3-2022

Predicting TF33-PW-100A Engine Failures Due to Oil Issues Using Survival Analyses

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THESIS

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AFIT-ENV-MS-22-M-191

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

AFIT-ENV-MS-22-M-191

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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 Acquisition and Project Management

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March 2022

AFIT-ENV-MS-22-M-191

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AFIT-ENV-MS-22-M-191

Abstract

In 2007, the Office of the Assistant Secretary of Defense for Sustainment pushed for the need to transition to a Condition Based Maintenance Plus (CBM+) initiative for weapon systems in the U.S. Department of Defense. The CBM+ initiative can help increase aircraft availability (AA) for the United States Air Force. There are many reasons where AA can be affected but one such issue is engine availability primarily due to oil issues. Within the CBM+ perspective, this study examines the risk of a jet engine failure due to an oil issue and attempts to predict an engine's time until next failure using survival analysis. Predicted engine's failure could be used to help pilots, maintainers, repair shops, and system program offices become better equipped to handle an oil issue before it occurs. The results of this study showed that as the engine's sorties on wing gradually increased, the risk of failure increased. In addition, this study found that a Weibull model with accelerated failure time was the most suitable model to predict the remaining life of the engine before it failed due to an oil issue. Based on the results, this study developed a field ready estimation tool that could be used by practitioners for predicting engine failures.

Acknowledgments

I would like to express my sincere appreciation to my faculty advisor, Dr. Seong-Jong Joo, for his guidance and support throughout the course of this thesis effort. The insight, mentorship, and experience were certainly appreciated. I would also like to thank my committee members for their time and input to strengthen my research. Next, I would like to thank the TF33 Equipment Specialists and CEMS team at Tinker Air Force base for the time and effort they put in to help with data collection in addition to taking the time to meet with Dr. Joo and me whenever needed. I am also grateful to AFMC/A4P for supporting this study. Lastly, I would like to thank my husband, for his unwavering support throughout the past 18 months, I would not be where I am today if it was not for you.

Anna M. Davis

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PREDICTING TF33-PW-100A ENGINE FAILURES DUE TO OIL ISSUES USING SURVIAL ANALYSIS

I. Introduction

1.1 Background

In 2007, the Office of the Assistant Secretary of Defense for Sustainment pushed for the need to transition from Condition Based Maintenance (CBM), which is a reactive maintenance approach, to Condition Based Maintenance Plus (CBM+), a preventative maintenance approach, to help increase aircraft availability (AA) for the United States Air Force (USAF). There are many reasons where AA can be affected but one such issue is engine availability. Without engines, powered aircraft cannot fly, directly hindering the mission. Mr. Rafael Garcia, former Director of the Propulsion Directorate at Tinker Air Force Base (AFB) once stated that aircrafts are simply dust covers for engines, noting the importance of engines for the USAF.

Similar with how AA is affected by many factors, engine availability can also be affected by a variety of factors such as oil issues, parts availability, foreign object damage (FOD), blade damage, scheduled time change, compressor stall, etc. One such issue that will be investigated further is engine oil failures, particularly in the TF33-PW-100A engines. The TF33-PW-100A engine, which powers the E-3 Advanced Warning and Control Systems (AWACS), has been plagued with frequent failures that negatively impact the E-3 availability. According to data collected from the Comprehensive Engine Management System (CEMS) from fiscal year 2007 to 2019, failures due to oil and related issues are one of the top five reasons for an Unscheduled Engine Removal (UER).

UERs occur when there is an unexpected failure or damage to the engine internally or externally, and, thus, the engine must be removed from the aircraft to be analyzed further to correct the issue. Removing the engine unexpectedly impacts the mission of the E-3, especially in a deployed environment, as the aircraft is then grounded until another engine becomes available to replace the defective one.

1.1.1 History of the TF33 Engine

The TF33 is one of the oldest engines in the United States Air Force (USAF) inventory and has been around for nearly 70 years with its design phase taking place during the 1950s with production and manufacturing taking place during the 1960s-1970s (NRC, 2007). Its Original Equipment Manufacturer (OEM) is Pratt and Whitney, and the TF33 engine has a total active inventory of roughly 1,000 units comprised of five variants. These engines service the B-52, KC-135, E-3 AWACS, and the E-8 Joint Surveillance and Target Attack Radar System (JSTARS). The five variants of the TF33 are: TF33-3/103, TF33-5, TF33-9, TF33-100A, and the TF33-102C (Brown and Perry, 2021). The TF33 helps support the mission of seven major commands: Air Force Global Strike Command (AFGSC), Air Education and Training Command (AETC), Air Force Reserve Command (AFRC), Air Mobility Command (AMC), Air National Guard (ANG), Pacific Air Force (PACAF), and Air Force Materiel Command (AFMC). The TF33 engines have most of their repairs completed at Tinker Air Force Base (TAFB) in Oklahoma City, Oklahoma.

1.1.2 Change in Maintenance Level Concept

Prior to 1992, the TF33 operated under a Three-Level Maintenance (3LM) concept:

- Organizational-Level Maintenance – light maintenance that does not require the engine to be completely removed from the aircraft
- Jet Engine Intermediate Maintenance (JEIM) – maintenance that usually requires the engine to be removed from the aircraft requiring more maintenance than at the organizational level
- Depot Level Maintenance – maintenance requiring major overhaul or complete rebuild of engine parts/components

In the early 1990's the USAF was undergoing a tremendous period of change at both depot and field organizations due to base closures, downsizing, and new maintenance concepts. These changes directly impacted how and where TF33 engine maintenance would be completed. In March 1992, the Secretary of the Air Force (SECAF) directed analysts to study the feasibility of transferring JEIM to the depot (Brown and Perry, 2021). After October 1992, the TF33 maintenance concept shifted towards a Two-Level Maintenance (2LM) Concept:

- Wing Retained Tasks (Organizational) – combination of previous Organizational-Level maintenance and light level JEIM work
- Depot Level Maintenance – combination of extensive level JEIM work and major overhauls

Ideally, the scope of work was designated in such a way where traditional engine repairs would be done at TAFB, which involved complete disassembly, clean/repair/replace components, and assemble engine from the reworked parts (Brown and Perry, 2021). Now, under the 2LM approach, there is the combination of existing depot level capability with intermediate level repairs formerly done by field units. Engines that cannot be repaired on the aircraft wing are brought into the depot but are only disassembled to the point necessary to make needed repairs, and the work scope teams will perform an in-depth inspection to determine the required maintenance (Brown and Perry, 2021).

The 2LM approach was supposed to combine extensive depot overhaul capability with intermediate level repair and save millions of dollars by 1995. The SECAF believed that "reducing maintenance staffing, equipment, and base level support without sacrificing force readiness" would save the USAF money, reduce repair turnaround time, and become an effective maintenance program (GAO, 1996). After The Honorable William J. Perry, the Secretary of Defense (SECDEF), and his team conducted an analysis on the impacts of 2LM in 1996, they concluded the 2LM implementation cost estimate had increased, and the expected net savings decreased from the 385 million dollars to 258 million dollars (GAO, 1996). In addition, repair turnaround time increased by at least eight days for three out of the four TF33 engine variants tested (GAO, 1996). Though many engine series reverted to the 3LM approach, the TF33 engine series maintained the 2LM approach, which has been the subject of debate on whether this has impacted the efficiency, reliability, and effectiveness of its performance (Brown and Perry, 2021).

1.1.3 TF33-100A and the E-3 AWACS

The TF33-100A as shown in Figure 1 services the E-3 AWACS aircraft with 162 engines active to date (Brown and Perry, 2021). Of all the TF33 engine variants, the TF33-100A flies the longest mission such as eight and a half hours without refueling during peace time and longer during war time when refueled, which particularly attributes to the amount of wear and tear the engines receive in comparison to other engine variants (Brown and Perry, 2021). There are four TF33-100A engines per aircraft, and each engine has a thrust of 20,500 pounds of thrust at sea level (PAO, 2015).

Figure 1. TF33 Engine (Pratt & Whitney, 2020)

E-3 AWACS as shown in Figure 2 provides surveillance in the sky for the USAF and its allies (NATO, 2021). The E-3 can "detect, track, identify and report potentially hostile aircraft operating at low altitudes, as well as provide fighter control of allied aircraft" (NATO, 2021). The E-3 carries a four-man flight crew in addition to 13-18 specialists depending on the mission and can reach a max speed of 530 miles per hour (Boeing, 2021). The aircraft is most known for its dome attached towards the end of the aircraft that has radars (both passive and radar detection) to provide vital information of aircrafts and naval ships below it to identify friend or foe for the situational awareness of pilots protecting a specific air space (PAO, 2015).

Figure 2. E-3 AWACS Aircraft (AF Technology, 2021)

1.1.4 Transitioning from Condition Based Maintenance (CBM) to CBM+

For most of the USAF's existence, the USAF had been operating from a sustainment perspective of "flying to failure" rather than a "flying to forecast" mindset (Mayer, 2020). CBM is centered on the concept of performing maintenance only when there is evidence of a need (DoD, 2008). The CBM concept was essentially fixated on fixing only what was broken, a reactive rather than preventative maintenance approach. As the world, businesses, technologies, and our adversaries continue to advance, there becomes a growing need to sustain the warfighter even longer and even more efficient to uphold the many goals outlined in the National Defense Strategy (DoD, 2008). Thus, in 2007, the Department of Defense implemented the CBM+ initiative that focuses on performing maintenance based on the evidence of need, of not only reactive but also proactive maintenance tasks, which is provided via Reliability Centered Maintenance (RCM) analysis along with other supporting processes and technology (DoD, 2008).

RCM is a logical decision process in which the analysis tool identifies the most applicable and effective maintenance task or other logical action such as establishing new inspection requirements through data analysis, field input, operational experience, or modifications (OUSD A&S, 2014). Data analysis would involve information such as predicted failure rates, failure modes and effects, equipment performance from similar weapon systems (if it is a new system), maintenance performance data, and materiel deficiency reporting (OUSD A&S, 2014). In its simplest term, RCM defines what must be done to a system to achieve the desired levels of safety, reliability, environmental soundness, and operational readiness at the best cost. RCM establishes the evidence of need for both reactive and proactive maintenance tasks for the CBM+ initiative to then apply and integrate the processes, technologies, and knowledge-based capabilities to improve the reliability and maintenance effectiveness of DoD systems and components (DoD Instruction 4151.22, 2020).

CBM is still encompassed within the CBM+ initiative as there is always a need to perform reactive maintenance. Figure 3 shows that, at the CBM+ core, CBM and RCM are needed to identify and perform the reactive and preventative maintenance needed to support the warfighter mission. CBM+ built upon RCM and CBM to enhance safety, increase maintenance efficiency, and ensure environmental integrity to achieve the ultimate goals of increasing system availability and decreasing costs throughout the life cycle (OUSD A&S, 2014).

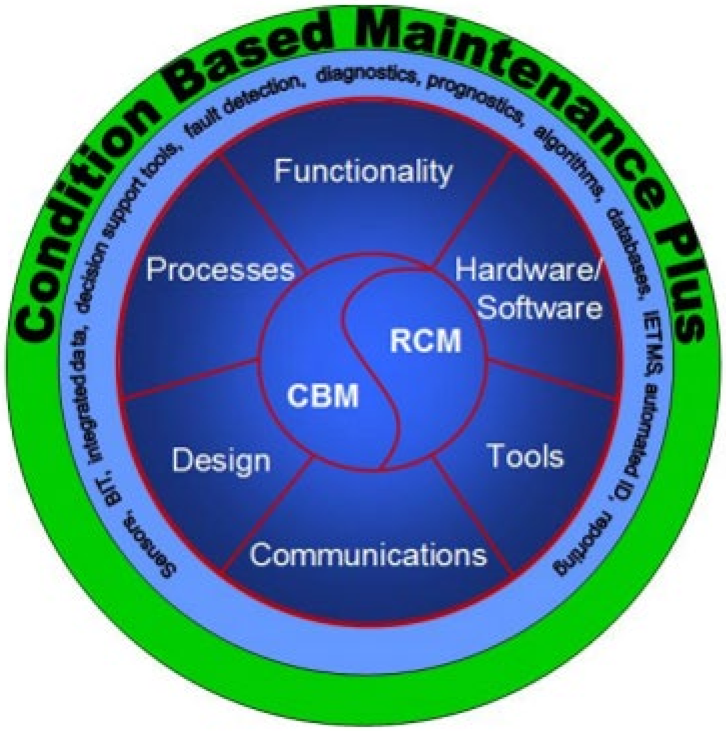


Figure 3. CBM+ Overview (OUSD A&S, 2014)

1.2 Problem Statement

Engines are constructed and established with designated/scheduled maintenance intervals and with the expectation that engines should remain operational until it is time to come in for scheduled maintenance, yet some will fail, even multiple times, before their scheduled maintenance interval due to oil issues. There is a growing need to prevent the number of UERs occurring as the push for AA continues, yet no studies have been done to predict engine failures due to oil issues or to identify factors that could contribute to oil issues and early failures. Addressing this gap allows for the opportunity to gain insights as to what factors help predict the remaining life of the engine before an oil issue occurs to prevent as many in-flight emergencies as possible that would result in grounded aircrafts.

1.3 Research Purpose

The purpose of this research is to implement a survival model, namely the Weibull Accelerated Failure Time Model, to predict the remaining life of the engines before it fails due to another oil issue. If a reliable model can be established with significant variables to predict the remaining useful life of the engine, pilots, maintainers, engine shops, and engine System Program Offices (SPO) can be better equipped and prepared to handle an oil related engine repair, making something that has once been unpredictable predictable.

1.4 Research Questions

Research Question 1: What covariates are significant in predicting engine failures due to oil issues?

Research Question 2: What is the engine's survival time at given operating hours?

1.5 Research Hypotheses

Hypothesis 1: The Total Operating Hours will affect engine failures.

Hypothesis 2: The Location of Engines will affect engine failures.

Hypothesis 3: The Time on Wing will affect engine failures.

Hypothesis 4: The Number of Sorties Flown will affect engine failures.

1.6 Methodology

Survival analysis will be used since the measure of interest is time until failure. Rossello and Gonzalez-Del-Hoyo (2021) argue that survival analysis is appropriate when there is interest in measuring time until the occurrence of an event. A parametric survival function will predict an engine's time until next failure, or survival time. Three types of survival methods will be employed: non-parametric, semi-parametric, and parametric. First, the Nelson estimate is a non-parametric approach, which will provide the cumulative hazard rate for recurrent events. The cumulative hazard rate is an estimate of the expected number of events for a unit that has been observed for a given amount of time (Therneau, 2021). Second, the Cox Proportional Hazards Model (PH Model) is a semi-parametric approach that allows evaluating hazards without having to choose an underlying probability distribution. It will also assess the frailty that determines if failures are independent of one another. Lastly, an accelerated failure time model with a Weibull probability distribution will be used for predicting survival time with significant covariates. Ahsan et al. (2019) analyzed different types of survival distributions and found the Weibull distribution was better than other probability distributions for predicting survival time.

The data used in this research was provided by the CEMS office and Equipment Specialists (ES) working on the TF33 Integrated Product Team (IPT) located at Tinker AFB. After data refinement, there were a total of 226 observations from calendar years 2007 through 2021. Of the 226 observations, there were 81 unique engine serial numbers. The difference between observations and unique engine serial numbers indicate there are engines with repeat failures and censored cases over the observation period.

1.7 Assumptions and Limitations

This study assumes that time-to-failure data follow a specific probability distribution for a parametric or accelerated failure time model. Time-to-failure data will be fitted to various probability distributions before specifying the parametric model. The major limitation of this study is collecting data for 81 out of 162 engines due to the change of the old database for the engines to CEMS. However, because these 81 engines are all engines available during the observation period, we are sure that the data set on the engines is unbiased.

1.8 Contributions

This study is a novel application of survival analysis to military jet engines. The results of this study will help the USAF implement CBM+ efficiently and effectively for maintaining TF33 engines. In addition, the framework used by this study can be expanded to other engines and components, which are managed under CBM+ and other programs. Maintainers and mission planners will get direct benefits from this study while logisticians are able to improve the accuracy of demand forecasts.

1.9 Thesis Overview

Following Chapter I, Chapter II provides an overview of previous research done in survival analysis in the aerospace, automobile, and medical sectors. Gaps are identified to show the lack of research on engine failures using a parametric accelerated-failure time model. Chapter III goes in depth of the three types of survival analysis used by this study. Chapter IV discusses the results with three types of survival analysis. Lastly, Chapter V concludes this study by discussing results on the research questions and hypotheses along with contributions, limitations, and future directions.

II. Literature Review

2.1 Chapter Overview

The purpose of this chapter is to review applications of survival analysis in the engineering and medical sectors. Majority of the studies relating to aircraft or engines used the Cox PH Model. Regarding aircrafts and/or engines, most survival analyses completed had the primary goal of finding covariates that were significant to use within the model. Survival models completed in the medical realm tended to focus on finding the most appropriate survival model to implement as there were a multitude of significant factors that had been identified to use within their models.

2.2 Survival Analysis

Survival analysis is the study of survival time and the factors that influence survival time (Kim and Bae, 2020). Essentially researchers are concerned with how long it takes for an event of interest such as a failure to occur and how the time until failure can be most accurately predicted (Mills, 2011: 1). The event of interest in the medical sector is typically death. An example of survival analysis is understanding how a cancer patient's age, gender, stage of cancer, previous remissions, and other explanatory variables impact their chances of survival as time continues. In the case of the TF33-100A engine, the event of interest is engine failure caused by an oil issue. A unique feature of survival analysis on engines is that engines can have recurrent failures whereas human subjects, can't have recurrent deaths. There are three main types of modeling techniques that can be used for survival analysis. First, non-parametric models can be used when there is no assumption on the probability distribution. Non-parametric models are typically used in preliminary analysis and cannot incorporate multiple covariates (Mills, 2011: 11). Examples of non-parametric models are life table estimates, the Kaplan-Meier estimator, and the Nelson estimator. Second, semi-parametric models can be used when there is no assumption about the shape of the hazard function. Unlike non-parametric models, researchers can use multiple covariates. Because these models are a part of the proportional hazard's family, there are strong assumptions on proportional hazards that should be tested (Mills, 2011: 11-14). Examples of semi-parametric models are Cox PH Models, which are the most popular and piecewise constant exponential models. Third, parametric models can be used when assumptions are made about the baseline probability distributions and how covariates could affect the functions. Deciding the shape ahead of time determines what type of a parametric model the researcher will use (Mills, 2011, 14-15). Once the shape is assumed, the researcher can select a PH model or an accelerated failure time (AFT) model. Examples of probability distributions used for parametric models are Weibull, exponential, Gamma, and Gompertz.

2.3 Relevant Research in the Aerospace Industry

Zaretsky et al. (2004) applied Weibull based models to conduct a reliability and life analysis on the NASA (National Aeronautics and Space Administration) energy efficient engine. Their goal was to investigate individual component's life distribution using various slopes for the Weibull and its subsequent effect on engine life prediction. Failure was determined on an engine if it met any of the six conditions: stress rupture, creep, yield, low-cycle fatigue, high-cycle fatigue or fracture mechanics. They assumed that each component's cumulative life distribution was represented by a Weibull distribution to determine a 95-99 percent confidence interval for the probability of survival of the entire engine in addition to the original equipment manufacturer's life calculations. They identified a common error in life prediction that they saw in other aerospace and non-aerospace scenarios. They found a misassumption that the life prediction of a combination of the same components within the system was the same as the lowest lived component within the system. However, they concluded that the system's life was lower than the lowest lived component within the system at a given reliability due to the probability of survival.

Jardine et al. (1987) applied a Weibull proportional hazards model to aircraft and marine engine failure data to determine the suitability of the model with engine failure data. They showed that proportional hazard models were frequently used in the medical sector, but not that frequently in the engineering sector. Regarding aircraft engine failure data, they found that the Weibull proportional hazards model was a good fit and acknowledged the metal particle level in engine oil as well as the environment of the engine were factors that influence an engine's failure time. They worked with the spectrometric oil analysis program (SOAP) analysts to collect data. According to their study, four metals: iron, chromium, copper, and magnesium were observed by SOAP analysts, and iron was determined to be of slight significance in the model. They found that flight hours since the last oil change was not significant and that there was not a higher level of metal particles soon after an oil change. Regarding marine gas turbine engine failure data, they analyzed six variables that could influence failures such as monthly starts and monthly hours, hours since last overhaul, ship identification codes where two covariates were used such as position in ship: 0 for port and 1 for starboard, and number of previous overhauls. They found number of previous overhauls was the only covariate not significant in the model, and, like the aircraft engine data, a Weibull proportional hazards model fit the data well.

Mukherjee et al. (2014) used predictive analysis of engine health for decision support in aircraft monitoring. They used data mining and time series graphs rather than a proportional hazards model or accelerated failure time model. They used four variables in their model based on how each associated parameter controlled the behavior of the engine. Among the four variables vibration, noise, carbon dioxide level, and temperature, the most significant variable was vibration. They predicted engine status using these four variables and provided preventative maintenance suggestions. In aircraft systems, they suggested using a piezoelectric accelerometer along with electronic processes technology for vibration analysis to store vibration data. They argued that the tools mentioned would help ground crew prevent excessive vibration without needing to run the engine on the ground.

Ahsan et al. (2019) conducted a reliability and survival analysis of gas turbine engines via a bathtub-shaped failure rate distribution, which used a Weibull distribution. Their goal was to find a failure rate distribution that allowed analysts to account for varying operating conditions for marine, power generation, and propulsion to accurately define maintenance intervals for gas turbine engines in support of RCM. The Weibull distribution was used as it was more appropriate to define failures. Djeddi et al. (2016) and Hungund et al. (2014) also asserted a Weibull distribution was most appropriate to conduct reliability analysis based on failure rate data of turbine engines. They concluded an increase in maintenance intervals resulted in a decline in mean time to failure. However, it would also result in preventative maintenance costs to rise.

Rakers (2012) conducted a case study to understand the influence of sustainment contract types such as time and material contracts versus outcome-based contracts on engine reliability using ordinary least square (OLS) regression, Weibull, and Cox models. The difference between OLS regression and survival analysis was that OLS did not include engines without any unscheduled repairs whereas survival models added information about timing, which made it possible to account for censoring. In addition, survival models analyzed the time to an event and included time-varying covariates while OLS did not (Mills, 2011: 11). He found that outcome-based contracts in the defense aero engine aftermarket decreased product reliability compared to time and material contracts. However, the influence of contract type on product reliability was smaller in the defense sector compared to the civil sector. He also found that outcome-based contracts did not help increase maintenance predictability compared to time and material contracts. In the OLS regression model, a contract type was significant for mean time between unscheduled events and inversion failure rate only. The regression model was able to measure a -10 to -18 percent change in engines that operated with outcome-based contracts compared to time and material contracts. This indicated there were more frequent unscheduled repairs. In the Weibull and Cox models, contract types, engine average flying hours per day, flying hours at the start of observation period, and customer fleet size were significant variables in both the Cox and Weibull models. He acknowledged the Cox model was sufficiently accurate though the accuracy was strengthened using the Weibull.

Thijssens and Verhagen (2020) conducted an extended Cox regression to time-on-wing data of Boeing 737 repairable parts. They chose the Cox regression model and included time-dependent variables as predictors. They found four significant factors to predict time-on-wing duration of components: the natural environment at the hub airport, maintenance history of components, age of aircraft on which the component is installed, and different modification designs. They argued the reliability of the display and air data inertial reference units tended to be better at hubs with a hot desert climate with the assertion that low humidity areas could "positively affect" degradation. They confirmed the display unit component had an issue where five different modification designs failed to meet the proportional hazards assumption, thus, had to implement stratification to the variable to satisfy the assumption. This was an issue that was prevalent when trying to use the PH model.

Verhagen and De Boer (2018) conducted a study regarding predictive maintenance for aircraft components using PH Models. They stressed the importance of preventative maintenance as opposed to reactive maintenance in reducing the number of unscheduled component failures and costs spent on unscheduled repairs. Longitudinal acceleration, mean ambient pressure, maximum roll rate, and commanded rudder force were significant variables to predict time until failures. When they compared the predicted failures to historical failures for all models, the time-independent PH Models had the better goodness-of-fit though the maximum likelihood estimation (MLE) value was better for the time-dependent PH Models. To achieve a reduction in failures, they adjusted scheduled maintenance intervals and used the predicted values of the covariates to assess the probability of failure over a specified time. In terms of weaknesses and limitations to this study, they should have used a separate set of maintenance data to validate their reliability forecast to measure the usefulness of the models for failures predicted/prevented and costs saved.

2.4 Relevant Research in the Automobile Industry

Wang et al. (2018) conducted reliability and survival analysis for automobile engines using conditional inference trees. They acknowledged the extensive use of the PH Models for reliability modeling. However, they argued that the lack of interpretability of PH Models hindered the ability to provide straightforward recommendations to car business owners. The conditional inference trees provided easily interpretable results to provide recommendations to fleet managers and their maintenance personnel. Six covariates were used in their survival model which were vehicle age in years, cumulative miles, average miles per year, job intensity between repair dates, and number of repairs. They found that vehicle age, number of repairs, cumulative miles, and job intensity were significant covariates impacting the reliability of automobile engines. They wanted to include drivers' behavior, operational information, geographical information, and environmental information since they felt it would strengthen the model however that data was not readily available.

2.5 Relevant Research in the Medical Sector

Research implementing the Weibull Accelerated Failure Time Model in the aircraft industry is scarce however there have been studies regarding the model in the medical field. Moghimi-Dehkordi et al. (2008) conducted a study that showed the statistical comparison of survival models relating to stomach cancer patients. In addition to Efron (1977), Oakes (1977), and Lawless (2005), they found that the Cox PH Model was the most popular survival analysis technique because it required less assumptions. They all agreed that while there were less assumptions needed for the model, it was often hard to satisfy the proportional hazards assumption where the hazard ratio was constant over time between two sets of covariates. Parametric models were more efficient to use, but it required more stringent assumptions for baseline probability distributions (Moghimi-Dehkordi et al., 2008). They determined if the assumptions to use a parametric model were met, then the analysis would be more powerful. They used the Akaike Information Criterion (AIC) as a measure of goodness of fit to compare amongst four models. The Weibull AFT model was the most favorable model for multivariate survival analysis. The Cox PH Model had the least favorable fit. They found that even though the Cox PH Model was the most common survival model to use in clinical research, parametric models such as those used in their study proved to be a better model of choice if all assumptions were met, which also agreed with the conclusion made by Zare et al. (2015). They determined parametric models had the advantage of measuring how the explanatory variables affected survival time which allowed for easier interpretation of the results rather than focusing on a conditional probability for the Cox PH Model.

Swindell (2009) conducted a study on how accelerated failure time models provided a useful statistical framework for aging research. He collected data from 16 survivorship experiments of mice and tried to find the effects of one or more genetic manipulations on a mouse's lifespan. He noted that accelerated failure time models had an advantage of displaying a deceleration factor, which showed an increase in the expected waiting time until failure (Mills, 2011: 117; Swindell, 2009). The deceleration factor characterized the multiplicative effect on survivorship well, which was a more meaningful measure than the hazard ratio. After comparing AIC results, he concluded that the model with a Weibull distribution was the best in almost every experiment for predicting time until failure. Swindell (2009) highlighted the importance of the deceleration factor.

2.6 Summary

This chapter reviewed studies using survival analysis in the engineering and medical sector. The Weibull accelerated failure time model was rarely used in the engineering area. There was also no research conducted on engine failures due to oil issues with a focus on survival analysis. Thus, there was inclusion of studies using other survival analysis methods on engines, human, and animal subjects. The Cox PH Model was a popular model on aircraft and engine analysis due to the model's restrictive assumption on baseline probability distribution. However the studies in the medical field found that parametric models, for example, survival models with a Weibull probability distribution, were better than other survival models when they were compared with AICs. The next chapter discusses survival models used for engine failures due to oil issues.

III. Methodology

3.1 Chapter Overview

The purpose of this chapter is to describe the methodology that will be used to analyze engine failures due to oil issues. Survival analysis will be used because the measure of interest is time until failure. Non-parametric, semi-parametric, and parametric models will be used. The chapter concludes with a discussion on data collection and covariates used.

3.2 Survival Models

As briefly stated in Chapter Two, there are three types of survival analysis. Non-parametric models make no assumptions on the shape of the hazard function nor how covariates affect the shape (Mills, 2011: 12). The most prominent non-parametric model is the KM estimator for single events, and Nelson estimator for recurrent events. Semi-parametric models make no assumption on the shape of the hazard function, however, these models do make an assumption on how the covariates affect the shape and assume that there is a proportional hazard between covariates over time (Mills, 2011: 12). The Cox PH Model is the most well-known semi-parametric model although the piecewise constant exponential model can be used for similar problems. Parametric models assume a shape of the hazard function and how the covariates affect the shape. A parametric model is used for understanding effects of time on covariates and the nature of time dependence (Mills, 2011: 12). Parametric models can be used with AFT or PH. A parametric PH Model assumes that covariates have a multiplicative effect on the hazard function, whereas a parametric AFT model assumes the covariates have a linear effect on the natural logarithm of the survival function (Mills, 2011: 116). There are differences in interpretation of the parameter estimates between PH and AFT models. PH Models are used for estimating hazards, whereas AFT models are used for predicting survival time (Mills, 2011: 129). This study attempts to predict survival time for engines that have failed due to oil issues. Accordingly, AFT models with Weibull, log-normal, and log-logistic probability distributions will be tested.

3.2.1 Non-Parametric Model

The Nelson estimator is a general starting point for conducting survival analysis for recurrent events as this non-parametric model can provide a visual representation of the cumulative hazard function (Therneau, 2021: 15; Nelson, 1969 and 1972). This study will use the Nelson estimator for analyzing recurrent engine failures. The Nelson estimator provides plots for cumulative hazard rates, which can be used for understanding failures. Disadvantages of the Nelson estimator include its inability to include continuous covariates and multiple categorical covariates (Mills, 2011: 12). The Nelson estimator serves the purpose of estimating the expected number of failures for an engine that has been observed for a given time. The formula of the Nelson cumulative hazard rate function is as follows:

$$\hat{A}(t) = \widehat{\sum_{t_j \leq t} \frac{d_j}{r_j}} \tag{1}$$

In equation (1), the cumulative hazard function is denoted as $\hat{A}(t)$, where d_j represents the number of individuals (i.e., engines) that fail at time t_j, and r_j represents the number of individuals at risk just prior to time t_j. The cumulative hazard function is based on the notion that the estimator is an increasing right-continuous step function with increments d_j/r_j at the observed failure times (Nelson, 1969 and 1972). The cumulative hazard rates can be plotted using the Nelson curve that shows the cumulative hazard rates over time.

3.2.2 Semi-Parametric Model

The Cox PH Model is one of the most well-known types of survival models due to six attractive features (Mills, 2011: 91). First, it is a semi-parametric model that doesn't need to choose a baseline probability distribution. Second, this model also tends to be a popular choice because of its ability to fit data well. Third, although the Cox PH Model contains an unspecified baseline hazard function, this model can still generate parameter estimates that confirm the effects of multiple covariates. Fourth, this model ensures hazards are always non-negative due to the exponential component because the hazard function is between zero and infinity. Fifth, the data can include survival times of censored cases in the likelihood estimator, where there is information regarding an individual's survival time, but the exact time is unknown. Sixth, the Cox PH Model can incorporate time-varying covariates, an important aspect in survival analysis. The equation for the Cox PH Model that incorporates time-varying covariates is as follows:

$$h_i(t) = h_0(t)\ exp\{\beta_1 x_{i1} + \beta_2 x_{i2}(t) \dots + \beta_k x_{ik}\} \quad (2)$$

In the equation (2), the hazard, h, for an individual or engine i at time t is the product of the baseline hazard function that is unspecified, $h_0(t)$, and the exponential set of covariates, x. Covariates can be fixed, e.g., x_{i1} or time dependent, e.g., $x_{i2}(t)$. There is no constant, β_0, as it is included in $h_0(t)$. From this equation, a hazard ratio is developed for each covariate. If the ratio is greater than one, the corresponding covariate will increase the risk of the event. If the ratio is less than one, the covariate will decrease the risk of the event. If the ratio is one, the covariate will have no effect on the risk of event. This model is known as a proportional hazards model because the hazard for any individual of interest, i.e., engines, is proportionally fixed for the hazard of other individuals (Mills, 2011: 88). Because the Cox PH Model assumes that the hazard ratio is constant and parallel over time between two covariates, the violation of the assumption should be tested after running the model (Moghimi-Dehkordi et al., 2008; Efron 1977; Oakes, 1977; Mills, 2011: 88). Cox PH Models with frailty are used for testing the independence of events. This study will include a PH Model with frailty to check the independence of engine failures. When running the Cox PH Model, this study will employ two types of time indicators such as flight hours and sorties flown. For evaluating two time indicators, concordance, log likelihood, and AIC measures along with analysis of variance (ANOVA) will be used.

3.2.3 Parametric AFT Models

Because a parametric model assumes a specific baseline probability distribution and estimates survival time, it is different from non-parametric and semi-parametric models that have no assumption on the baseline probability distribution and estimate hazard ratios. Because the goal of this study is estimating survival time, AFT models will be used for analyzing engine failures due to oil issues. If a covariate has a coefficient of greater than one, its effect is positive on survival time. If a covariate has a coefficient of less than one, its effect is negative on survival time. AFT models will also generate scale. If the scale is below one, failures are increasing at a decelerating rate. If the scale is above one, failures are increasing at an increasing rate. The equation for AFT models is as follows:

$$\ln t_j = \boldsymbol{x}_j \boldsymbol{\beta} + z_j \tag{3}$$

In Equation (3), survival time is expressed as the natural logarithm, $ln\ t_j$, and contains a linear function, where a vector of covariates is denoted as $\boldsymbol{x}_j$, the vector regression coefficients are denoted as $\boldsymbol{\beta}$, and the error that assumes a density function as z_j. The distribution form of the density function determines the shape of the model. The different types of probability distributions that will be explored to fit survival time are Weibull, log-normal, and log-logistic distributions. The parametric model with a specified probability distribution is estimated by using a maximum likelihood estimation. Once the survival time has been fitted to a distribution, there will be an assessment of the overall goodness-of-fit for models with different probability distributions using the AIC to determine which distribution best fits the data. For different types of time indicators, models will be also evaluated using AIC.

The validity of models will be assessed using log-likelihood results. If a log-likelihood result of a full model is smaller than that of the null model, the full model is better than the null model.

3.3 Data Collection

The data for this study was provided by the CEMS office at Tinker AFB. CEMS is a USAF database system that pulls raw data from the Integrated Maintenance Data System (IMDS) that is inputted by maintainers once a flight is completed (Stephens, 2020). The data set included 81 unique TF33-PW-100A engines with 226 observations from quarter one of 2007 through quarter three of 2021, which was pulled on 6 December 2021.

3.4 Covariates

There are four covariates in the models for determining the effects of the covariates on engine failures due to oil issues. Because the E-3 AWACS orbit the sky to provide services as a mobile air traffic control tower, there could be numerous factors contributing to engine failures due to oil issues. Since oil leaks can occur throughout different compartments of the engine, these issues are not necessarily concentrated in one component. For example, oil could leak from a broken seal in the O-ring, a tailpipe, a gearbox tower shaft, a gearbox breather, a fan case, a carbon seal, a bearing unit, a fuel control mount pad, a power take off shaft, etc. Upon further inspection by the maintenance crew either at the depot or a deployed location, repairs are completed by replacing a part or resealing the area of concern. Other oil related issues include high or low oil consumption, high or low oil pressure, contaminated oil, dirty/contaminated/saturated oil due to foreign material, and adverse oil consumption trend.

This study considers two types of time indicators and two covariates. Two time indicators are Time on Wing and Sorties on Wing. Two covariates are Total Operating Hours and Locations of Engines. Time on Wing (TOW) denotes the number of hours an engine has been on the aircraft before being removed due to an issue or scheduled overhaul. Sorties on Wing (SOW) denotes the number of sorties an engine has been on the aircraft before being removed for repair or scheduled overhaul. Total Operating Hours denotes the total number of hours the engine has been in service for since production, which indicates the age of an engine. Location of Engines will be binary. If the engine is located in the 552nd Flying Squadron at Tinker AFB, Location of Engines takes one. If the engine is not located in the 552nd Flying Squadron at Tinker AFB, Location of Engine takes zero.

3.5 Fitting Survival Time to Probability Distributions

Survival time will be fitted to the three different probability distributions. TOW and SOW will be fitted to the probability distributions separately. Survival time will fitted to probability distributions using R and R packages (R Core Team, 2020).

3.6 Summary

This chapter described the methodology that is planned to be used for the analysis of engine failures due to oil issues. The non-parametric survival model was described, namely the Nelson estimate. The semi-parametric survival model included the Cox PH Model with frailty. The parametric section described the importance of using a probability distribution beforehand to fit the survival data and discussed the different models that could be used. The survival models with Weibull, log normal, and log logistic models will be compared to determine the best fit parametric model to predict failures. It was also discussed that an accelerated failure time model will be used to focus on comparing survival times of engine failures due to oil issues rather than comparing hazards. Lastly, it was discussed that the data was collected via CEMS and that the covariates to be analyzed were total time and location as the main covariates with TOW and SOW being compared against one another as the survival time indicator. The next chapter focuses on the analysis and results from the non-parametric, semi-parametric, and parametric models.

IV. Results and Discussion

4.1 Chapter Overview

The purpose of this chapter is to discuss the results from the non-parametric, semi-parametric, and parametric models. Discussed first is the number of failures that occurred as well as summary statistics of the data, which will focus on the Total Operating Hours of the Engine or Total Time, TOW, and SOW. Second, a Nelson analysis is conducted to report the risk of an oil related failure using TOW and SOW. Third, a Cox PH Model with frailty is analyzed featuring the various covariates used to then report the model strength by interchanging TOW and SOW in addition to comparing the model strength when taking the natural logarithm of the Total Time covariate. Fourth, TOW and SOW are fitted as the survival time indicator and the results of which parametric model between Weibull, log normal, and log logistic is the best fitting model based on the AIC are discussed. Then, results of the chosen parametric model are discussed, again using TOW and SOW to show a full model comparison of using different survival times. Upon selecting the best fit model, Chapter Four concludes with a discussion of the predicted engine survival time based on the covariates used.

4.2 Transitions and Summary Statistics

The first subject analyzed is the number of oil related failures that occurred within the number of observations. There were 226 total observations, 81 of which were unique identifiers which indicates engine serial numbers with repeat failures. Table 1 shows how many engines transitioned from either no oil related failures to one oil related failure, no oil related failures to censored observations, one oil related failure to another oil related failure, and one oil related failure to censored observations. A censored observation occurs when a failure is not reported either because a failure did not occur at all, or a failure did not occur within the period of observation (2007-2021).

Table 1. Oil Transitions Table

	1	Censored
0	41	40
1	21	37

41 engines experienced an oil related failure after not having a reported oil related failure prior to the event. 40 engines experienced either no oil related failure or were censored observations during the period of observation. 21 engines experienced an oil related failure back-to-back. 37 engines experienced either no oil related failure or were censored observations during the period of observation after having a reported oil failure prior to the event.

In addition to a transitions table capturing non-events to events like Table 1, Table 2 shows transitions to each state where it depicts how many oil related failures a unique engine experienced within the period of observation. The below table considers only engines that have failed due to an oil related issued.

Table 2. Oil Transitions Table to Each State

State	0	1	2	3	4
1	40	24	14	2	1

40 engines did not experience an oil related failure within the period of observation. 24 engines experienced an oil related failure only one time within the period of observation. 14 engines experienced an oil related failure twice within the period of observation. Two engines experienced an oil related failure three times within the period of observation.

Lastly, one engine experienced an oil related failure four times within the period of observation.

Next, the summary statistics were computed for the covariates and the below information was displayed in Table 3. The minimum total time captured for an engine was 12,326 hours whereas the maximum total time captured for an engine was 39,098 hours with a median total time of 22,890 hours.

TOW varied greatly between 2.4 hours and 7,322 hours. An engine can be pulled after a short duration on the wing if the aircrew notes an immediate problem in flight and grounds the plane for the engine to be inspected further. If the maintainers confirm a problem, that engine is subsequently pulled off the aircraft and the TOW duration is logged. It is important to note that TF33-PW-100A engines are typically pulled from the aircraft when the engine approaches 6,000 hours as this is the time indicator for an overhaul. However, if an engine is reported as not having any issues or surpasses 6,000 hours during a flight mission, the aircrew and maintainers can submit paperwork to leave the engine on past the 6,000-hour threshold. Though the maximum time recorded within the observational period is 7,322 hours, the median TOW is 1,231.7 hours.

Regarding total sorties flown, the minimum value was 2,559 total cycles with a maximum value of 13,290 total cycles and a median value of 5,546 total cycles. The SOW had a minimum of 2 cycles, maximum of 1,826 cycles and median of 335.5 cycles. When an aircraft takes off and lands, it is considered as one cycle. If an aircrew is performing "touch and go's" which is when the aircraft lands briefly and immediately takes off without coming to a complete stop, that is considered one half of a cycle. One reason SOW can have a minimum value of 2 cycles is if the aircrew notices an issue upon take off, during the flight, or on landing and provides the maintenance crew with their input which then leads to the maintenance crew evaluating the engine and removing the engine from the wing if an issue is spotted.

Lastly, the natural logarithm of the total time was taken to see if subsequent models to be ran would have a stronger fit. By taking the natural logarithm of the total time, it limits the variability of the data, making numbers smaller, thus, making it easier to interpret and understand the regression coefficients within each model by magnifying those respective values. Taking the natural logarithm of the total time can also point out non-normal data if they are present in the model. When taking the natural logarithm of total time, the values are more compressed than the original total time inputs, with a minimum value of 9.42, maximum value of 10.57, and median value of 10.04. Table 3 shows summary statistics of variables.

Table 3. Summary Statistics of Variables

	Total Time (hrs)	Time on Wing (hrs)	Total Sorties (cycles)	Sorties on Wing (cycles)	Natural Log Total Time
Minimum	12,326	2.4	2,559	2.0	9.420
1st Quartile	19,787	464.6	4,705	116.2	9.893
Median	22,890	1,231.7	5,546	335.5	10.040
Mean	24,363	1,868.5	6,632	454.4	10.069
3rd Quartile	28,086	3,072.7	8,840	722.8	10.240
Maximum	39,098	7,322.0	13,290	1,826.0	10.570

4.3 Non-Parametric Analysis - Nelson Estimate

A Nelson analysis was tried using the two different survival time indicators such as TOW and SOW. Two different survival time indicators were used to see how an engine’s hazard changes with time in relation to how much TOW it has versus how many SOW it has. Four plots will be displayed, two under each survival time. Under TOW, a Nelson plot is computed to show how the risk of failure changes with time and a Nelson plot with the inclusion of the location covariate is used to show how the risk of failure differs at a given location. Under SOW, the same approach is taken where two plots are computed. Figure 6 will show how the risk of failure changes with number of sorties flown and the other plot will show how the risk of failure changes with number of sorties flown at different locations.

4.3.1 Using Time on Wing as Survival Time

When using TOW as the survival time indicator in the Nelson model, two plots are computed. Figure 4 is a graphical depiction of an engine’s cumulative hazard rates with TOW as the survival time indicator along with the 95 percent confidence intervals. As the engine’s TOW gradually increases, cumulative hazard rates increase. Figure 5 is a graphical depiction of how an engine’s cumulative hazard rates change at a given location. As the engine’s TOW gradually increases, cumulative hazard rates for engines located at Tinker AFB within the 552nd Flying Squadron is higher than those of engines located at else. However, since the confidence intervals for location are mostly overlapping, it indicates no significant difference between locations.

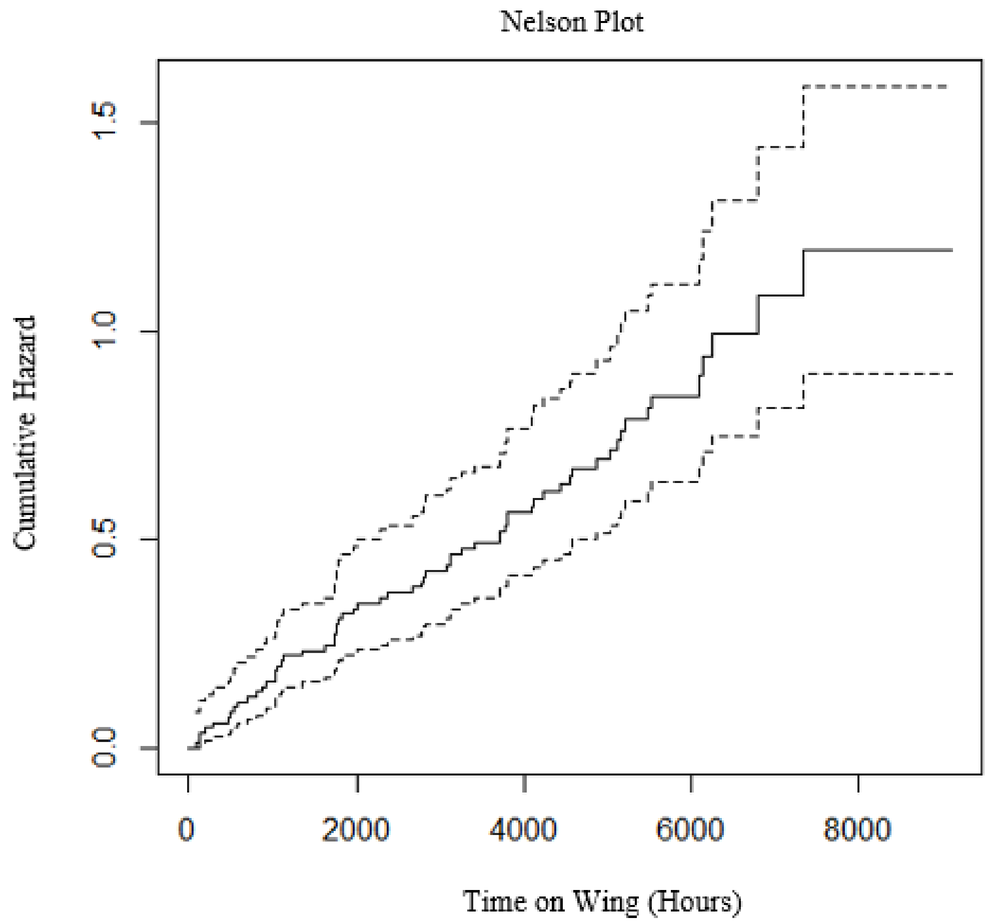


Figure 4. Survival Plot Using TOW

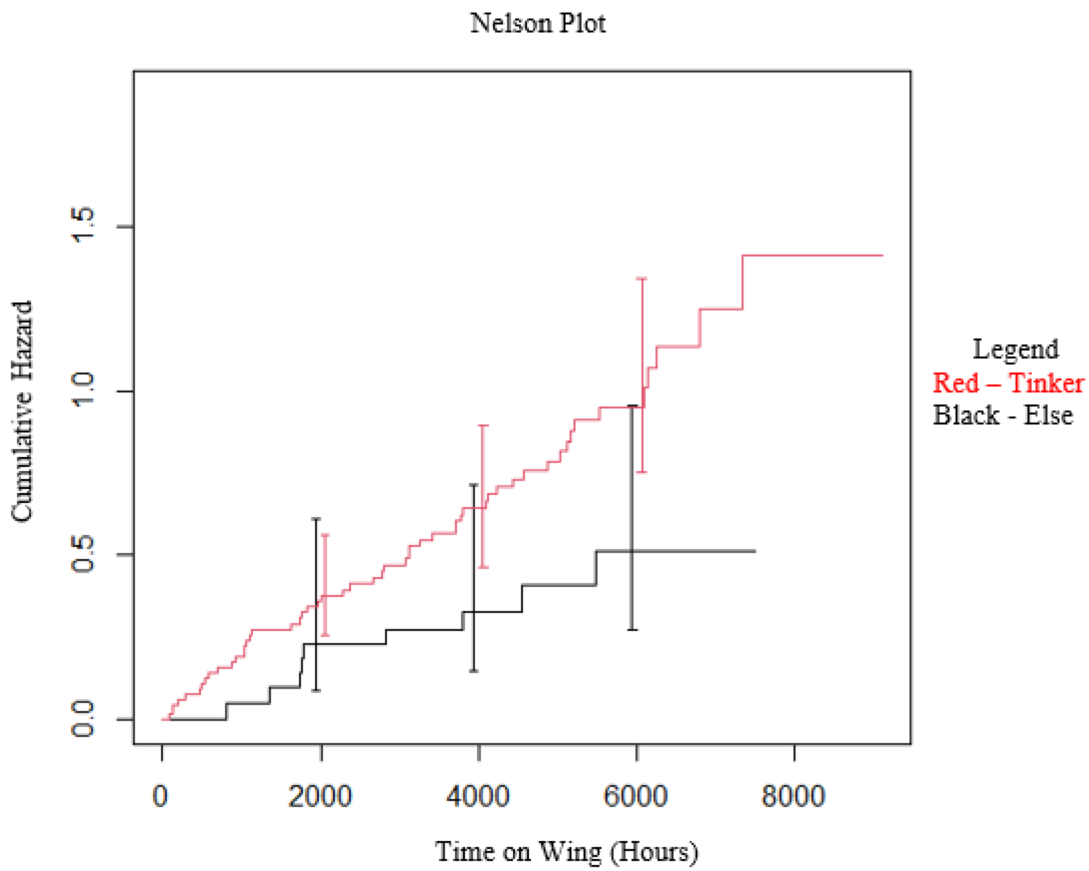


Figure 5. Survival Plot Using TOW Based on Location

4.3.2 Using Sorties on Wing as Survival Time

When using SOW as the survival time indicator in the Nelson model, two plots are computed. Figure 6 is a graphical depiction of an engine's cumulative hazard rates with SOW as the survival time indicator along with the inclusion of the 95 percent confidence intervals. As the engine's SOW gradually increases, cumulative hazard rates increase. Figure 7 is a graphical depiction of how an engine's cumulative hazard rates change at a given location. As the engine's SOW gradually increases, cumulative hazard rates for engines located at Tinker AFB in the 552nd Flying Squadron is higher than those of engines located at else. However, since the confidence intervals for location are mostly overlapping, it indicates no significant difference between locations.

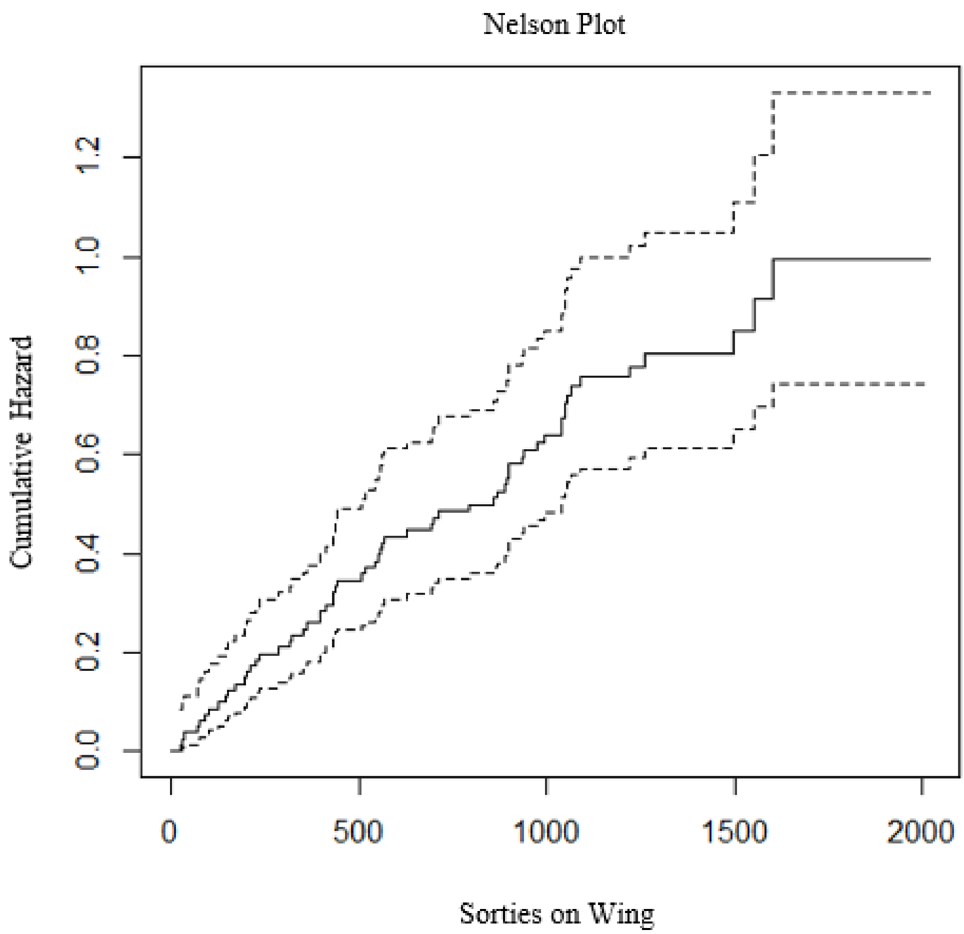


Figure 6. Survival Plot Using SOW

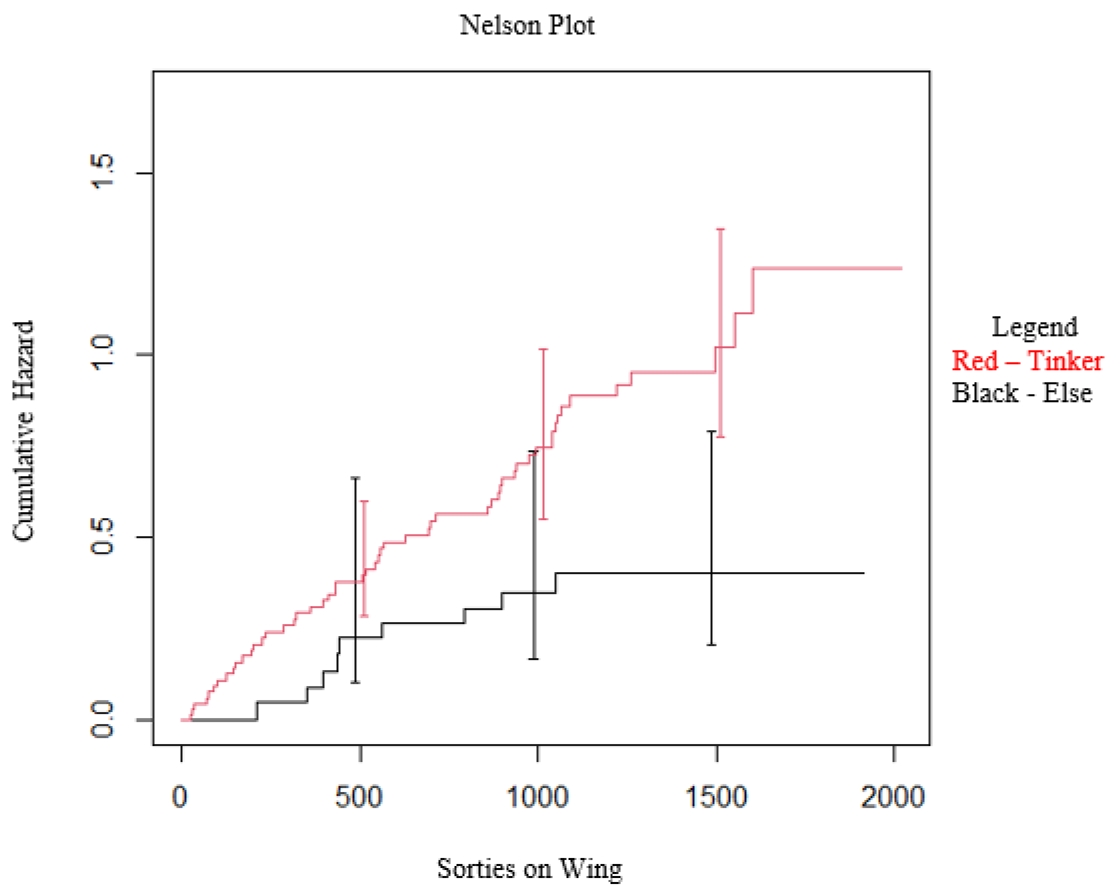


Figure 7. Survival Plot Using SOW Based on Location

4.4 Semi-Parametric Analysis – Cox PH Models with Frailty

A Cox PH Model with frailty analysis was completed to test various Cox PH Models strengths and show how a semi-parametric model differs between parametric models. The two survival time indicators, TOW and SOW were compared in addition to comparing the difference between using the total time covariate and natural logarithm of the total time covariate when both covariates were paired with the location covariate. Section 4.4.1 will address using TOW as the survival indicator while comparing the total time covariate to the natural logarithm covariate. Section 4.4.2 will address using SOW as the survival indicator while comparing the total time covariate to the natural logarithm covariate. Section 4.4.3 will address overall model strength when comparing all four Cox PH Models.

4.4.1 Using Time on Wing as Survival Time Indicator

When using TOW as the survival time indicator and including the total time and location as the covariates, Cox PH Model 1 indicated the total time covariate was not significant at a 0.05 significance level. The location covariate was also not significant at a 0.05 significance level, but it barely missed significance by 0.004. To interpret the covariates in a Cox PH Model, the exponentiated coefficients were examined. The exponentiated coefficients represent the multiplicative effects on the hazard, which is referred to as the hazard or risk ratio. If the hazard ratio is greater than one, the covariate being examined is associated with an increased hazard of having a failure. If the hazard ratio is less than one, the covariate being examined is associated with a decreased hazard of having a failure. If the hazard ratio is equal to one, there is no effect of the covariate on the hazard. Since the total time covariate's exponentiated coefficient is 1.00, there is no association between the covariate and failure. With location having an exponentiated coefficient of 2.038, there is an increased hazard of having a failure for the engines located at Tinker AFB. The frailty measure in the model had a p-value of 0.340, which indicated that failures were independent. The concordance index for Cox PH Model 1 was 0.677 indicating it was considered a significant model. Models must have a concordance of 0.55 or larger to be considered significant. The model also had an associated AIC of 553.415. Table 4 shows coefficient estimates for the covariates.

Table 4. Cox PH Model 1 using TOW and Total Time

Covariate	Beta Coefficient	Exponentiated Coefficient	Standard Error Coefficient	p Value
Total Time	-0.00004222	1.00	0.00002374	0.075
Location	0.7119	2.038	0.3619	0.054
Frailty (ID)	-	-	-	0.340
Concordance: 0.677 (standard error = 0.045)				
AIC: 553.415				

When using TOW as the survival time indicator and including the natural logarithm of total time and location as the covariates, Cox PH Model 2 indicated the natural logarithm of the total time covariate was significant at a 0.05 significance level, while the location covariate was not significant at a 0.05 significance level. Again, Location barely missed significance by 0.002. Since the natural logarithm of total time covariate's exponentiated coefficient is 0.2916, there is a decreased hazard of having a failure. With location having an exponentiated coefficient of 2.0541, there is an increased hazard of having a failure for the engines at Tinker AFB. The frailty of the model had a p-value of 0.330 which indicated that failures were independent. The concordance index of Cox PH Model 2 was 0.677 indicating it was considered a significant model. The model also had an AIC of 552.427. Table 5 shows coefficient estimates for the covariates.

Table 5. Cox PH Model 2 using TOW and Natural Logarithm of Total Time

Covariate	Beta Coefficient	Exponentiated Coefficient	Standard Error Coefficient	p Value
Natural Logarithm of Total Time	-1.2325	0.2916	0.6011	0.040
Location	0.7198	2.0541	0.3703	0.052
Frailty (ID)	-	-	-	0.330
Concordance: 0.677 (standard error = 0.044)				
AIC: 552.427				

4.4.2 Using Sorties on Wing as Survival Time

When using SOW as the survival time indicator and including the total time and location as the covariates, Cox PH Model 3 indicated the total time covariate was not significant at a 0.05 significance level, while the location covariate was significant at a 0.05 significance level. Since the total time covariate's exponentiated coefficient is 1.00, there is no effect of the covariate on hazards. With location having an exponentiated coefficient of 2.449, there is an increased hazard of having a failure. The frailty of the model had a p-value of 0.350, which indicated that failures are independent. The concordance of Cox PH Model 3 was 0.683 indicating it was considered a significant model. The model also had an associated AIC of 570.073. Table 6 presents coefficient estimates for the covariates.

Table 6. Cox PH Model 3 using SOW and Total Time

Covariate	Beta Coefficient	Exponentiated Coefficient	Standard Error Coefficient	p Value
Total Time	-0.00003903	1.000	0.00002342	0.096
Location	0.89560	2.449	0.3689	0.015
Frailty (ID)	-	-	-	0.350
Concordance: 0.683 (standard error = 0.044)				
AIC: 570.073				

When using SOW as the survival time indicator and including the natural logarithm of total time and location as the covariates, Cox PH Model 4 indicated the natural logarithm of the total time covariate was not significant at the 0.05 significance level, while the location covariate was significant at a 0.05 significance level. The natural logarithm of total time barely missed significance by 0.006. Since the natural logarithm of total time covariate's exponentiated coefficient is 0.3221, there is decreased hazard of having a failure. With location having an exponentiated coefficient of 2.4612, there is an increased hazard of having a failure. The frailty of the model had a p-value of 0.340, which indicated that failures are independent. The concordance index of Cox PH Model 4 was 0.684 indicating it is considered a significant model. The model also had an associated AIC of 569.248. Table 7 shows coefficient estimates for the covariates.

Table 7. Cox PH Model 4 using SOW and Natural Logarithm of Total Time

Covariate	Beta Coefficient	Exponentiated Coefficient	Standard Error Coefficient	p Value
Natural Logarithm of Total Time	-1.1328	0.3221	0.5935	0.056
Location	0.9007	2.4612	0.3696	0.015
Frailty (ID)	-	-	-	0.340
Concordance: 0.684 (standard error = 0.044)				
AIC: 569.248				

4.4.3 Comparison of Cox PH Models 1 through 4

After running each Cox PH Model with frailty under the different time indicators and covariate scenarios, a comparison of each model's concordance and AIC was completed to determine which Cox PH Model was the strongest amongst semi-parametric models. Table 8 summarizes each Cox PH Model concordance and associated AIC. In reference to concordance and AIC, a larger value in concordance signifies a stronger model. However, a smaller value in AIC signifies a stronger model. Based on the information calculated in the analysis, Cox PH Model 4 had the highest concordance at 0.684, but the lowest AIC is associated to Cox PH Model 2 with a value of 552.427. When values compete with one another, the practitioner will determine which model to move forward with. Therefore, if it is decided to use concordance as the deciding factor, Cox PH Model 4 with SOW as the time indicator and the natural logarithm of total time and location as the covariates is the strongest model. In the same token, if using Cox PH Model 2 as the semi-parametric model of choice, then at a 0.05 significance level, location is not a significant covariate whereas the natural logarithm of total time is. Though there were conflicting results regarding model strength, it was determined that oil failures were independent.

Table 8. Comparison of Cox PH Models

Cox PH Models	Concordance	AIC
1 – TOW + TT + Location	0.677	553.415
2 – TOW + NL TT + Location	0.677	552.427
3 – SOW + TT + Location	0.683	570.073
4 – SOW + NL TT + Location	0.684	569.248

4.5 Parametric Model Analysis

An analysis was completed comparing various parametric accelerated failure time models. Section 4.5.1 will discuss the initial analysis where three probability models are used to assume the shape of the function. The three probability models used for comparison are the Weibull, log normal, and log logistic models. For this analysis, the two survival time indicators, TOW and SOW, were compared to determine which survival time indicator best fit each of the three models. Section 4.5.2 will compare the null model of the chosen parametric model to the chosen parametric model with covariates to determine if adding covariates strengthen the model. TOW will be used as the survival time indicator for the model including covariates total time and location for one scenario and covariates natural logarithm of total time and location for the second scenario to show how the strength of the model changes by taking the natural logarithm of total time. Section 4.5.3 will also compare the null model of the chosen parametric model to the chosen parametric model with included covariates to determine if adding covariates strengthen the model, but the model will use SOW as the survival time indicator. In the same instance, covariates total time and location will be used in the third scenario and covariates natural logarithm of total time and location for the fourth scenario to show how the strength of the model changes by taking the natural logarithm of total time. Section 4.5.4 will address overall model strength when comparing all four parametric model scenarios. Lastly, section 4.5.5 will discuss the predicted engine survival time based on the parametric model scenario chosen.

4.5.1 Fitting TOW and SOW as Survival Time

As a reminder, parametric analysis involves choosing a probability distribution ahead of time. To ensure the best distribution is chosen for further survival analysis, three probability models were compared amongst each other. The three probability models used for the parametric model comparison were the Weibull, log normal, and log logistic models. For this analysis, the two survival time indicators, TOW and SOW, were compared to determine which survival time indicator best fit each of the three models. Only survival time data is considered without covariates to determine which model best fits the raw data without the influence of covariates. Table 9 shows the AIC for each model when using TOW as the survival time. When using TOW as the survival time, the

Weibull model has the lowest AIC at 3,852.973 and, therefore, is the strongest probability distribution to use for further analysis.

Table 9. AIC Comparison using TOW

	Probability Distribution Choice		
	Weibull	Log Normal	Log Logistic
AIC	3852.973	3936.298	3920.470

Before proceeding, a comparison will be made between AICs using SOW as the time indicator. The results are included in Table 10. When using SOW as the survival time, the Weibull model has the lowest AIC at 3,220.356 and, therefore, is the strongest probability distribution to use for further analysis. This analysis and performance of the AIC affirms that survival data is best fitted with a Weibull model as indicated within the literature review of the medical sector.

Table 10. AIC Comparison using SOW

	Probability Distribution Choice		
	Weibull	Lognormal	Log logistic
AIC	3220.356	3293.883	3281.689

When comparing the TOW AIC of the Weibull to the SOW AIC of the Weibull, the SOW AIC is lower than the TOW AIC by a value of 632.617. The lower AIC for SOW with the Weibull model is the stronger model to move forward with for analyzing survival time.

4.5.2 Weibull Model Comparison using Time on Wing

With the Weibull model having the lowest AIC in both scenarios in section 4.5.1, that model was chosen as the probability distribution to conduct the remainder of the analysis. The next step is to compute the log-likelihood, which is an internal assessment to determine if covariates contribute beneficially to the model or if the model is better without covariates. The log-likelihood is computed for the null model, which does not include covariates, and the model including covariates. Though the AIC for SOW with the Weibull model shows to be the best model to move forward with, this analysis will also include TOW comparisons for the purposes of showing how the values differ between the different covariates being used in addition to how model strength differs using the AIC, log-likelihood, and ANOVA. In Table 11, the log-likelihood is compared between the null model, scenario one, which includes covariates total time and location, and scenario two, which includes covariates natural logarithm of total time and location. A log-likelihood with a value closest to zero indicates a stronger model. Based on the below information, scenario two, using the natural logarithm of total time and location is the strongest model when using TOW as the survival time with a value of -605.1.

Table 11. Weibull Model Comparison using TOW

	Log-likelihood
Null Model	-609.1
Scenario 1 – TT + Location	-605.5
Scenario 2 – NL TT + Location	-605.1

Due to the closeness of log-likelihood values between scenario one and scenario two, AIC and ANOVA are used for comparing two scenarios. Table 12 shows the results. The AIC for scenario two is slightly better as it is preferred. ANOVA was not applicable as the test noted the models were not significantly different from each other.

Table 12. Comparison of Weibull Scenario 1 and 2

Scenario	AIC	ANOVA
Scenario 1 – TT + Location	1218.935	N/A
Scenario 2 – NL TT + Location	1218.115	N/A

A practitioner may choose either model if they want to focus on AIC as the decision factor. The practitioner can also look at the statistical values of the coefficients to determine which scenario is best suited to move forward with. Table 13 presents coefficient estimates for scenarios one and two. To interpret the continuous covariate total time (0.0000362) in scenario one, we must exponentiate the coefficient and subtract one from it, then multiply the result by 100. When doing so, this means that when holding the covariate of location constant, each additional total time hour is associated with a 0.00362 percent increase in the expected time to failure. To interpret the categorical covariate of location (-0.720) in scenario one, since it has a negative sign, engines located at the 552nd Flying Squadron at Tinker AFB have a shorter survival time. The coefficient can be estimated by exponentiating -0.720 resulting in 0.4867. To interpret this result, engines located at the 552nd Flying Squadron at Tinker AFB are not effective in delaying failures as they decrease the survival time by a factor of 0.4867. Since the coefficient is less than one, engines located at the 552nd Flying Squadron tend to have shorter survival time than those located at else. The natural logarithm covariate does not provide a direct interpretation since it is not in its natural form. But, since the natural logarithm covariate takes the natural logarithm of each total time data point, we know that total time has a negative impact on survival time. In both scenarios, neither covariate is significant at the 0.05 significance level. However, in scenario two, both covariates are significant at the 0.10 significance level. When the significance results are similar, the practitioner may choose the scenario that provides the best interpretability for the intended audience.

Table 13. Comparison of Weibull Scenario 1 and 2 Covariates

Scenario	Covariate	Beta Coefficient	Standard Error Coefficient	z Score	p Value
1	Total Time	0.0000362	0.0000230	1.58	0.115
	Location	-0.720	0.376	-1.92	0.055
2	Natural Logarithm of Total Time	1.0534	0.5733	1.84	0.066
	Location	-0.7225	0.3730	-1.94	0.053

4.5.3 Weibull Model Comparison using Sorties on Wing

In this section, the Weibull model is used again, and the log-likelihood is computed for the null model and the model including covariates. The model will use SOW as the time indicator. As shown in Table 14, the log-likelihood is compared between the null model, scenario three, which includes covariates total time and location, and scenario four, which includes covariates natural logarithm of total time and location. Again, a log-likelihood with a value closest to zero indicates a stronger model. Based on the below information, scenario four, using the natural logarithm of total time and location is the strongest model when using TOW as the survival time with a value of -515.7.

Table 14. Weibull Model Comparison using SOW

	Log-likelihood
Null Model	-521.3
Scenario 3 – TT + Location	-516.1
Scenario 4 – NL TT + Location	-515.7

Like the scenarios in section 4.5.2, due to the closeness of log-likelihood values between scenario three and scenario four, a comparison will be made using AIC and ANOVA. Table 15 shows results of comparison for scenarios three and four. The AIC for scenario four is slightly better as it is preferred to have a lower value, and ANOVA is not applicable.

Table 15. Comparison of Weibull Scenario 3 and 4

Scenario	AIC	ANOVA
Scenario 3 – TT + Location	1040.295	N/A
Scenario 4 – NL TT + Location	1039.482	N/A

As stated in section 4.5.2, due to the models not being statistically different, the practitioner can use their best judgement to move forward with a chosen model. A practitioner may choose either model if they want to focus on AIC as the decision factor. The practitioner can also look at the statistical values of the coefficients to determine which scenario is best suited to move forward with. Table 16 provides the statistical values from scenarios three and four. To interpret the continuous covariate total time (0.0000387) in scenario three, we must exponentiate the coefficient and subtract one from it, then multiply the result by 100. When doing so, this means that when holding the covariate of location constant, each additional total time hour is associated with a 0.00387 percent increase in the expected time to failure. To interpret the categorical covariate of location (-0.912) in scenario three, since it has a negative sign, engines located at the 552nd Flying Squadron at Tinker AFB have a shorter time until failure. The coefficient can be estimated by exponentiating -0.912 resulting in 0.4017. To interpret this result, engines located at the 552nd Flying Squadron at Tinker AFB are not effective in delaying failures as they decrease the survival time by a factor of 0.4017. Since the coefficient is less than one, engines located at the 552nd Flying Squadron are harmful to survival. The natural logarithm covariate does not provide a direct interpretation since it is not in its natural form. But, since the natural logarithm covariate took the natural logarithm of each total time data point, we know that total time is harmful to survival time based on the total time covariate. In both scenarios, neither have both covariates significant at the 0.05 significance level, but both scenarios have one covariate significant at the 0.05 significance level. In the case that the statistical values produce similar results, the practitioner may choose the scenario that provides the best interpretability for the intended audience.

Table 16. Comparison of Weibull Scenario 3 and 4 Covariates

Scenario	Covariate	Beta Coefficient	Standard Error Coefficient	z Score	p Value
3	Total Time	0.0000387	0.0000230	1.68	0.093
	Location	-0.912	0.379	-2.41	0.016
4	Natural Logarithm of Total Time	1.1093	0.5742	1.93	0.053
	Location	-0.9116	0.3765	-2.42	0.015

4.5.4 Weibull Model Comparison of Weibull Scenario 1 through 4

This section addresses how scenario's one through four differ with each of the model's strength and characteristics compared in Table 17. Using SOW as the survival time gives a log-likelihood closer to zero and lowest AIC reading, with ANOVA being negligible for all scenarios, indicating that SOW is the stronger model of choice. Using SOW as the time indicator can be confirmed as the strongest choice from the analysis completed in section 4.5.1 when TOW and SOW were fitted to the three probability distributions to determine which survival time and probability distribution was the strongest, revealing that SOW and the Weibull model were the strongest pairing. Regarding which scenario between three and four is stronger is splitting hairs. However, scenario four edges out scenario three by -0.4 in the log-likelihood and 0.813 in the AIC and both models not being statistically different from each other. Though scenario four narrowly edges out scenario three in model strength, for the purposes of audience interpretability, scenario three will be used to predict engine survival time in the following section. Of note, the scale was included below to show that in all scenarios, failures were increasing at an accelerating rate.

Table 17. Comparison of Weibull Scenarios 1 through 4

Scenario	Log-likelihood	Scale	AIC	ANOVA
Scenario 1 – TOW + TT + Location	-605.5	1.02	1218.935	N/A
Scenario 2 – TOW + NL TT + Location	-605.1	1.02	1218.115	N/A
Scenario 3 – SOW + TT + Location	-516.1	1.03	1040.295	N/A
Scenario 4 – SOW + NL TT + Location	-515.7	1.03	1039.482	N/A

4.5.5 Predicting Engine Survival Time

To predict engine survival time, an accelerated failure time model must be used. From the analysis in section 4.5.1, the Weibull accelerated failure time model will be used as that model has the lowest AIC. Scenario 3, using SOW as the time indicator with total time and location as the covariates will also be used due to the interpretability of the data. Because the models are not statistically different between scenario three and four, it is safe to run the analysis using scenario three.

Table 18 provides an example of five engines and what their respective survival time is. The second row provides the coefficients from scenario three to include its intercept that is not represented but attached in Appendix C. The following rows beneath the second provide the raw data computed from CEMS that is attached in Appendix A. The Estimated Life Column predicts each engine's survival time by taking the values of the coefficients multiplied by corresponding observations. This generates a number that is equal to the natural logarithm of estimated life like the accelerated failure time equation provided in section 3.2.3. Therefore, to express the results in absolute terms, the estimated life is exponentiated and the resulting number of estimated life is expressed in terms of sorties. The SOW data are provided by CEMS and is attached in Appendix A. The Sorties until Next Failure takes the SOW data and subtracts it from Estimated Life of the engine to provide how much life is remaining for that specific engine before failure due to an oil issue. When looking Table 18, Engines 1, 2, 3, and 5 have a lower estimated survival time than Engine 4 that is not located at Tinker. The estimation of engine survival time in Table 18 provides an example of how this data can be used to help pilots, maintainers, engine shops, and engine SPOs become better equipped to handle an oil issue before it occurs.

Table 18. Failure Time Estimate

	Intercept	Total Time	Location (1 for Tinker; 0 for Else)	Scale	Estimated Life	Sorties on Wing	Sorties until Next Failure
Coefficient	*7.21*	*0.0000387*	*-0.912*	*1.03*	*N/A*	*N/A*	*N/A*
Engine 1	N/A	31,552.20	1	N/A	1,860.02	317.00	1,543.02
Engine 2	N/A	37,486.90	1	N/A	2,356.44	1,299.00	1,057.44
Engine 3	N/A	36,197.00	1	N/A	2,238.34	941.00	1,297.34
Engine 4	N/A	36,911.40	0	N/A	5,891.85	288.00	5,603.85
Engine 5	N/A	35,413.40	1	N/A	2,169.50	1,263.00	906.50

4.6 Summary

Chapter four reported the analysis and results from the non-parametric, semi-parametric, and parametric models. The number of oil events that occurred were discussed via a transitions table where it was shown 40 engines did not experience an oil related failure within the period of observation, 24 engines experienced an oil related failure only once within the period of observation, 14 engines experienced an oil related failure twice within the period of observation, two engines experienced an oil related failure three times within the period of observation, and one engine experienced an oil related failure four times within the period of observation. The summary statistics was also displayed where the covariates were officially introduced and discussed.

Next, a Nelson estimate was conducted and showed that as an engine's TOW or SOW gradually increases, cumulative hazard rates increase. In addition, location was not statistically significant due to the confidence intervals overlapping in each TOW and SOW plot.

Four Cox PH Models with frailty were analyzed and compared to report the differing model strength when interchanging TOW and SOW as the time indicator and interchanging total time and the natural logarithm of total time as one of the covariates. The models produced conflicting results in which it then falls on the practitioner to decide which model is to be used. In every model, frailty was not significant which indicated failures were independent.

After conducting the semi-parametric analysis, a parametric analysis was performed where it was determined the Weibull accelerated failure time model using SOW as the survival time indicator resulted in the strongest parametric model to use based on AIC. Though SOW was the better survival time indicator, TOW was also included in the remainder of the analysis to compare the model strengths. It was determined the null Weibull model was not stronger than the Weibull model that included covariates. When the SOW and TOW models with the inclusion of covariates were compared, SOW models were in fact stronger than the TOW models. Though using the natural logarithm of total time showed to be a stronger covariate than the total time covariate for the Weibull model using SOW and location, it was decided to use the model that included the total time covariate. This decision was made due to the easier interpretability of results that came with using total time as one of the covariates. Because it was determined that the two models in question were not statistically different, either model would be appropriate to use. The final step in this analysis involved predicting engine survival time based on the model with SOW as the survival time indicator and total time and location as the covariates. An example of predicted engine survival time was provided for the first five engines in terms of sorties until the next oil related failure. The next chapter will provide a conclusion and recommendation.

V. Conclusion

5.1 Chapter Overview

The purpose of this chapter is to summarize the results and to address the research questions and hypotheses. The significance and limitation of this research are discussed. Finally, directions for future research will be discussed.

5.2 Conclusion

Three survival analysis approaches such as non-parametric, semi-parametric, and parametric models were attempted. The non-parametric model with the Nelson estimate showed cumulative hazard rates along with 95 percent confidence intervals. Regardless of whether TOW or SOW was used, it was determined that as the engine's TOW and SOW increases, cumulative hazard rates increase. In these models, location was not significant.

The Cox PH Model with frailty was implemented as the semi-parametric model of choice to provide an example of how the data would look should a researcher use a semi-parametric model rather than a parametric model. The models used did not assume a probability distribution, and there was no intercept used, which was a distinguishing factor between semi-parametric and parametric models. It was determined that the Cox PH Model had conflicting results, with concordance being stronger when using SOW, but AIC being smaller when using TOW as the time indicator. In these situations, it is up to the practitioner to decide which factor will be used to choose the model to move forward with. In every scenario, the frailty test concluded that failures were independent.

In the parametric analysis, three accelerated failure time models were tested using two different survival time indicators. It was determined the Weibull model using SOW as the time indicator was the strongest model. Multiple Weibull models were tested using SOW and TOW as the time indicator to show how the results differed. Based on the results, using SOW as the survival time gave a log-likelihood closer to zero and lowest AIC reading with ANOVA being negligible for all scenarios, indicating that SOW was the stronger model of choice. It was decided to use location and total time as the covariates rather than using the natural logarithm of total time to replace the total time covariate due to the easier interpretability of computed results. The final stage of research analysis involved the prediction of engine survival time. The prediction of engine survival time was computed using SOW as the time indicator and total time and location as the covariates. An example of predicted engine survival time was provided for the first five engines in terms of sorties until next failure due to an oil related issue.

5.3 Research Questions and Hypotheses

There are two research questions for this study.

Research Question 1: What covariates are significant in predicting engine failures due to oil issues?

The significance level prior to engaging in the research was established at 0.05. Therefore, to be considered a significant covariate, the covariate's associated p-value must be at or below 0.05. Based on the various models run and choosing to move forward with the Weibull accelerated failure time model using SOW as the time indicator with total time and location as the covariates, only the location covariate was considered a significant variable. The associated p-value for the location covariate was 0.016. The total time covariate had an associated p value of 0.093. Total time was not a significant covariate, but location was a significant covariate.

Research Question 2: What can be the engine's survival time at given operating hours?

The engine's survival time at a given operating hour was computed using parametric accelerated failure time models. Using sorties, this study provided engines' survival time.

There are four hypotheses in this study.

Hypothesis 1: The Total Operating Hours will affect engine failures.

Total Operating Hours became designated as the total time covariate in which the Weibull accelerated failure time model determined when holding the covariate of location constant, each additional total time hour is associated with a 0.00387 percent increase in the expected time to failure. However, because the covariate was not significant at the 0.05 significance level, total time showed no effect on engine failures.

Hypothesis 2: The Location of Engines will affect engine failures.

The Weibull accelerated failure time model determined since the categorical covariate location was negative (-0.912), engines located at the 552nd Flying Squadron at Tinker AFB had a shorter time until failure. Since the coefficient is less than one, location showed a negative effect on the engines located at Tinker AFB. The covariate was significant at the 0.05 significance level.

Hypothesis 3: The Time on Wing will affect engine failures.

When looking at TOW as a survival time indicator, based on the analysis conducted in sections 4.5.1 and 4.5.2, TOW was a suitable option to pursue. However, the associated covariates were determined not significant when using TOW as the survival time indicator, which would result in TOW not affecting engine failures.

Hypothesis 4: The Number of Sorties Flown will affect engine failures.
The number of sorties flown was designated as SOW in the analysis. Based on the analysis conducted in sections 4.5.1 and 4.5.3, the location covariate was determined to be significant when using SOW as the time indicator, while total time was not. Therefore, the SOW does affect engine failures. SOW is a significant factor in affecting engine failures

5.4 Significance of Research

This study attempted to predict engine failures due to oil related issues, which has not been attempted. This study fills this gap using a Weibull AFT model for predicting engines' survival time. The findings of this study will help pilots, maintainers, engine shops, and engine SPOs become better equipped to handle an oil issue before it occurs.

5.5 Limitations

This study includes 81 engines out of 162 engines, which are managed under ACC (Air Combat Command). In addition, only two covariates are tested. Lastly, due to the inconsistencies of data being recorded into CEMS from 1994 to 2006, data collection started in calendar year 2007.

5.6 Future Directions

Future studies may address the limitations of this study by analyzing all 162 engines and including additional covariates such as mission types, cycle time, deployed at a specific location, repair types, time since the last overhaul, and overhaul location. In addition, the framework of this study can be applied to other engines and components that are managed by serial numbers.

5.7 Summary

This study provided a foundation for future research to be conducted in analyzing how oil related issues affected failures of the TF33-PW-100A engines. It was determined that with the data provided, as the engine's SOW increases, the risk of failure increases. The Weibull accelerated failure time model was the strongest parametric model to use in survival analysis while using SOW as the survival time indicator. With the model used, only location was considered a significant covariate, suggesting engines located at the 552nd Flying Squadron failed more often due to an oil issue as opposed to other locations. Engine survival time was estimated using the model, which would help pilots, maintainers, engine shops, and engine SPOs for handling an oil issue before it occurs. Finally, limitations were discussed, and future directions were proposed to strengthen the analysis used to accurately predict an engine's survival time.

Appendix A – Data

ID	TOW	SOW	Oil	Any	Location Tinker
1	1760.8	317	1	1	1
1	5934.7	1299	0	0	1
2	3260.8	941	1	1	1
2	714.4	288	0	0	0
3	3742.1	1263	0	1	1
4	2270.7	927	0	0	0
5	4353.8	1158	0	1	1
5	1561.2	272	0	0	1
6	801.2	208	1	1	0
6	2759.4	689	0	1	0
6	483.5	183	0	0	0
7	1065.7	196	1	1	1
7	904.7	310	1	1	1
7	1695	501	0	1	0
7	286.5	95	0	0	1
8	643.4	199	0	0	0
8	3893.5	853	0	1	1
8	774.8	330	0	0	1
9	478.3	68	1	1	1
9	4999.2	982	1	1	0
10	3769.3	615	0	0	1
10	3357.6	739	0	1	1
10	380.7	188	0	0	0
11	5494.6	1560	0	0	1
12	85.7	25	0	0	1
12	5836.5	1145	0	0	0
12	373.2	272	0	0	0
13	1086.6	426	0	0	0
13	3623	1004	0	0	1
14	3874.4	814	0	1	0
14	678.7	83	1	1	0
14	2950.1	477	0	0	0
15	4277	1157	0	1	1
15	15.9	16	0	0	1
16	487.3	99	1	1	1
16	4547.7	837	1	1	1
16	840.4	100	0	0	1
17	2666.3	726	0	0	1
17	1560.8	315	1	1	1
17	6.2	5	0	0	1

18	6575.9	1826	0	0	1
19	1727.7	433	1	1	1
19	16.9	4	1	1	0
19	9.1	2	0	1	1
19	2.4	2	1	1	0
19	2336.2	607	1	1	1
19	681.9	204	0	0	1
20	136.9	32	1	1	1
20	4855.6	903	0	1	0
20	127.1	41	1	1	1
21	4574.5	896	1	1	1
21	1130.9	155	0	1	1
22	3609	992	0	1	1
22	187.9	115	0	0	1
22	15.9	16	0	0	1
23	132.1	43	0	1	1
23	2356.8	697	0	0	1
23	59.4	34	0	0	1
23	230.4	49	0	1	1
23	5.7	4	0	0	0
23	14.6	3	0	1	1
24	115.8	45	0	0	1
24	9.1	3	0	0	0
24	5407.8	1213	1	1	1
24	432.1	154	0	0	0
24	18.5	18	0	0	1
25	84.6	30	1	1	1
25	2174.8	711	0	0	0
25	902.4	316	0	1	1
25	1018	170	0	0	1
26	608.5	180	0	0	1
26	4665.8	1672	0	1	0
26	345.7	144	0	0	1
27	447.8	161	0	0	1
27	17.3	6	0	0	0
27	1000.9	129	0	1	1
27	2752.8	605	0	0	0
28	916.7	168	1	1	1
28	4203.7	921	0	0	0
29	199.9	76	1	1	1
29	3414.6	1062	0	0	0
30	177.6	53	0	1	1
30	515.8	98	1	1	1
30	55.3	20	0	1	0

30	27.1	7	0	1	0
30	5483.3	886	1	1	1
31	1030.1	236	1	1	1
31	974.5	322	1	1	1
31	4438.8	1208	0	0	1
32	600.8	189	0	0	1
32	3212.6	602	1	1	0
32	889.9	425	0	0	1
33	1127.6	322	1	1	1
33	3300.6	549	1	1	1
33	3471.3	702	0	0	1
34	271.4	77	0	1	1
34	2514.8	474	1	1	1
34	3648.9	825	0	1	1
35	476.8	120	0	1	1
35	3272.4	1268	0	0	1
36	4416	891	0	1	1
36	24.7	18	0	0	1
37	3420.8	700	1	1	1
37	2875.3	582	0	0	1
37	2192.1	739	0	0	1
38	2201.1	787	0	1	0
38	3899.5	764	1	1	1
38	560.2	254	0	0	0
39	1920.6	492	0	0	1
39	2801.3	786	0	1	0
39	561.8	259	0	0	1
40	4796.9	832	0	1	1
40	1714.6	527	0	0	1
41	2693.9	405	0	1	1
41	13.1	2	0	0	0
41	1887.2	461	0	0	1
41	1142.8	417	0	0	1
42	2231.4	513	0	0	1
42	1270	405	0	0	0
43	6115.8	1057	0	0	1
43	683.8	164	1	1	1
43	736.1	92	0	0	1
44	1794	398	1	1	0
44	460.5	127	0	1	1
44	2616.2	335	1	1	1
45	2373.3	567	1	1	1
45	1129.9	397	0	0	1
45	292.2	90	1	1	1

45	6.2	5	0	0	1
46	1068.3	255	0	0	1
46	274	94	1	1	0
46	4474	1052	0	1	0
47	1615.5	398	1	1	1
47	1055.9	120	1	1	1
47	147	44	1	1	0
47	2146.6	415	0	1	1
48	974.6	312	0	1	1
48	1616	338	0	1	1
49	2725.4	430	0	1	1
49	2617.5	652	0	1	1
49	588.7	96	0	0	0
50	285.2	88	1	1	1
50	958.4	336	0	1	1
50	1873.2	476	1	1	1
50	952.9	396	0	0	1
51	878.6	284	1	1	1
51	3397.8	876	0	1	1
51	11.6	4	0	0	1
51	1089.5	442	0	1	1
52	1436	257	0	1	1
52	791.2	104	0	1	1
52	2265.7	342	0	1	1
52	325.1	92	0	0	0
53	5426.1	1305	0	0	1
54	5554.5	1170	0	1	1
54	1780.1	328	1	1	1
54	14.5	13	0	0	1
55	670.1	174	0	0	0
55	160.7	16	0	1	0
55	1213	420	0	0	1
56	534.9	145	1	1	1
56	3585.8	943	1	1	1
56	602.6	264	0	0	1
57	1828.4	362	1	1	1
57	4318.2	678	1	1	1
57	2962.9	490	0	0	1
58	4461	1517	0	0	0
59	1042.7	223	1	1	1
59	1250.4	321	1	1	1
59	981.3	607	0	0	0
60	750.2	168	0	1	1
60	47.2	22	0	0	1

60	457.7	186	0	0	1
61	1096.8	125	1	1	1
61	186.2	58	0	1	1
61	2430.7	509	1	1	1
61	59.7	19	1	1	1
61	1888.3	371	0	0	1
62	2632.2	758	0	1	1
62	1897.2	314	0	0	1
63	4959.3	1130	0	1	1
63	146.9	124	0	0	0
64	4166.3	900	0	1	1
64	1747.3	469	0	1	1
65	5173.3	994	1	1	1
65	573.7	216	0	1	1
65	54.4	19	0	0	1
66	2809.9	411	1	1	1
66	3910.5	864	0	0	1
67	257.8	45	0	0	1
67	2864.1	386	1	1	1
67	1548.8	278	0	0	1
67	2667.2	899	0	0	0
68	3080.8	625	1	1	1
68	4250.8	1078	0	1	1
69	846.4	192	0	1	1
69	3325.7	715	0	0	0
70	2335.3	608	0	0	1
70	1380.6	282	1	1	1
70	1481.5	714	1	1	1
70	990.8	194	0	0	0
71	3493.7	782	0	1	0
71	933.2	121	0	1	1
71	112.2	71	0	1	1
72	3183.1	538	0	1	1
72	841.6	293	0	1	1
72	287.7	90	0	1	1
72	1298	738	0	0	0
73	592.1	199	1	1	1
73	3048.4	724	0	1	1
73	902.3	548	0	0	0
74	3588.5	914	0	0	0
75	2710.1	638	0	1	1
75	3370.1	1276	0	0	0
76	3696	799	0	1	0
77	5521.8	1515	0	1	0

77	4	3	0	0	0
78	134.1	23	1	1	1
78	4074.8	1218	0	1	0
79	7322	1335	0	0	1
79	10.3	8	0	1	0
80	2822.3	719	0	0	1
80	14.2	12	0	0	1
81	220.7	77	0	0	0
81	3823.2	1179	0	0	1
81	2161	359	0	0	1

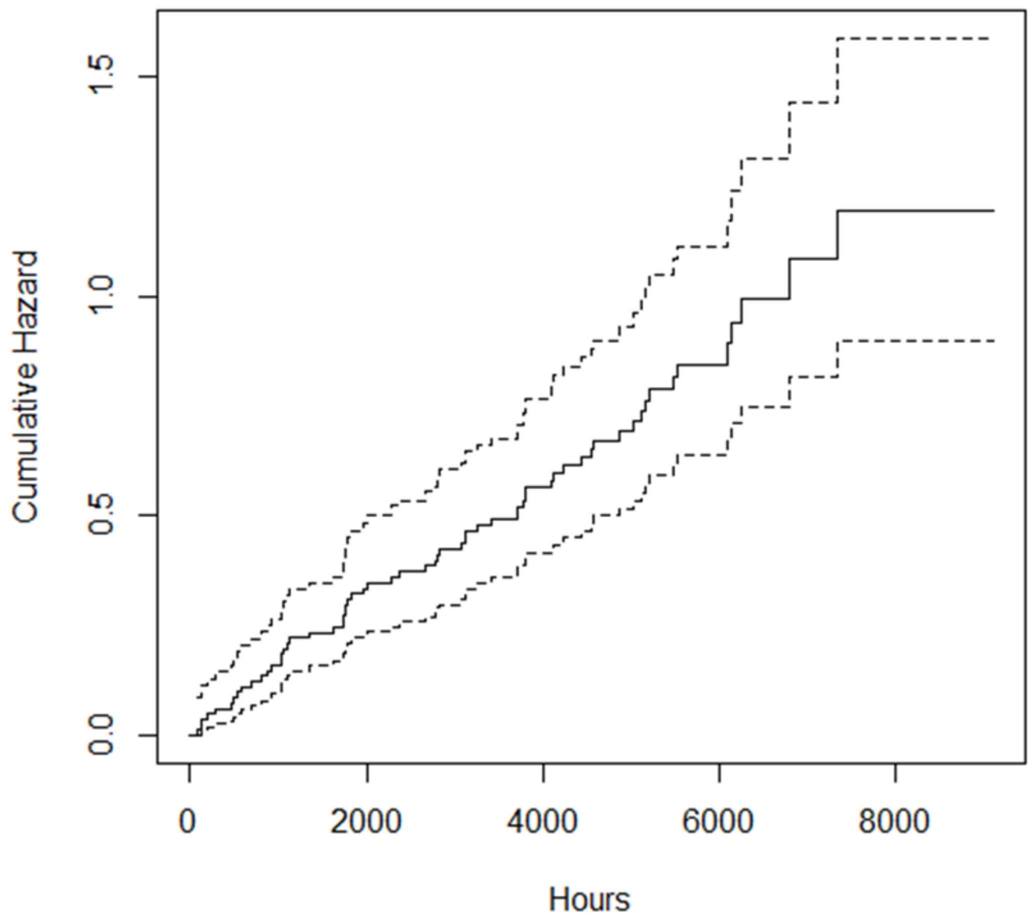
Appendix B – R Scripts and Results

```
> library(survival)
> library(eha)
> dat<-read.csv("anna_recurrent_2.csv
> survcheck(Surv(Start, Stop, Oil) ~ 1, id=ID, data=dat)
Call:
survcheck(formula = Surv(Start, Stop, Oil) ~ 1, data = dat, id =
ID)
Unique identifiers       Observations        Transitions
               81                226                 62
Transitions table:
      to
from    1 (censored)
  (s0) 41         40
  1    21         37
Number of subjects with 0, 1, ... transitions to each state:
       count
state    0  1  2 3 4
  1     40 24 14 2 1
  (any) 40 24 14 2 1
> summary(dat)
       ID              SN                TotalTime          TOW

 Min.: 1.00      Length:226          Min.:12326      Min.:   2.4

 1st Qu.:22.00   Class:character   1st Qu.:19787   1st Qu.: 464.6

 Median :39.50   Mode:character    Median :22890   Median :1231.7

 Mean   :39.29                     Mean   :24363   Mean   :1868.5

 3rd Qu.:57.00                     3rd Qu.:28086   3rd Qu.:3072.7

 Max.   :79.00                     Max.   :39098   Max.   :7322.0

Start      Stop        TotalSorties        SOW              Sstart

Min.  :0   Min.: 2.4    Min.: 2559   Min.   :   2.0    Min.   :0

1st Qu.:0 1st Qu.:464.6 1st Qu.:4705 1st Qu.: 116.2    1st Qu.:0

Median :0 Median :1231.7 Median: 5546 Median : 335.5   Median :0

Mean :0   Mean   :1868.5 Mean : 6632  Mean   : 454.4   Mean   :0

3rd Qu.:0 3rd Qu.:3072.7 3rd Qu.: 8840 3rd Qu.: 722.8  3rd Qu.:0

Max. :0   Max.   :7322.0 Max.   :13290 Max.   :1826.0  Max.   :0

Sstop          RemovalSRAN     Location          ReasonRemovalCode

Min.:   2.0     Min.   :2039   Length:226         Min.   :    69.0

1st Qu.: 116.2 1st Qu.:4837   Class :character   1st Qu.:   199.0
```

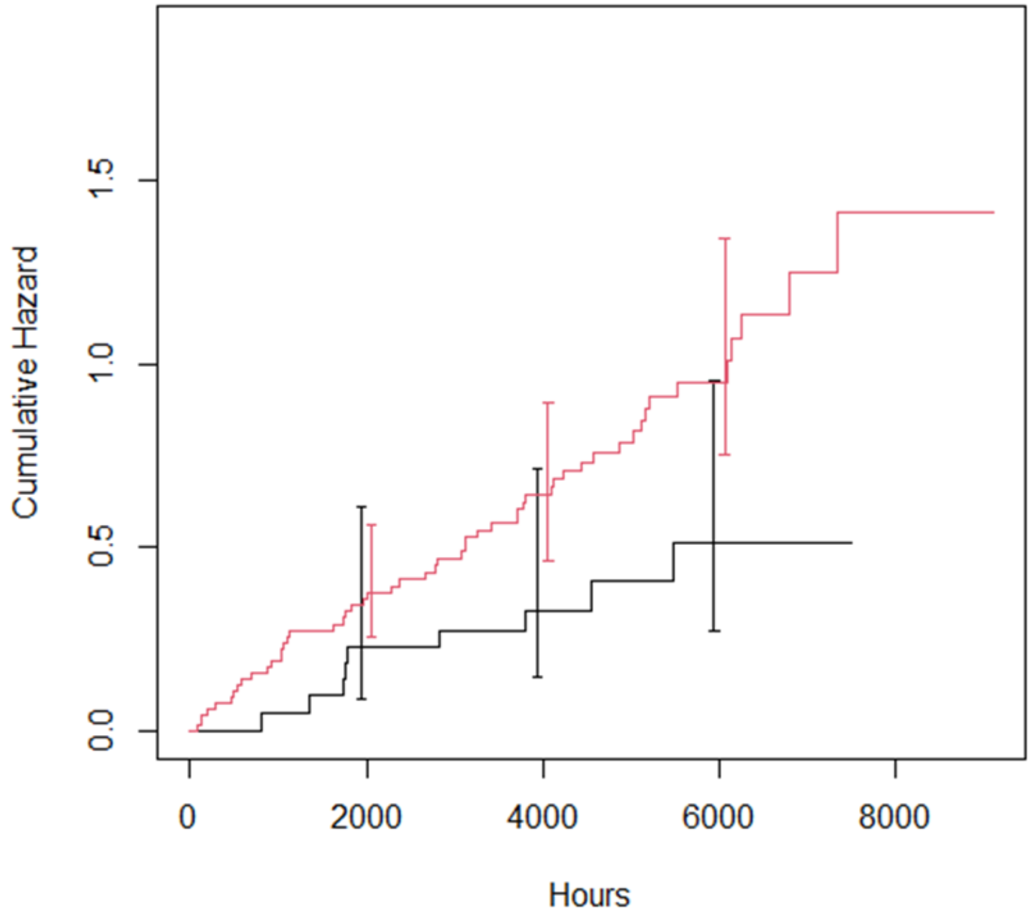
```
Median : 335.5 Median :4837   Mode  :character   Median :   303.0
Mean   : 454.4 Mean   :4388                      Mean   :  1017.2
3rd Qu.: 722.8 3rd Qu.:4837                      3rd Qu.:   591.8
Max.   :1826.0 Max.   :5270                      Max.   :135315.0
    Reason                Oil              Any            ACTailNo
 Length:226         Min.   :0.0000   Min.   :0.0000   Length:226
 Class :character   1st Qu.:0.0000   1st Qu.:0.0000   Class
:character
 Mode  :character   Median :0.0000   Median :1.0000   Mode
:character
                    Mean   :0.2743   Mean   :0.5619
                    3rd Qu.:1.0000   3rd Qu.:1.0000
                    Max.   :1.0000   Max.   :1.0000
   Loc_Tinker          Ln_TT            Sqrt_TT          Ln_TS
 Min.   :0.0000   Min.   : 9.420   Min.   :111.0   Min.   :7.850
 1st Qu.:0.0000   1st Qu.: 9.893   1st Qu.:140.7   1st Qu.:8.453
 Median :1.0000   Median :10.040   Median :151.3   Median :8.620
 Mean   :0.7345   Mean   :10.069   Mean   :154.9   Mean   :8.726
 3rd Qu.:1.0000   3rd Qu.:10.240   3rd Qu.:167.6   3rd Qu.:9.088
 Max.   :1.0000   Max.   :10.570   Max.   :197.7   Max.   :9.490
```

USING TOW

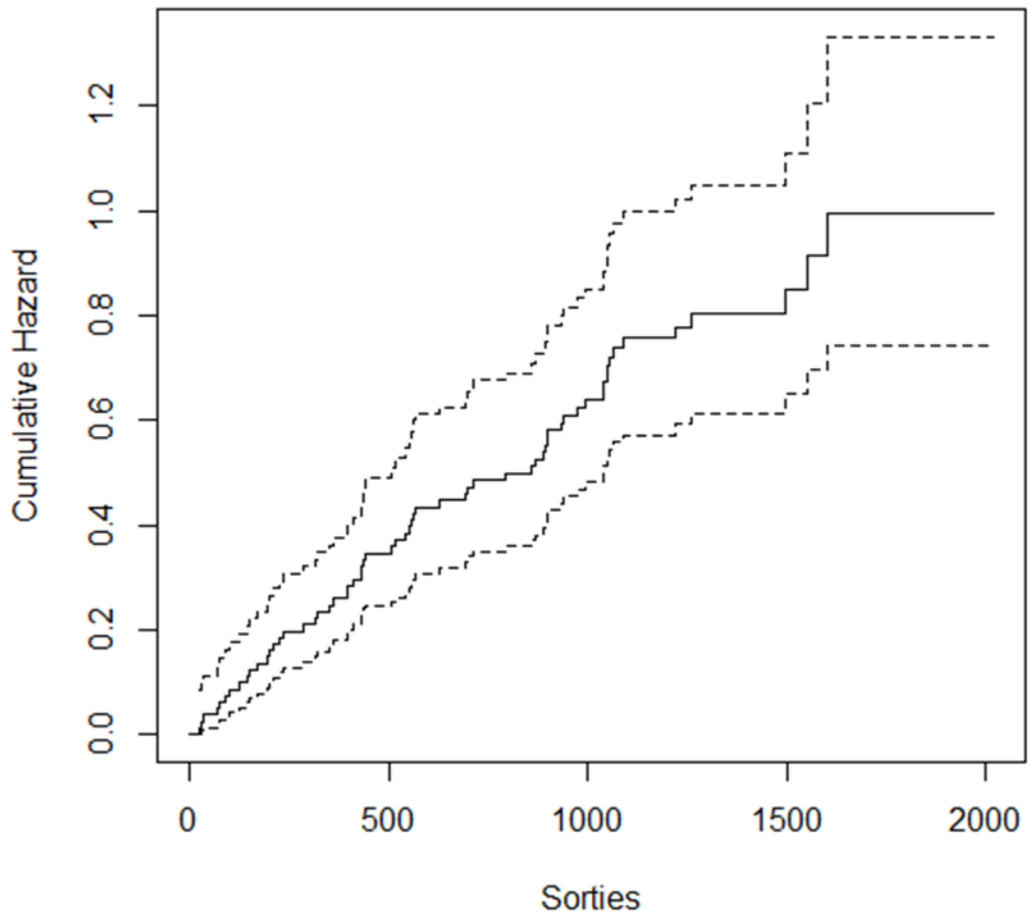
```
> #Nelson ANALYSIS
> hours.fit <- survfit(Surv(Start, Stop, Oil) ~1, data=dat,
id=ID)
> plot(hours.fit, cumhaz=TRUE, xlab="Hours", ylab="Cumulative
Hazard")
```



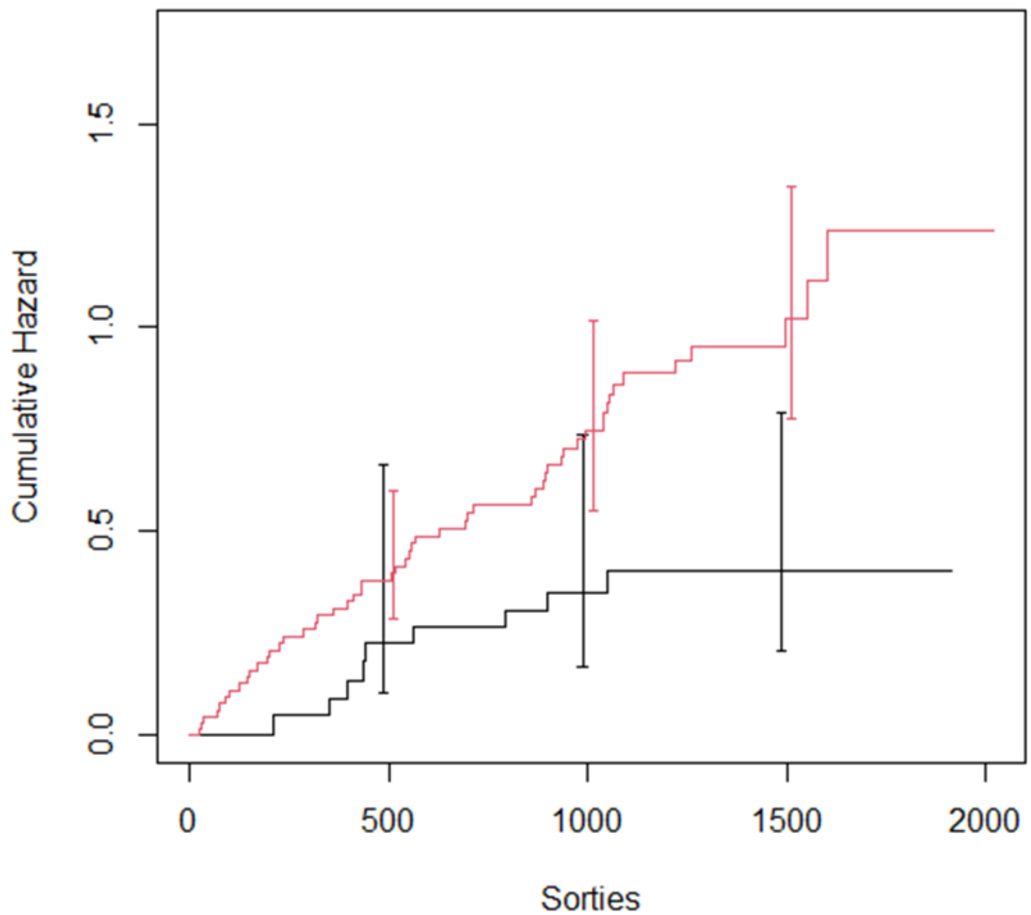

```
# Cumulative hazard curve by location

> hours.loc <- survfit(Surv(Start, Stop, Oil) ~ Loc_Tinker, dat,
id=ID)

> plot(hours.loc, cumhaz=TRUE, col=1:2, conf.times=c(2000, 4000,
6000), xlab="Hours", ylab="Cumulative Hazard")
```




```
# Nelson analysis using sorties (SOW)

> sorties.fit <- survfit(Surv(Sstart, Sstop, Oil) ~1, data=dat,
id=ID)

> plot(sorties.fit, cumhaz=TRUE, xlab="Sorties", ylab="Cumulative
Hazard")
```




```
# Cumulative hazard curve by location

> sorties.loc <- survfit(Surv(Sstart, Sstop, Oil) ~ Loc_Tinker,
dat, id=ID)

> plot(sorties.loc, cumhaz=TRUE, col=1:2, conf.times=c(500, 1000,
1500), xlab="Sorties", ylab="Cumulative Hazard")
```




```
# Cox PH Models with Frailty
# Cox PH Frailty Model with Hours (TOW) and TT, Loc
> frailty.hours<-coxph(Surv(TOW, Oil)~TotalTime + Loc_Tinker +
frailty(ID), data=dat)
> summary(frailty.hours)
Call:
coxph(formula = Surv(TOW, Oil) ~ TotalTime + Loc_Tinker +
frailty(ID),
    data = dat)
  n= 226, number of events= 62
              coef       se(coef)  se2       Chisq DF   p
TotalTime   -4.222e-05 2.374e-05 2.284e-05 3.16  1.00 0.075
Loc_Tinker   7.119e-01 3.695e-01 3.619e-01 3.71  1.00 0.054
frailty(ID)                                7.97  7.03 0.340
           exp(coef) exp(-coef) lower .95 upper .95
TotalTime      1.000     1.0000    0.9999     1.000
Loc_Tinker     2.038     0.4907    0.9879     4.204
Iterations: 10 outer, 37 Newton-Raphson
     Variance of random effect= 0.1308518   I-likelihood = -274.9
Degrees of freedom for terms= 0.9 1.0 7.0
Concordance= 0.677  (se = 0.045 )
```

```
Likelihood ratio test= 22.28  on 8.91 df,   p=0.008
> extractAIC(frailty.hours)
[1]   8.914876 553.414598
# TotalTime and Loc_Tinker are significant at alpha = 0.10.
# Shared frailty is insignificant.

# Cox PH Frailty Model with Hours (TOW) and Ln_TT, Loc
> frailty.hours.2<-coxph(Surv(TOW, Oil)~Ln_TT + Loc_Tinker +
frailty(ID), data=dat)
> summary(frailty.hours.2)
Call:
coxph(formula = Surv(TOW, Oil) ~ Ln_TT + Loc_Tinker +
frailty(ID),
    data = dat)
  n= 226, number of events= 62
            coef    se(coef) se2    Chisq DF   p
Ln_TT       -1.2325 0.6011   0.5760 4.20  1.00 0.040
Loc_Tinker   0.7198 0.3703   0.3619 3.78  1.00 0.052
frailty(ID)                         8.73  7.65 0.330
           exp(coef) exp(-coef) lower .95 upper .95
Ln_TT         0.2916     3.4296   0.08976    0.9472
Loc_Tinker    2.0541     0.4868   0.99410    4.2442
Iterations: 10 outer, 38 Newton-Raphson
     Variance of random effect= 0.1437459   I-likelihood = -274.5
Degrees of freedom for terms= 0.9 1.0 7.6
Concordance= 0.677  (se = 0.044 )
Likelihood ratio test= 24.48  on 9.52 df,   p=0.005
> extractAIC(frailty.hours.2)
[1]   9.522726 552.426957
# Ln_TT is significant at alpha = 0.05
#Loc_Tinker is significant at alpha = 0.10.
# Shared frailty is insignificant.

# Cox PH Frailty Model with Sorties
> frailty.sorties<-coxph(Surv(SOW, Oil)~TotalTime + Loc_Tinker +
frailty(ID), data=dat)
> summary(frailty.sorties)
Call:
coxph(formula = Surv(SOW, Oil) ~ TotalTime + Loc_Tinker +
frailty(ID),
    data = dat)
  n= 226, number of events= 62
            coef       se(coef)  se2       Chisq DF   p
TotalTime   -3.903e-05 2.342e-05 2.257e-05 2.78  1.00 0.096
Loc_Tinker   8.956e-01 3.689e-01 3.625e-01 5.89  1.00 0.015
frailty(ID)                                7.64  6.81 0.350
           exp(coef) exp(-coef) lower .95 upper .95
TotalTime      1.000     1.0000    0.9999     1.000
Loc_Tinker     2.449     0.4084    1.1882     5.046
```

```
Iterations: 10 outer, 35 Newton-Raphson
     Variance of random effect= 0.1254098   I-likelihood = -283.2
Degrees of freedom for terms= 0.9 1.0 6.8
Concordance= 0.683  (se = 0.044 )
Likelihood ratio test= 23.88  on 8.7 df,   p=0.004
> extractAIC(frailty.sorties)
[1]   8.70296 570.07316
# TotalTime is significant at alpha=0.10.
# Loc_Tinker is significant at alpha=0.025.
# Shared frailty is insignificant.

# Cox PH Frailty Model with Sorties (SOW)and Ln_TT, Loc
> frailty.sorties.4<-coxph(Surv(SOW, Oil)~Ln_TT + Loc_Tinker +
frailty(ID), data=dat)
> summary(frailty.sorties.4)
Call:
coxph(formula = Surv(SOW, Oil) ~ Ln_TT + Loc_Tinker +
frailty(ID),
    data = dat)
  n= 226, number of events= 62
            coef    se(coef) se2    Chisq DF   p
Ln_TT       -1.1328 0.5935   0.5700 3.64  1.00 0.056
Loc_Tinker   0.9007 0.3696   0.3627 5.94  1.00 0.015
frailty(ID)                         8.20  7.28 0.340
           exp(coef) exp(-coef) lower .95 upper .95
Ln_TT         0.3221     3.1043    0.1007     1.031
Loc_Tinker    2.4612     0.4063    1.1927     5.079
Iterations: 10 outer, 35 Newton-Raphson
     Variance of random effect= 0.1349812   I-likelihood = -282.8
Degrees of freedom for terms= 0.9 1.0 7.3
Concordance= 0.684  (se = 0.044 )
Likelihood ratio test= 25.62  on 9.16 df,   p=0.003
> extractAIC(frailty.sorties.4)
[1]   9.161475 569.248349
# Ln_TT is significant at alpha=0.10.
# Loc_Tinker is significant at alpha=0.025.
# Shared frailty is insignificant.

> # Parametric Models
> Weibull<-survreg(Surv(TOW, Oil)~1, dist="weibull", data=dat)
> summary(Weibull)
Call:
survreg(formula = Surv(TOW, Oil) ~ 1, data = dat, dist =
"weibull")
             Value Std. Error     z      p
(Intercept) 8.8699     0.1657 53.52 <2e-16
Log(scale)  0.0484     0.1054  0.46   0.65
Scale= 1.05
Weibull distribution
Loglik(model)= -609.1   Loglik(intercept only)= -609.1
```

```
Number of Newton-Raphson Iterations: 7
n= 226
```
(Using TotalTime)
```
> Weibull.1<-survreg(Surv(TOW, Oil)~TotalTime+Loc_Tinker,
dist="weibull", data=dat)
> summary(Weibull.1)
Call:
survreg(formula = Surv(TOW, Oil) ~ TotalTime + Loc_Tinker, data =
dat,dist = "weibull")
                Value Std. Error     z      p
(Intercept)  8.54e+00   6.67e-01 12.79 <2e-16
TotalTime    3.62e-05   2.30e-05  1.58  0.115
Loc_Tinker  -7.20e-01   3.76e-01 -1.92  0.055
Log(scale)   2.33e-02   1.05e-01  0.22  0.825
Scale= 1.02
Weibull distribution
Loglik(model)= -605.5   Loglik(intercept only)= -609.1
        Chisq= 7.31 on 2 degrees of freedom, p= 0.026
Number of Newton-Raphson Iterations: 7
n= 226
> extractAIC(Weibull.1)
[1]    4.000 1218.935
```
(Using Ln_TT)
```
> Weibull.2<-survreg(Surv(TOW, Oil)~Ln_TT+Loc_Tinker,
dist="weibull", data=dat)
> summary(Weibull.2)
Call:
survreg(formula = Surv(TOW, Oil) ~ Ln_TT + Loc_Tinker, data =
dat,
    dist = "weibull")
              Value Std. Error     z     p
(Intercept) -1.1948     5.7682 -0.21 0.836
Ln_TT        1.0534     0.5733  1.84 0.066
Loc_Tinker  -0.7225     0.3730 -1.94 0.053
Log(scale)   0.0174     0.1053  0.16 0.869
Scale= 1.02
Weibull distribution
Loglik(model)= -605.1   Loglik(intercept only)= -609.1
        Chisq= 8.13 on 2 degrees of freedom, p= 0.017
Number of Newton-Raphson Iterations: 7
n= 226
> extractAIC(Weibull.2)
[1]    4.000 1218.115
> #Fitting TOW as Survival Time
> library(fitdistrplus)
> dat<-read.csv("oil_any_failures_input_transformed.csv")
> my_data<-dat$TOW
> fit_w<-fitdist(my_data, "weibull")
> fit_ln<-fitdist(my_data, "lnorm") #Lognormal distribution
> fit_ll<-fitdist(my_data, "llogis") #Log-logistic distribution
```

```
> gofstat(list(fit_w, fit_ln, fit_ll), fitnames=c("Weibull",
"lnorm", "llogis"))
Goodness-of-fit statistics
                               Weibull     lnorm    llogis
Kolmogorov-Smirnov statistic 0.08964667 0.1399779 0.1239403
Cramer-von Mises statistic   0.41204323 1.5690327 0.6759582
Anderson-Darling statistic   3.34886716 9.8507817 6.6694766
Goodness-of-fit criteria
                               Weibull    lnorm   llogis
Akaike's Information Criterion 3852.973 3936.298 3920.470
Bayesian Information Criterion 3859.815 3943.139 3927.311

> #Parametric Models
> Weibull<-survreg(Surv(SOW, Oil)~1, dist="weibull", data=dat)
> summary(Weibull)
Call:
survreg(formula = Surv(SOW, Oil) ~ 1, data = dat, dist =
"weibull")
            Value Std. Error     z      p
(Intercept) 7.487      0.174 43.09 <2e-16
Log(scale)  0.079      0.106  0.75   0.46
Scale= 1.08
Weibull distribution
Loglik(model)= -521.3   Loglik(intercept only)= -521.3
Number of Newton-Raphson Iterations: 7
n= 226
```

Using TotalTime

```
> Weibull.3<-survreg(Surv(SOW, Oil)~TotalTime+Loc_Tinker,
dist="weibull", data=dat)
> summary(Weibull.3)
Call:
survreg(formula = Surv(SOW, Oil) ~ TotalTime + Loc_Tinker, data =
dat, dist = "weibull")
                Value Std. Error     z      p
(Intercept)  7.21e+00   6.69e-01 10.77 <2e-16
TotalTime    3.87e-05   2.30e-05  1.68  0.093
Loc_Tinker  -9.12e-01   3.79e-01 -2.41  0.016
Log(scale)   3.23e-02   1.06e-01  0.30  0.761
Scale= 1.03
Weibull distribution
Loglik(model)= -516.1   Loglik(intercept only)= -521.3
        Chisq= 10.27 on 2 degrees of freedom, p= 0.0059
Number of Newton-Raphson Iterations: 9
n= 226
> extractAIC(Weibull.3)
[1]    4.000 1040.295
```

Using Ln_TT

```
> Weibull.4<-survreg(Surv(SOW, Oil)~Ln_TT+Loc_Tinker,
dist="weibull", data=dat)
> summary(Weibull.4)
```

```
Call:
survreg(formula = Surv(SOW, Oil) ~ Ln_TT + Loc_Tinker, data =
dat, dist = "weibull")
              Value Std. Error     z     p
(Intercept) -3.0273     5.7773 -0.52 0.600
Ln_TT        1.1093     0.5742  1.93 0.053
Loc_Tinker  -0.9116     0.3765 -2.42 0.015
Log(scale)   0.0259     0.1061  0.24 0.807
Scale= 1.03
Weibull distribution
Loglik(model)= -515.7   Loglik(intercept only)= -521.3
        Chisq= 11.09 on 2 degrees of freedom, p= 0.0039
Number of Newton-Raphson Iterations: 10
n= 226
> extractAIC(Weibull.4)
[1]    4.000 1039.482
> #Fitting Sorites on Wing aka SOW as Survival Time
> my_data<-dat$SOW
> fit_w<-fitdist(my_data, "weibull")
> fit_ln<-fitdist(my_data, "lnorm") #Lognormal distribution
> fit_ll<-fitdist(my_data, "llogis") #Log-logistic distribution
> gofstat(list(fit_w, fit_ln, fit_ll), fitnames=c("Weibull",
"lnorm", "llogis"))
Goodness-of-fit statistics
                                Weibull     lnorm    llogis
Kolmogorov-Smirnov statistic 0.06834037 0.1362658 0.1109283
Cramer-von Mises statistic   0.28739228 1.2935339 0.5683531
Anderson-Darling statistic   2.23109075 8.0190900 5.4675674
Goodness-of-fit criteria
                                Weibull    lnorm   llogis
Akaike's Information Criterion 3220.356 3293.883 3281.689
Bayesian Information Criterion 3227.198 3300.724 3288.530
> anova(Weibull.3, Weibull.4)
                   Terms Resid. Df    -2*LL Test Df  Deviance
Pr(>Chi)
1 TotalTime + Loc_Tinker       222 1032.295 NA        NA       NA
2     Ln_TT + Loc_Tinker       222 1031.482=  0 0.8132791      NA
> anova(Weibull.1, Weibull.2)
                   Terms Resid. Df    -2*LL Test Df  Deviance
Pr(>Chi)
1 TotalTime + Loc_Tinker       222 1210.935 NA        NA       NA
2     Ln_TT + Loc_Tinker       222 1210.115 =  0 0.8208234     NA
>anova(CoxModel.3, CoxModel.4)
Analysis of Deviance Table
 Cox model: response is  Surv(SOW, Oil)
 Model 1: ~ TotalTime + Loc_Tinker
 Model 2: ~ Ln_TT + Loc_Tinker
   loglik  Chisq Df P(>|Chi|)
1 -283.34
2 -282.94 0.7851  0 < 2.2e-16 ***
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> anova(CoxModel.1, CoxModel.2)
Analysis of Deviance Table
 Cox model: response is  Surv(TOW, Oil)
 Model 1: ~ TotalTime + Loc_Tinker
 Model 2: ~ Ln_TT + Loc_Tinker
   loglik  Chisq Df P(>|Chi|)
1 -275.07
2 -274.60 0.9269  0 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 074-0188

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

TITLE AND SUBTITLE

Predicting TF33-PW-100A Engine Failures Due To Oil Issues Using Survival Analysis

5a. CONTRACT NUMBER
N/A

5b. GRANT NUMBER
AFMC/A4P 2017-182

5c. PROGRAM ELEMENT NUMBER
N/A

6. AUTHOR(S)

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5d. PROJECT NUMBER
N/A

5e. TASK NUMBER
N/A

5f. WORK UNIT NUMBER
N/A

7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S)
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8. PERFORMING ORGANIZATION REPORT NUMBER

AFIT-ENV-MS-22-M-191

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
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10. SPONSOR/MONITOR'S ACRONYM(S)

AFMC/A4P

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

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

13. SUPPLEMENTARY NOTES

14. ABSTRACT

In 2007, the Office of the Assistant Secretary of Defense for Sustainment pushed for the need to transition to a Condition Based Maintenance Plus (CBM+) initiative for weapon systems in the U.S. Department of Defense. The CBM+ initiative can help increase aircraft availability (AA) for the United States Air Force. There are many reasons where AA can be affected but one such issue is engine availability primarily due to oil issues. Within the CBM+ perspective, this study examines the risk of a jet engine failure due to an oil issue and attempts to predict an engine's time until next failure using survival analysis. Predicted engine's failure could be used to help pilots, maintainers, repair shops, and system program offices become better equipped to handle an oil issue before it occurs. The results of this study showed that as the engine's sorties on wing gradually increased, the risk of failure increased. In addition, this study found that a Weibull model with accelerated failure time was the most suitable model to predict the remaining life of the engine before it failed due to an oil issue. Based on the results, this study developed a field ready estimation tool that could be used by practitioners for predicting engine failures.

15. SUBJECT TERMS
Engine failure, oil issues, survival analysis, survival time, Weibull Accelerated Failure Time Model

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, AFIT/ENS
					19b. TELEPHONE NUMBER *(Include area code)*
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Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39-18