, this study provided the results to answer the established research questions. The study provided cumulative hazard rates using hours flown or the number of sorties flown as the time indicator, which would help maintainers, mission planners, and logisticians improve their tasks. Additionally, the location variable was not significant in Cox proportional hazards models, which showed no significant effect on aircraft failures.

Contributions

Contributions of this study are twofold: first, presenting a research framework for future studies for various airplanes, and second, presenting cumulative hazard rates that practitioners can use. This study presents an application for similar systems and components with minor changes.

Limitations

There are three major limitations in this study. First, this study employs non-parametric and semi-parametric models and, thus, fails to include fully parametric models that can predict survival time. Second, this study has only one covariate on location. Last, this study contains multiple types of recurrent events.

Recommendations for Future Research

Since this research did not examine the exact reasons for failures, such as the exact component or parts, additional data can provide a more comprehensive analysis on predicting failures. Additionally, broadening the scope to other types of aircraft can be beneficial for comparison. Future studies that include additional independent variables benefit from examining other factors that may be causing the recurrent failures. For predicting survival time, parametric models are desirable. Lastly, some bases have implemented the initial phases of Condition-Based Maintenance and would be a great source for future research.

Bibliography

Air Force Headquarters A4PA. (2019). *LIMS-EV (LIMSEV) - LIMS-EV Fleet Asset Status - "A One-Stop-Shop."* https://www.my.af.mil/gcss-af/USAF/ep/contentView.do?contentType=EDITORIAL&contentId=c2D8EB9D62D713923012DA93A41500BC4&programId=t2D8EB9D641D2F50801420B020EDF0766&channelPageId=s6925EC1337D20FB5E044080020E329A9

Air Force Materiel Command. (2011) *Requirements For Secondary Items (D200A, D200N).* AFMCMAN 23-1, Interim Change 4. Wright-Patterson AFB, OH.

Air Mobility Command. (2018, May 14). KC-135 Stratotanker. Retrieved February 21, 2021, from https://www.amc.af.mil/About-Us/Fact-Sheets/Display/Article/977523/kc-135-stratotanker/

Allignol, A., Beyersmann, J., & Schmoor, C. (2016). Statistical issue in the analysis of adverse events in time-to-event data. *Pharmaceutical statistics, 15*(4), 297-305. doi:10.1002/pst.1739

Chen, C., Christopher Williams, R., Marasinghe, M. G., Ashlock, J. C., Smadi, O., Schram, S., & Buss, A. (2015, May 12). *Assessment of Composite Pavement Performance by Survival Analysis: Journal of Transportation Engineering: Vol 141, no 9*. Journal of Transportation Engineering. Retrieved January 26, 2022, from https://ascelibrary.org/doi/abs/10.1061/(ASCE)TE.1943-5436.0000784

Costa, M. de A., Joaquim Pedro de Azevedo Peixoto Braga, & Andrade, A. R. (2020, August 19). *A data-driven maintenance policy for railway wheelset based on Survival Analysis and Markov decision process*. Wiley Online Library. Retrieved January 26, 2022, from https://onlinelibrary.wiley.com/doi/abs/10.1002/qre.2729

DeFrank, Joshua D., "A Condition Based Maintenance Approach to Forecasting B-1 Aircraft Parts" (2017).Theses and Dissertations.793.

Dong, T., Haftka, R. T., & Kim, N. H. (2020). Advantages of Condition-Based Maintenance over Scheduled Maintenance Using Structural Health Monitoring System. In 1208780205 901099318 L. Kounis (Ed.), *Reliability and Maintenance: An Overview of Cases* (pp. 27-47). London, UK: IntechOpen. doi:https://dx.doi.org/10.5772/intechopen.83614

Ebden, M., Stranjak, A., & Roberts, S. Visualizing uncertainty in reliability functions with application to aero-engine overhaul. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, *59*(1) (2010), 163–173. https://doi.org/10.1111/j.1467-9876.2009.00692.x

Hochstein, A., Ahn, H., Leung, Y. T. and Denesuk, M., (2013). "Survival analysis for HDLSS data with time-dependent variables: Lessons from predictive maintenance at a mining service provider," *Proceedings of 2013 IEEE International Conference on Service Operations and Logistics, and Informatics*, pp. 372-381, doi: 10.1109/SOLI.2013.6611443.

HQ ACC/A4M. (2018, July 2). *Logistics Maintenance Performance Indicator Reporting Procedures*. Air Combat Command Instruction 21-118. Retrieved February 26, 2022, from https://static.e-publishing.af.mil/production/1/acc/publication/acci21-118/acci21-118.pdf

Jardine, A. K. S., Lin, D., & Banjevic, D. (2005, November 3). *A review on machinery diagnostics and prognostics implementing condition-based maintenance*. Mechanical Systems and Signal Processing. Retrieved January 31, 2022, from https://www.sciencedirect.com/science/article/abs/pii/S0888327005001512

Li, Y., Peng, S., Li, Y., & Jiang, W. (2020). A review of condition-based maintenance: Its prognostic and operational aspects. *Frontiers of Engineering Management*, *7*(3), 323–334. https://doi.org/10.1007/s42524-020-0121-5

Mills, M. (2011). *Introducing survival and event history analysis*. SAGE.

Narain, S., Stefanov, D. G., Chau, A. S., Weber, A. G., Marder, G., Kaplan, B., Malhotra, P., Bloom, O., Liu, A., Lesser, M. L., Hajizadeh, N., & Group, N. C. O. V. I. D.-19 R. C. (2020, August 5). *Comparative survival analysis of immunomodulatory therapy for COVID-19 'cytokine storm': A retrospective observational cohort study*. SSRN. Retrieved January 31, 2022, from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3627337

Navarra, K., Lawton, R., McCusker, S., & Hearrell, N. (2007). An Enterprise Strategy for Implementing Conditioned-Based Maintenance Plus (CBM+) Research in the USAF. *Proceedings of the 2007 IEEE Aerospace Conference*. Paper # 1124.

Nelson, W. Hazard plotting for incomplete failure data. *Journal of Quality Technology*, 1(1) (1969), 27–52. https://doi.org/10.1080/00224065.1969.11980344.

Nelson, W. Theory and applications of hazard plotting for censored failure data. *Technometrics*, 14(4) (1972), 945–966. https://doi.org/10.1080/00401706.1972.10488991.

R Core Team. (2019). R: A Language and Environment for Statistical Computing. Vienna, Austria. Retrieved from What is R?: https://www.r-project.org

Serbu, J. (2019, July 23). Air force has high HOPES AI can boost Aircraft Readiness cut maintenance costs. Retrieved February 21, 2021, from https://federalnewsnetwork.com/dod-reporters-notebook-jared-serbu/2019/07/air-force-has-high-hopes-ai-can-boost-aircraft-readiness-cut-maintenance-costs/

Sherbrooke, C. C. (1997, January 1). *Using Sorties vs. Flying Hours to Predict Aircraft Spares Demand*. Retrieved January 31, 2022, from https://www.semanticscholar.org/paper/Using-Sorties-vs.-Flying-Hours-to-Predict-Aircraft-Sherbrooke/01ac8f11b30f17225c9b16add3211bc0ae298df2

Simmons, C. (n.d.). Delta seeks 100 percent reliability with predictive maintenance technology. Retrieved February 22, 2021, from https://news.delta.com/delta-seeks-100-percent-reliability-predictive-maintenance-technology

Slay, M., & Sherbrooke, C. (1997, April). *Predicting Wartime Demand for Aircraft Spares*. Defense Technical Information Center. Retrieved January 31, 2022, from https://www.researchgate.net/publication/235021708_Predicting_Wartime_Demand_for_Aircraft_Spares

Smith, T. (2003). USAF Condition Based Maintenance Plus (CBM+) Initiative. *Air Force Magazine*, 84 (5), 102.

Sun, J., Wang, F., & Ning, S. (2020). Aircraft air conditioning system health state estimation and prediction for predictive maintenance. *Chinese Journal of Aeronautics*, *33*(3), 947–955. https://doi.org/10.1016/j.cja.2019.03.039

Therneau, T. (2020). A Package for Survival Analysis in R. R package version 3.1-11. *Modeling Survival Data: Extending the Cox Model*.

Traskos, M. (2018, July 5). Condition-based maintenance and risk quantification. Retrieved February 22, 2021, from https://www.lectromec.com/condition-based-maintenance/Under Secretary of Defense for Acquisition Technology and Logistics. (2012). *Condition Based Maintenance Plus (CBM+) for Materiel Maintenance*, DoDI 4151.22. Retrieved March 1, 2017, from http://dtic.mil/whs/directives/corres/pdf/415122p.pdf.

US Air Force. (n.d.). Fact Sheet: Conditioned-Based Maintenance Plus. AcqNotes. Retrieved March 1, 2017, from http://www.acqnotes.com/acqnote/careerfields/condition-based-maintenanceplusпercent 0A.

US Government Accountability Office. (2013). *High-Risk Series: An Update,* GAO-13-283. US Government Accountability Office, Washington DC Retrieved March 1, 2017, from http://www.gao.gov/assets/660/652133.pdf.

US Government Accountability Office. (2015). *High-Risk Series: An Update,* GAO-15-290. US Government Accountability Office, Washington DC Retrieved March 1, 2017, from https://www.gao.gov/assets/670/668415.pdf

REPORT DOCUMENTATION PAGE	Form Approved OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From - To)*
24-03-2022	Master's Thesis	September 2020 - March 2022

4. TITLE AND SUBTITLE
Examining Failures of KC-135s Using Survival Analysis

5a. CONTRACT NUMBER
N/A

5b. GRANT NUMBER
AFMC/A4P 2017-182

5c. PROGRAM ELEMENT NUMBER
N/A

6. AUTHOR(S)
Unseth, Vanessa, I.R., Capt, USAF

5d. PROJECT NUMBER
N/A

5e. TASK NUMBER
N/A

5f. WORK UNIT NUMBER
N/A

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Air Force Institute of Technology
Graduate School of Engineering and Management (AFIT/EN)
2950 Hobson Way
Wright-Patterson AFB OH 45433-7765

8. PERFORMING ORGANIZATION REPORT NUMBER
AFIT-ENS-MS-22-M-173

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Air Force Materiel Command
Ms. Andrea Truman
Bldg 262, Spruce Way
Wright-Patterson AFB, OH 45433-7765
karen.parker.4.ctr@us.af.mil

10. SPONSOR/MONITOR'S ACRONYM(S)
HQ/AFMC

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
DISTRIBUTION STATEMENT A. APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

13. SUPPLEMENTARY NOTES

14. ABSTRACT
The United States Air Force manages an inventory of 396 KC-135 Stratotanker aircraft. With mission capability rates falling and total non-mission capability supply rates increasing, it is necessary to take a deeper look at recurrent failures. The study applies non-parametric and semi-parametric survival models to a dataset retrieved from LIMS-EV to look at the duration(s) until failure for the KC-135. Results of non-parametric models show cumulative failure rates increase as sorties or flight hours increase. In addition, semi-parametric models or Cox proportional hazards models with frailty confirm that locations or air bases are not associated with recurrent failures.

15. SUBJECT TERMS
Survival Analysis/KC-135/Condition-Based Maintenance/Predicting Failures

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			Seong-Jong Joo, Lt Col (Retired), PhD., USAF
					19b. TELEPHONE NUMBER *(Include area code)*
U	U	U	UU	46	937-255-3535 x4761 / seong-jong.joo@afit.edu