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Examining the Drivers of C-130J Maintenance Requirements through Multiple Regression Analysis

Andrew V. Gill

EXAMINING THE DRIVERS OF C-130J MAINTENANCE REQUIREMENTS THROUGH MULTIPLE REGRESSION ANALYSIS

THESIS

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Abstract

As a result of increasing system complexity and cost, new aircraft acquisition, upgrade and repair timelines continue to lengthen. As a result, aircraft are kept in service longer than originally intended. Therefore, age-related wear continues to play a large part in determining mission-capable status, and therefore, aircraft availability (AA) rates. Combined with decreasing fleet sizes and manpower resource pools, each aircraft declared not mission capable (NMC) exerts an out-sized influence upon fleet AA rates. This research used multiple regression analysis to identify and quantify the effects of age, Major Command (MAJCOM) and operating location ambient weather on unscheduled not mission capable time. The research found that age and ambient weather have a small but statistically significant effect upon unscheduled not mission capable time, while MAJCOM does not appear to have a statistically significant effect. The research serves as a foundational study to identify and propose new and more in-depth research into the root causes of the identified effects.

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I would like to thank my advisor, Dr. William Cunningham, for his wisdom, patience and faith in me. His guidance was invaluable, especially during the many times I painted myself into logical corners. My sincerest thanks go to Mr. Daniel Kelly and Mrs. Eilanna Price, my Air Force Life Cycle Management Center sponsors, not only for providing me with guidance, but for letting my imagination run wild in search of answers. Finally, I would like to thank my family and friends for tolerating long nights, panicked texts, and long periods of absence. Your love and support got me through, and I couldn't have done it without you.

Andrew V. Gill

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Table of Contents

Contents

List of Figures

List of Tables

EXAMINING THE DRIVERS OF C-130J MAINTENANCE REQUIREMENTS THROUGH MULTIPLE REGRESSION ANALYSIS

I. Introduction

General Issue

The Air Force is charged with properly maintaining equipment in order to deploy in service of the United States of America at any given time. However, the ability to sustain aircraft at a particular level of readiness is difficult to accurately predict, because unforeseen corrosion and equipment wear often drive unscheduled requirements, represented by unscheduled not-mission capable (NMCU) time. Aircraft availability rates are one of the primary measures of the Air Force's ability to accomplish its assigned mission, defined as the percentage of the fleet that is fully mission capable (FMC) at a given time. Aircraft able to safely perform all assigned mission sets are considered fully mission capable (FMC), while aircraft that are unable to perform some or any assigned missions are partially mission capable (PMC) and not mission capable (NMC), respectively. NMC time is further broken down into scheduled and unscheduled time. Scheduled NMC time refers to time used for inspections and scheduled maintenance executed on a flying hour or sortie basis, and composes a significant part of the support cost of the aircraft (Marks and Hess, 1981). On the other hand, unscheduled maintenance is required due to detected aircraft damage, corrosion, fatigue and all other safety of flight issues. By its very nature, unscheduled maintenance is difficult to predict, and thus presents a threat to the Air Force's ability to maintain an appropriate level of readiness.

Department of Defense (DoD) budget limitations in recent years have forced both aircraft fleets and their associated maintenance resource pools to become smaller and increasingly strained (Kiley, 2001). As shown in figure 1, the acquisition and development time between successive variants of the C-130 has grown considerably, while C-130 fleet sizes have shrunk.

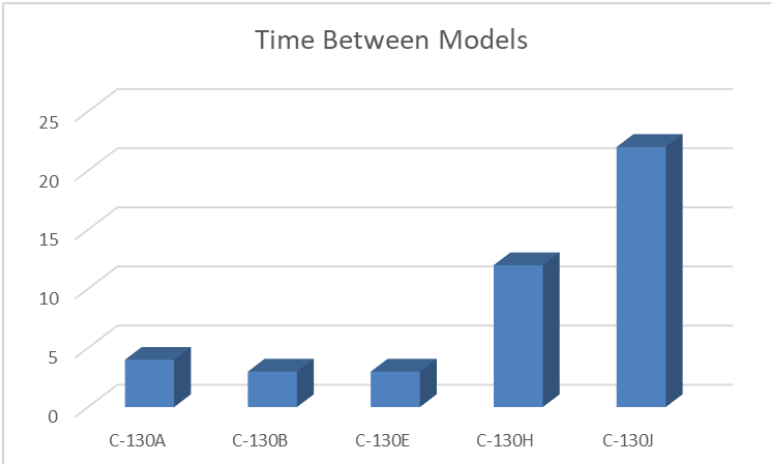

Figure 1: Time Between C-130 Variants

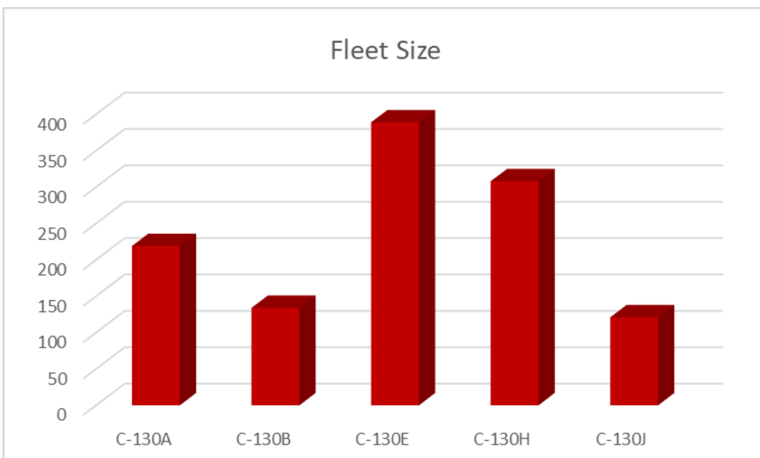

Figure 2: C-130 Variant Fleet Sizes

Meanwhile, mission requirements have not appreciably decreased, placing greater demands on each aircraft. Therefore, each not-mission capable aircraft has an increasingly large impact on overall fleet readiness. There are a nearly infinite number of factors, acting alone or in concert, which may affect an airframe's airworthiness. However, the primary drivers of unscheduled time and their degree of impact are not well understood. Consequently, the United States Air Force (USAF)**,** as represented by the Air Force Life Cycle Management Center (AFLCMC), has sponsored research to investigate and identify the factors which most strongly affect aircraft wear and tear. Specifically, AFLCMC would like to identify how changes in airframe age, Major Command (MAJCOM), and operating location weather affect unscheduled Not Mission Capable (NMC) time.

Problem Statement

The USAF operates and maintains aircraft in extremely varied conditions. Each operational aircraft is subject to a distinct combination of factors which may affect wear. In order to fully utilize time, manpower, and budgetary resources, it is imperative that the Air Force understand what factors most affect fleet readiness.

Research Question

The objective of this research is to determine if aircraft age, MAJCOM, and weather conditions affect aircraft NMC time. This is to serve as a foundational study which would enable future researchers to examine root causes of any identified effects of the independent variables. Therefore, the research question is as follows:

RQ: Do aircraft age, MAJCOM and operating location weather affect unscheduled not mission capable time? If so, to what degree?

Research Focus

This study will focus on the effects of aircraft age, MAJCOM and operating location weather on monthly unscheduled Not Mission Capable (NMC) time for 121 individual serial-numbered C-130J airframes at 14 operating locations across the Continental United States (CONUS) and overseas during the period from April 1999 to December 2017.

Investigative Questions (IQs)

In order to answer the research question, several sub-questions must be answered, as there are nearly infinite factors which may have an impact on unscheduled NMC time. As foundational research, it is useful to first address the most likely factors as determined by the relevant research. Those factors were identified as aircraft age, MAJCOM and operating location weather.

The first investigative question concerns whether aircraft tail number age has a statistically significant effect upon the monthly NMC time. There are several complications to this question. First, a complex system's "age" is somewhat difficult to determine. Previous researchers have used tail number age, average fleet age, MDS age, major subsystem age, number of flight hours and number of sorties all as relevant measures of "aircraft age" each with its own benefits and limitations. Further investigation is needed to determine the best measure of aircraft age and the best way to represent this measure. For the purposes of this research, aircraft tail number age in months is used as the measure of interest.

IQ3: Does the age of the airframe affect the amount of not mission capable time in a particular month? If so, to what degree?

H_0: Aircraft age does not have a statistically significant effect upon unscheduled NMC time.

H_A: Aircraft age has a statistically significant effect upon unscheduled NMC time.

The second investigative question examines *who* is operating the aircraft, rather than *where* the aircraft is operated. This is an important distinction as each aircraft is directly tied to the host Wing's mission. For instance, due to mission requirements, AETC bases have a larger number of both sorties and flight hours. A reasonable person may therefore assume that by flying the aircraft more often, the aircraft is more likely to break and experience unscheduled NMC time. This type of "common sense" reasoning is examined later in the study.

IQ_2: Does the Major Command (MAJCOM) operating the aircraft affect the occurrence of not mission capable time?

H_0: MAJCOM does not have a statistically significant effect upon unscheduled NMC time.

H_A: MAJCOM has a statistically significant effect upon unscheduled NMC time.

The final investigative question examines if weather factors have an effect upon unscheduled NMC time. While compiled into a single investigative question, each environmental factor will have its own effect, level of significance, and importance in the final regression model. Therefore, each will be examined separately, but are addressed together for brevity.

IQ1: Do the various atmospheric weather conditions experienced on the ground at the operating location have an effect on not mission capable time?

H_0: Environmental factor (E_i) does not have a statistically significant effect upon unscheduled NMC time.

H_A: Environmental factor (E_i) has a statistically significant effect upon unscheduled NMC time.

Methodology

In order to answer the investigative questions, all 121 serial-numbered C-130Js were analyzed over a period spanning from MDS introduction in April of 1999 to December of 2017. The study consists of a multiple regression model to determine those variables which have a statistically significant effect upon the dependent variable. Logistics, Installation and Mission Support – Enterprise View (LIMS-EV) is the Air Force's central logistics data hub and provided all aircraft and maintenance data for each month of the selected period. For each aircraft, LIMS-EV provided the month in which the events occurred, the aircraft's operating location, the MAJCOM to which the aircraft was assigned, the amount of time the aircraft was possessed by that unit, the amount (and type) of not mission capable time registered in the month, the number of flight hours and sorties, as well as their average duration. Weather data was provided by the 14th Weather Squadron, and included various measures each for average temperature, windspeed, pressure and precipitation data. The data was merged into a master file and analyzed for erroneous or extraneous data. Several variables were then calculated from the available information for usefulness and account for likely multicollinearity. The most appropriate variables were selected and used to build the initial regression model. Statistically insignificant variables were removed and the model was checked to ensure linear regression assumptions were not violated. Finally, the residuals were analyzed for Cook's distance and leverage to determine which data points were outliers and the degree to which they affected the outcome of the model. Each coefficient was then analyzed for significance and leverage.

Assumptions

The research focused only on the 121 aircraft C-130J fleet. This was done in order to isolate the age, MAJCOM and weather effects from any MDS effects which could mask the effects of the factors in isolation. While it is inappropriate to assume these effects are perfectly generalizable across all aircraft types and missions, it is reasonable to assume that a well-fit model will provide insights across the entire USAF inventory, and provide justification for further research.

Since maintenance data is sourced from Logistics, Installation and Mission Support - Enterprise View (LIMS-EV), it is assumed the data is complete and paints an accurate portrayal of maintenance actions according to the guidance outlined in T.O. 00-20-2. However, as there is latitude regarding how and when an aircraft is to be reported NMC, it stands to reason that there will be variance in procedure between units. For instance, if a unit were to choose not to report an aircraft as NMC when the issue is discovered vice when the aircraft is due to fly, the full NMC time would not be recorded. Without further research into this phenomenon's prevalence, it is impossible to determine how data from different MAJCOM sources should be treated differently, if at all.

The USAF's 14th Weather Squadron provided weather data for all locations. Weather data is assumed to be representative of average environmental factors throughout the month. There are advantages and disadvantages to this approach. Using mean values across a month risks losing a great deal of variation, some of which could be extremely important. For instance, Hurricane Katrina destroyed several buildings on Keesler AFB in August of 2005. However, the reported weather data (windspeed in particular) for this month does not show anything out of the ordinary. In this way, the effects of brief, extreme events are muted in favor of general conditions. Since corrosion and material wear are slow processes, the lost variation is considered acceptable. Furthermore, it is well understood that aircraft that are operational and undertaking sorties will not experience operating location weather at all times. However, without extremely detailed information regarding each mission, its duration and en-route stations, weather at home operating locations must be taken as representative. It is therefore assumed that weather data is representative of the general operating conditions a subject aircraft will be subjected to whilst stationed at the subject base.

Delimitations

This study will not examine the effect individual pilots and individual commanders have upon NMC time, and will assume all aircraft in a given fleet are equally affected by the flying culture, mission and demands of the command. This research will not examine operators that fall outside USAF control, as maintenance data is not collected in the same way and cannot be examined equivalently. Research will not identify *why* examined factors are relevant, nor will it identify mitigating organizational best practices or identify proposals that may affect broader USAF operations. The research also will not attempt to determine appropriate resourcing levels or budgetary concerns.

Implications

The implications of this research are far-reaching. Many researchers have analyzed a variation of this issue for decades, but a consensus has yet to be found. While extremely unlikely, a model with an adjusted R^2 value nearing 1 (perfect prediction of all variation) would be able to nearly always predict when an aircraft would break, given reasonable predictions for variables occurring in the future. The value of such a model cannot be understated. However, even a less robust model can provide extremely valuable insights.

With an appropriate model, engineers and acquisition professionals would be able to determine the optimal time to upgrade, overhaul or replace existing aircraft. This could be achieved by analyzing the point at which the cost of upgrade/overhaul exceeds the cost of a new acquisition. However, there is some evidence that with appropriate maintenance and upgrades, aircraft can be operated indefinitely (Foster and Hunsaker, 1984). In this case, a new acquisition would only be justified to meet a new requirement or maintain technological superiority over an enemy.

Given that the models incorporate weather data unique to each operating location, a sufficiently robust model has implications for aircraft basing as well. Assuming that insights from the model can be generalized to the larger Air Force Inventory, basing decisions could be made which would incorporate the full costs of maintenance (material and manpower) at a particular location.

With sufficient research, each of the significant factors can be analyzed and root causes determined. For instance, if windspeed is found to be a significant factor in unscheduled NMC time, why is that so? With this information, effective countermeasures can be developed to mitigate the effects.

Preview

This chapter described the problem statement, research objectives, research focus, research question, investigative questions, methodology, assumptions, delimitations and implications associated with conducting a multiple regression analysis on age, MAJCOM and weather factors which may have an effect upon unscheduled Not Mission Capable time.

Chapter II will discuss the relevant literature discussing how age affects material wear, how operators affect wear, and how weather affects wear. Chapter III outlines the methodology used to collect and analyzed the data. Chapter IV discusses the results of the regressions and the tests used to validate the outcomes. Chapter V summarizes the results of the data, provides answers to the investigative questions and suggests further research.

II. Literature Review

Chapter Overview

This chapter seeks to summarize and review the relevant literature concerning the effects of age, operator and weather on complex systems' failure rates. The question of how age affects aircraft has been studied for decades. As such, there is a large and well-developed body of work from which to draw insight.

Age Effects

Conventional wisdom holds that aircraft age is the most pressing underlying cause of increasing maintenance requirements and costs. This issue has increased in urgency in recent decades as acquisition timelines continue to lengthen, especially for those aircraft which are not adapted from commercial-off-the-shelf options.

Table 1: USAF Airlift Aircraft Acquisition Timelines

MDS	Request	Award	Fielding	Award Gap (Y)	Fielding Gap (Y)	Total (Y)
C-130	1951	1951	1955	0	4	4
KC-135*	1954	1955	1957	1	2	3
C-141*	1960	1961	1963	1	2	3
C-5	1964	1965	1969	1	4	5
KC-10*	1975	1977	1980	2	3	5
C-17	1980	1981	1995	1	14	15
KC-46*	2007	2011	2019	4	8	12
* denotes aircraft developed from pre-existing commercial aircraft						

As acquisition costs have increased and timelines have lengthened, Air Force leaders have consistently come to rely on airframe overhaul and upgrade in lieu of system replacement in order to maintain a technological edge. This methodology, while cost-effective, introduces airframe senescence as a real threat to aircraft maintenance resource intensity, as aircraft have begun to be kept in service many multiples of their original intended service life. Therefore, researchers have examined the effects of age on aircraft maintenance requirements and costs for decades.

One of the first studies of the effects of age on aircraft and their subsystems was Nelson's (1977) examination of Air Force engine workloads. Nelson sought to establish a causal relationship for increasing material and labor costs associated with engine maintenance in order to determine when engine replacement was optimal. Nelson found age was responsible for "increasing costs in terms of both absolute dollars and as a percentage of total life-cycle costs," attributable to increasing depot maintenance costs. He also found that costs increased as a function of the engine's complexity and performance. As engines became more powerful, ran hotter and more complex, they become more difficult and costly to maintain (Nelson, 1977). Nelson himself identified that the study was hampered by a few inherent and unavoidable drawbacks. First, Nelson sought to extrapolate insights from an incredibly small sample of only 12 data points, casting doubt on the universality of his conclusions. This was unavoidable simply because reliable cost and maintenance data simply did not exist. Second, Nelson's data points were from a period of rapid technological improvements in engine technology. Recognizing this, Nelson sought to separate design from age effects by introducing a normalizing equation which compared the engine in question from a hypothetical state of the art engine. Of note was Nelson's seemingly perverse finding that engine workloads seemed to decrease as the interval between engine overhauls increased. Nelson explained this finding as being a result of engineers' lack of confidence in the engine early in its lifecycle, when an engine's reliability issues have yet to be found and eliminated. As these issues are remedied, the engineers become more confident in the engine's reliability in tandem with the engine itself becoming more reliable.

Foster and Hunsaker (1984) conducted a study on the effect of aircraft aging and usage on maintenance costs using eight-year samples of several MDSs. As is typical of studies from this time period, lack of data was a concern. However, while finding evidence for a steady, gradual increase attributable to age, they did not find any point at which costs drastically increase. However, Foster and Hunsaker address the conventional wisdom of the "bathtub" or "hazard" curve, which describes the behavior of maintenance costs throughout the lifecycle of a system. The theory states that early in a system's lifecycle, costs are high as maintenance adjusts to the new system and identifies systemic weaknesses. As the system matures, maintenance costs level out, then rise again as the system reaches senescence and begins to wear out. Foster and Hunsaker did not find this to conform to reality. They posit that since systems are composed of many systems, each being replaced at varying intervals, a complex system cannot be treated in the same way as a simple system, which may conform to the bathtub curve. In essence, a complex system like an aircraft is both old and new at the same time (Foster and Hunsaker, 1984).

In 1988, Aloha Airlines flight 243 experienced an explosive decompression in-flight, tearing a portion of aircraft skin from the fuselage, resulting in one fatality and 64 serious and minor injuries (NTSB, 1989). The cause was found to be accumulated disbonding and fatigue damage in the S-10L lap joint as a result of abnormally high pressurization cycles. At the time of the accident, the 737 in question was 20 years old, and had accumulated 35,496 flight hours and 89,680 pressurization cycles, the second-highest in the worldwide 737 fleet (the highest was also an Aloha Airlines aircraft).

Boeing considered aircraft in excess of 60,000 cycles “high time,” as the 737 had been designed for a service life of 20 years and 75,000 cycles. This information is useful to establish flight hours and pressurization cycles as relevant measures of aircraft age apart from airframe chronological age. For reference, average intended service life for a military aircraft is about 20 years (Dixon, 2005). The oldest C-130Js, the newest variant of the C-130, are nearing the 20 year mark.

Hildebrandt and Sze (1990) also sought to determine the effect of age on maintenance costs from 1981 to 1986. Hildebrant and Sze’s study was one of the first with access to high-quality longitudinal data, and as such, found much more modest age-related effects, on the order of one half percent (.5%) when accounting for fuel and support costs. However, the peculiarities of the Air Force budgeting process may have muted the age effects. This is one of the downfalls of using cost data vice direct inputs. Unfortunately, the Air Force budgeting and costing process is not sufficiently responsive to actual changes in activity cost, relying instead upon historical spending to allocate future budgets. Further complicating their study, Hildebrandt and Sze used an average fleet age variable which treated all aircraft variants as the same age.

Berens, Hovey and Skinn (1991) conducted a study attempting to develop a mathematical model to predict the occurrences of stress fractures in aircraft. The researchers determined that since aircraft usage is typically measured in flight hours and sorties, the logical variable which combines the two is average sortie duration.

Stoll and Davis (1994) found small aircraft age effects (1.4 to 5.4 percent per year) growth in on-equipment workloads over approximately nine years (1983-1992) when examining ten Navy aircraft.

Kiley (2001) did not find that age was the primary driver of rising O&M costs, but the study was not limited to aircraft, rather to all military equipment. Kiley was commissioned by the Congressional Budget Office to do a review of the relevant literature, and therefore did not conduct original experimental research. However, he surmised that the consensus was that costs rose from one to three percent with each additional year.

Pyles' 2003 study for the RAND Corporation was the most comprehensive to date. Pyles chose to examine direct inputs (manhours and materials) as well as costs. Pyles' work is unique in that the differing phases of a system's lifecycle were each treated differently with different growth rates. This was an attempt to isolate pure age effect from other events, such as early lifecycle "bathtub" effects. Ultimately, Pyles found several age related growths of maintenance and "fly away" costs. He also established that different aircraft have different age-related growth effects, generally a function of the complexity of the aircraft (which roughly correlates to aircraft cost). Pyles' incorporation of an acceleration factor led to several insights, including differences amongst MDSs which seem to indicate that more complex aircraft have a larger (and faster accelerating) growth effect.

By contrast, Dixon (2005), studying commercial aircraft, found that the effects of age tend to decelerate over the life of the fleet, and fleets with an average age of 12-25 years show approximately zero growth in maintenance costs. Dixon's regression methodology is very similar to the methodology used in this study. Dixon used the log of the total maintenance costs per flight hour in order to leverage the interpretation benefits of elasticities rather than unit changes. Ultimately, Dixon found that age effects do exist and are significant, but only in the steep portions of the “bathtub effect.” For the purposes of this study, this is most useful to interpret as occurring after the second “d-check,” which is generally after the twelfth year of operation or 18,000 flight hours.

The Air Force Scientific Advisory Board (2011), conducted a survey of a multitude of organizations involved in extending the lives of aircraft in order to determine best practices. Of note, the Board found that failure modes are due more to age than to usage, and occur more rapidly when the aircraft is on the ground than when in flight. Furthermore, relative to fighter/attack aircraft, cargo aircraft have a lower severity usage per year, which reduces the effect usage has on the overall effect. The Board also identified the two distinct types of aging: chronological and cyclic. Chronological aging is typified by system obsolescence, corrosion and environmental degradation at the basing location, while cyclic aging involves fatigue cycles (as with Aloha Airlines 243), as well as thermal cycling and stress damage. Conducting a linear regression analysis on 133 C-130s of 12 different models, the Board found maintenance man hours had a strong linear dependence on a condition based maintenance value, with better than three quarters of its value derived from aircraft age and corrosion. The overall model has an adjusted R^2 value of .57, described as a “good fit.”

It seems then, that any multiple regression which seeks to determine the effects of age on maintenance would do well to incorporate several salient points:

1. Study a single MDS rather than several, in order to eliminate technological changes and mask the age effect with differences in MDS

2. Study direct inputs rather than costs, in order to avoid confounding the effect with budgetary issues
3. Look beyond obvious explanations when presented with perverse results
4. If possible, model the effects of age in the various periods of a system's lifecycle
5. Incorporate pressure cycles (represented as sorties) into the analysis to isolate the effects of age
6. In order to incorporate flight hours as well as sorties, incorporate average sortie duration into the analysis
7. Use logarithmic transformations to leverage the explanatory advantages of elasticities as well as to normalize data
8. In order to more purely isolate age effects, examine cargo aircraft, as they have less severe usage effects.

Operator Effects

Do certain commands fly their planes harder? Very few analyses have been conducted to determine differences between the commands directly, as they are generally more focused on cost and direct input analysis. However some studies address these effects, however obliquely.

The NTSB (1989), in its examination of the 1988 Flight 243 incident, found that Aloha Airlines' own procedures created a higher likelihood of failure, as Aloha had not been conducting the proper maintenance checks associated with a higher time aircraft, prescribed both by Boeing and the FAA. This effect can be seen less as a difference in stresses due to a particular carrier than it is as a "tradeoff" between scheduled and unscheduled maintenance. Were Aloha to conduct the proper preventative maintenance actions, the accident could have been avoided entirely. Furthermore, the particularities of Aloha's region and routes led to a high accumulation of pressurization cycles, as the aircraft was primarily used for island-hopping in the Hawaiian chain. This was also a mitigating factor, as the aircraft rarely reached the altitude required for the max pressure differential, meaning the actual pressurization cycle was considerably lower than the reported value of sorties. This is one of the hazards in using sorties as a proxy for pressurization cycles, as the two are not synonymous.

Dixon (2005) also examined the difference in operators of commercial aircraft. As he examined commercial aircraft and there is little differentiation between the various carriers and the way in which they operate their fleets, Dixon came to the conclusion that different operators do not have a significant effect on wear. However, it would be irresponsible to perfectly transcribe this result to military aircraft. Each MAJCOM has drastically different missions and use their aircraft in different ways. For instance, there is not a commercial carrier whose sole mission is training new pilots, similar to Air Education and Training Command (AETC).

Therefore, the literature would seem to indicate that while there do not appear to be effects between operators and the way they fly generally, there may be differences attributable to varying mission sets.

Weather Effects

Reductions in Department of Defense (DoD) and United States Air Force (USAF) budgets following the Cold War resulted in five rounds of base closures under the Base Realignment and Closure (BRAC) program, which progressively consolidated more aircraft in fewer locations. A further consequence of reducing the number of bases at which aircraft are stationed is that any weather effects which may occur at one location or another are intensified relative to the entire fleet. Therefore, it is imperative to understand how ambient weather at the operating location affects maintenance, particularly corrosion.

Quitmeyer (2008) serves as a useful primer on corrosion generally, and which conditions must be present for it to occur. Corrosion is the degradation of metals as a result of electrochemical activity, defined as dissolving, eroding or eating away gradually. She highlights that for corrosion to occur, the following must be present: an anode (a positive electrode), a cathode (a negative electrode), an electrolyte (any substance with free ions that acts as a conductive medium, and an electrical connector. As shown in other studies, aircraft on the parking apron have all the requisite elements to experience significant corrosion.

Biscaia, Chastre, Silva and Manuel (2019) describe the effects of various simulated environmental effects on glass bonded to a concrete substrate. The four cycles examined each neatly correlate with various environmental factors of interest. Salt fog cycles (products of temperature, relative humidity and ambient air salinity), wet-dry cycles (correlated with relative humidity and precipitation), and temperature cycles between -10° C and +30° C as well as between +7.5° C and +47.5° C, which correspond with colder and warmer daily temperature cycles.

Zayed, Garbatov and Guedes Soares (2018) studied the effect of relative humidity, chlorides and temperature on the corrosion of ship hull plates. Per their results, the most important factor affecting corrosion is relative humidity, which directly correlates to the amount of time the electrochemical process is allowed to continue. Second is temperature, as it affects relative humidity, dew point, duration of wetness (through drying time), and the speed at which corrosion occurs. Corrosion occurs more quickly in high temperatures as the ions move more freely between the electrodes. Finally, the presence of chlorides (as in salt water) directly affects the corrosion process as the chlorides provide the requisite electrolyte.

Kong, Dong, Fang, Xiao, Guo, He, and Li (2016) further corroborate these findings, as their study of corrosion of copper plates in Turpan, China perfectly align with the findings of Zayed, Garbatov and Guedes Soares (2018). The researchers found that corrosion rates depends upon presence of pollutants in the form of sulfur dioxide (air pollution) and chorides (salt water), as well as time of wetness (humidity/precipitation) and metal drying rate (temperature). Furthermore, the researchers found that coatings increased the copper plates' resistance to corrosion, but the effect was dampened in higher temperatures.

Cai, Zhao, Ma, Zhou and Chen (2018) also concur with these results, concluding that atmospheric corrosion is a complex process that depends on the interaction of relative humidity, temperature, pollutants and wind. The researchers further relate that temperature's effect on the speed of chemical reactions is well documented in the form of the Arrhenius equation, which directly states that the speed of a chemical reaction will increase if all other variables are held constant. Furthermore, the effect of high humidity is illustrated by the Peck relationship, which states that metals will corrode at an accelerated rate when placed in a sufficiently high humidity environment. Finally, the presence of electrolytes is controlled as a function of windspeed/turbulence, distance from the coast and presence of rain.

Sabir and Ibrahim (2017) studying corrosion in several Saudi Arabian cities, also concur with these findings, finding humidity, temperature, time of wetness, and precipitation are the prime factors which affect corrosion. Furthermore, aside from the proximity to the ocean providing an ample source of chlorides, burning fossil fuels also introduces sulfur dioxide. This has implications for aircraft basing away from population centers which generally have a higher concentration of air pollution.

Naseri, Baraldi, Compare and Zio (2016) attempt to predict availability of oil and gas equipment in an extreme cold-weather environment. The researchers find that environmental factors have a compounding effect along with asset age. While this appears to be an elementary finding (age would also roughly correlate to duration of exposure), it also necessitates that examinations of these factors must be taken together to determine the total effect.

Given the bulk of research, it is clear that any model seeking to capture the effects of corrosion would need to utilize variables which can measure humidity, temperature, time of wetness and precipitation.

Research Gap

In order to justify research, it must be established that the current literature does not address the specific area we seek to study. With regards to the interrelated effects of aircraft age, operator and weather, no such research has been accomplished to date, despite a clear argument for its inclusion. This research seeks to address this gap in institutional knowledge. Furthermore, all studies seeking to understand age effects have sought to examine either costs or direct inputs. No study to date has examined unscheduled not mission capable time.

Summary

This section conducted a thorough review of the extant literature concerning the effects of age, operator and weather on complex systems. It is clear that the various effects are interrelated and often compound one another. Therefore, it is imperative that these effects be analyzed as a part of the whole.

The next section will outline the method used to conduct the experiment and the variables chosen to represent the effects described in this section.

III. Methodology

Chapter Overview

The purpose of this chapter is to outline the method used to construct the regression model and describe the purpose for each of the component variables.

Research Design

Multiple regression is the best method to determine the effect of each independent variable on a dependent variable. At the conclusion of the process, regression will also produce a predictive equation which can be used to forecast future values of the dependent variables, assuming that the regression was conducted properly with sound data and valid assumptions. For this reason, multiple regression was chosen as the most appropriate method to analyze the effect of several independent variables (each representing the most appropriate measures of age, command and weather) upon unscheduled not mission capable time.

Airframe Appropriateness

Before describing the model itself, it is useful to outline the reasoning behind selecting the population of interest, as the C-130J is especially well suited to this type of analysis. First, as cargo aircraft have lower severity of usage (USAF Scientific Advisory Board, 2011), the C-130J stands above fleets like the A-10, which experiences higher usage stresses. In this way, the effects of age, command and weather can be more easily determined. As a corollary, the C-130J has a fairly stable mission set which is easily modeled using sortie and flying hour data. Other airframes, such as the F-16, have a diverse mission set, each of which has a different usage profile, which can change fairly rapidly. The F-16 fleet would require additional mission variables to determine how "hard" the aircraft had been flown. It is also for this reason that EC-130Js were excluded from the data, despite being reported as part of the same fleet by LIMS-EV. The different mission profile would have introduced a confounding factor to the data.

As the C-130J entered service in 1999, the entire lifespan of the airframe is contained within the data set, which enables modeling of break-in effects and the stabilization of the same. Being a relatively new aircraft also places the entirety of its life span within the era of reliable maintenance data. Thus it can be reasonably assumed older data is accurate.

Also in contrast to the F-16, the C-130J has a relatively small fleet, at 121 individual serial numbered airframes. The combination of a small fleet and short history means that the results are true for the entire population rather than a representative sample.

Data Collection

In order to begin, it was necessary to identify the list of all serial numbered C-130J aircraft in LIMS-EV. This returned both C-130Js and EC-130Js, which were removed as detailed above. After narrowing to only C-130Js, the search resulted in 121 aircraft across 18 year span. Then, each variable of interest needed to be identified and queried. LIMS-EV provided maintenance workload data in the form of total maintenance man hours (TMMH), on/off equipment MMH, and both scheduled and unscheduled NMC time. Furthermore, LIMS-EV provided the month of interest, operating MAJCOM, Operating Base, and total unit possessed time. LIMS-EV also provided usage measures in the form of hours flown, sorties flown and average sortie duration.

With airframe workload data collected, each month needed weather data for the appropriate operating base. Initially, weather data was sourced from National Oceanographic and Atmospheric Administration (NOAA) and National Weather Service

(NWS) databases, but data availability was extremely inconsistent and often missing for actual operating locations, necessitating the use of proxy stations which were up to 20 miles away from the location of interest. Since this would introduce an unacceptable level of uncertainty to the data, a new source was required. Instead, weather data was acquired from the USAF 14th Weather Squadron. The information included monthly extreme high temperature, mean maximum daily temperature, mean temperature, mean minimum daily temperature, monthly extreme low temperature, mean wind speed, mean atmospheric pressure, mean dew point temperature, mean relative humidity, precipitation in inches, number of days with precipitation and the percentage of the month which experienced precipitation. Further rounding out the data set, elevation data was sourced from Google Earth. The combination of workload and weather data resulted in 14,459 data points.

At this point, it was apparent that not all variables would be appropriate or useful in the proposed regression. Therefore, some variables needed to be calculated and added to the dataset. Aircraft age (in months) was calculated by taking the difference between the tail number's entered active service date and the current date. MDS age was calculated by taking the difference between the MDS's entered active service date and the current date. Average fleet age averaged the ages of all tails present in the fleet during the current month. Cumulative hours and cumulative sorties variables were created by totaling all previous hours and sorties, respectively. Mean temperature difference was calculated by subtracting mean minimum daily temperature from mean maximum daily temperature. Finally, the percentage time in possession was calculated by dividing total in possession time by the total time available in each month.

A cursory analysis of the data revealed that not all data points would be relevant to the analysis. First, rows in which the unit had possession of the aircraft for less than 10% of the effective month were removed, as these data points would be equally weighted with months in which the unit had 100% possession of the aircraft. These rows were often “duplicate months” used for accounting purposes, in which a depot logged maintenance man hours against a particular tail number, but did not have physical possession of the aircraft in order to fly sorties. Conversely, rows in which >90% of in possession time was spent in scheduled maintenance were also removed. Since an aircraft in scheduled maintenance (often for phase inspection) can neither accumulate sorties nor be unscheduled not mission capable, these data points would only serve to confound the analysis. After cleaning, the remaining data has only 457 (3.7%) of the data points with total in possession times less than 50% and only 308 (2.5%) data points with more than 50% of time scheduled NMC. Despite the much higher quality data received from the 14th Weather Squadron, 313 lines remained with no weather data at all. These values would also serve to confound analysis, and were thus removed from the dataset. After all cleaning, the data set consisted of 12,090 individual tail number, month, operator and location combinations.

Model Design

While the dataset is fairly robust and contained a great deal of useful information, many sets of variables effectively measure the same effects. Therefore, it was important to identify those variable sets which measured similar or related phenomena and select the most useful of the variables, so as to avoid multicollinearity. Multicollinearity is the condition where two variables are directly or incidentally related to one another, and its presence in a regression model severely undermines the usefulness of the model. The first pair of related variables were the MAJCOM and the base. By definition, each base belongs to a particular MAJCOM, so these variables will always be inextricably linked. In deciding which to use, base was discarded because the base and its weather are also linked by definition, whereas more variation exists within each MAJCOM.

Next, it was necessary to examine the various measures of an aircraft's age and usage factors, namely aircraft age, hours flown, cumulative hours, sorties flown, cumulative sorties and average sortie duration. Age, as a condition of the research question, must be included, so the variables which closely correlate with age should be eliminated as well. It stands to reason that as an aircraft ages, its cumulative hours and sorties will as well, so both of these variables must be discarded. However, the hours and sorties logged in a particular month are both useful variables for analysis. Unfortunately, since these are also linked by definition (i.e. as a sortie is conducted, hours increases), only one variable can remain. Since an aircraft experiences its highest stress loads during takeoffs and landings, sorties is a more appropriate measure of the stresses exerted on an airframe. However, in order to account for hours flown, average sortie duration (ASD) was also included in the model (Berens, Hovey and Skinn, 1991).

The weather data contained several sets of variables with likely multicollinearity. First, a measure of operating environment temperature must be selected. Maximum and minimum temperatures experienced in a month are not representative of an entire month, and must be discarded. In contrast, the maximum and minimum mean temperatures have interesting implications for corrosion (Cai, Zhao, Ma, Zhou, Chen, 2018). However, as these temperatures tend to fluctuate together with the seasons, only one measure can be used. Since neither measure in isolation is fully representative of the conditions, the mean temperature becomes the most appropriate measure of the general conditions in the month. In order to measure the changes in temperature, the model also includes the mean temperature difference between the mean maximum and mean minimum. Next, elevation and atmospheric pressure are also directly related to one another, since as elevation increases, atmospheric pressure decreases. Given it's greater degree of variability (elevation doesn't change from month to month), pressure was chosen as the most appropriate measure. Next, measures of relative humidity must be selected. Dew point is simply the temperature at which dew begins to form, and is therefore directly related to both temperature and humidity. Relative humidity is a calculated measure from temperature and the air's water content. Therefore, the relative humidity was the most appropriate measure, and also benefitted from being the most important measure of corrosion prevalence (Kong, Dong, Xiao, Guo, He, Li, 2016). Finally, precipitation had three different measures, each with advantages and disadvantages. Precipitation in inches was the most accurate measure of precipitation, but the variable did not distinguish if the precipitation was part of a single storm or several throughout the month, which directly affects time of wetness (Sabir and Ibrahim, 2017). Furthermore, much of the data was missing, making the variable nearly useless. Days experiencing precipitation was a better measure of the month's conditions, but "experiencing precipitation" was treated as a binary condition: either it occurred or it did not. Therefore, even the briefest of showers would be recorded equally with a torrential downpour. Finally, percentage of the month experiencing precipitation remained. While this also suffers from a lack of contextual information, the greater degree of variability made it the best measure of precipitation in a month. With this complete, the variables which were to compose the model had been selected.

Variables

Per the research question, the dependent variable for this research is "hours spent in unscheduled not mission capable status", defined as the amount of time an aircraft spends unable to complete any of its assigned missions for a previously unforeseen maintenance action. The independent variables are:

- Command, defined as the Major Command with operational control of the aircraft.
- Age, defined as the number of months since aircraft delivery to the Air Force.
- Sorties, defined as the number of sorties completed in a given month.
- Average sortie duration, defined as the average amount of time spent on each sortie.
- Mean temperature, defined as the mean temperature during a given month.
- Mean temperature difference, defined as the difference between mean maximum and minimum temperatures.
- Mean wind speed, defined as the mean wind speed experienced during the month.
- Mean pressure, defined as the mean atmospheric pressure experienced during the month.
- Mean Relative Humidity, defined as the mean relative humidity experienced during the month.

- Precipitation frequency, defined as the percentage of time during the month in which precipitation fell.

After identifying each variable, it is important to determine if each is normally distributed. Each variable was plotted and examined for normality. A selection of the variables are shown in the following figures.

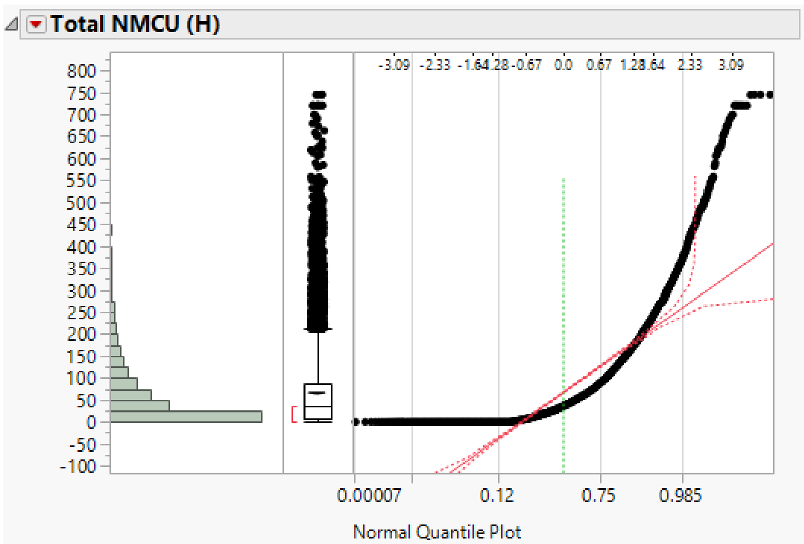

Figure 3: Distribution of Total Not Mission Capable – Unscheduled Hours

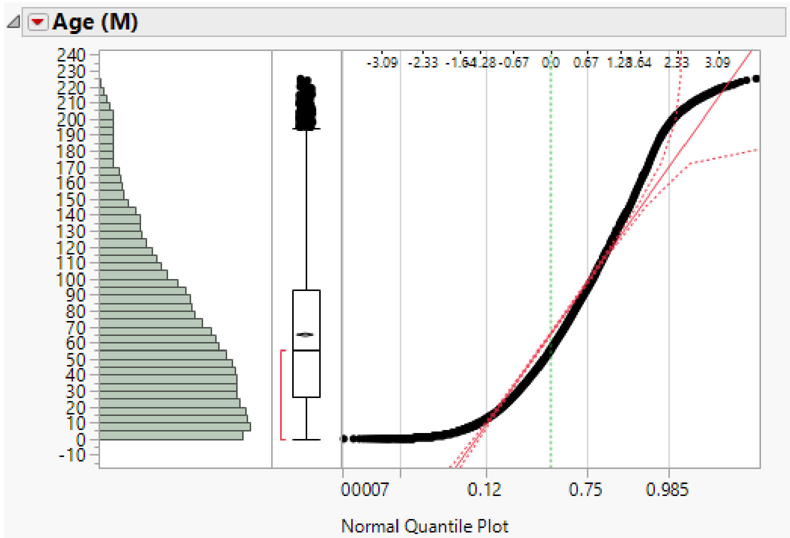

Figure 4: Distribution of Aircraft Age in Months

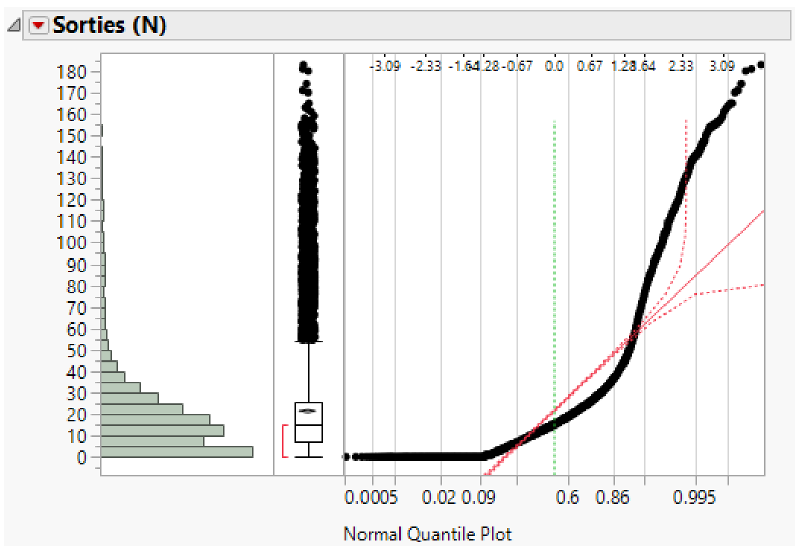

Figure 5: Distribution of Aircraft Sorties

Several variables showed evidence of skewness, making a logarithmic transformation appropriate. Given that natural logarithms cannot be taken on negative or zero values, conditional transformations must be applied to each variable as necessary, prior to taking the natural logarithm of the variable. These transformations took the form of a simple y=ln(y+1) transformation. In this way, zero values would remain zeroes after the full transformation. This method also has the added benefit of turning all regression coefficients into elasticities (Dixon, 2005).

Experiment

After identifying the variables, the model was imported into JMP13 to conduct regression analysis. The initial model was run with all variables present. The model was then examined for goodness of fit and overall statistical significance, as well as individual variable significance and effect. Successive models eliminated those variables which were statistically insignificant. This process was repeated until all variables were statistically significant and the model met all regression assumptions.

Summary

This section outlined the methodology used to collect data, select appropriate variables, build the regression model and refine the model. The next section outlines the results of the various models and extracts meaning from the results.

IV. Analysis and Results

Chapter Overview

This chapter discusses the results of the multiple regression analysis and what each variable means in the larger context of the model. Furthermore, each of the investigative questions will be addressed.

Results of Simulation Scenarios

The first regression model contained all of the selected variables identified above in order to identify the effects of age, MAJCOM and weather on unscheduled not mission capable time.

Prediction Expression

$$
\begin{aligned}
&-15.69910888 \\
&+\text{Match}\left(\text{Command}\right)\begin{pmatrix} \text{"AETC"} & \Rightarrow 0.1623918449 \\ \text{"AFMC"} & \Rightarrow -2.026699061 \\ \text{"AFRC"} & \Rightarrow 0.5727959088 \\ \text{"AMC"} & \Rightarrow 0.2019329261 \\ \text{"ANG"} & \Rightarrow 0.1246938458 \\ \text{"PACAF"} & \Rightarrow 0.3193131531 \\ \text{"USAFE"} & \Rightarrow 0.645571382 \\ \text{else} & \Rightarrow . \end{pmatrix} \\
&+0.1288948867 \bullet \text{Age (Months) - LN} \\
&+0.3733637505 \bullet \text{Sorties (N) - LN} \\
&+0.3418383082 \bullet \text{ASD (H) - LN} \\
&+0.2906275643 \bullet \text{Mean Temp (°F) - LN} \\
&+-0.60679546 \bullet \text{Mean Temp Diff (°F) - LN} \\
&+0.1940656524 \bullet \text{Mean Windspeed (kts) - LN} \\
&+2.6619057982 \bullet \text{Mean Pressure (mbs) - LN} \\
&+-0.09407103 \bullet \text{Mean Precip Freq (\%) - LN} \\
&+-0.177522921 \bullet \text{Mean Humidity (\%) - LN}
\end{aligned}
$$

Figure 6: Prediction Expression – Null Model, All Variables

Summary of Fit

RSquare	0.189014
RSquare Adj	0.187958
Root Mean Square Error	1.64294
Mean of Response	3.091407
Observations (or Sum Wgts)	11536

AICc	BIC
44210.75	44335.71

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	15	7247.308	483.154	178.9954
Error	11520	31095.400	2.699	Prob > F
C. Total	11535	38342.708		<.0001*

Figure 7: Summary of Fit – Null Model, All Variables

As shown in Figure 7, the model's original R^2 value was quite low, at .19. To investigate the cause of the poor fit, a cursory examination of the residual by predicted plot showed that the dependent variable's relatively high number of zero values had biased the model, as shown in Figure 8.

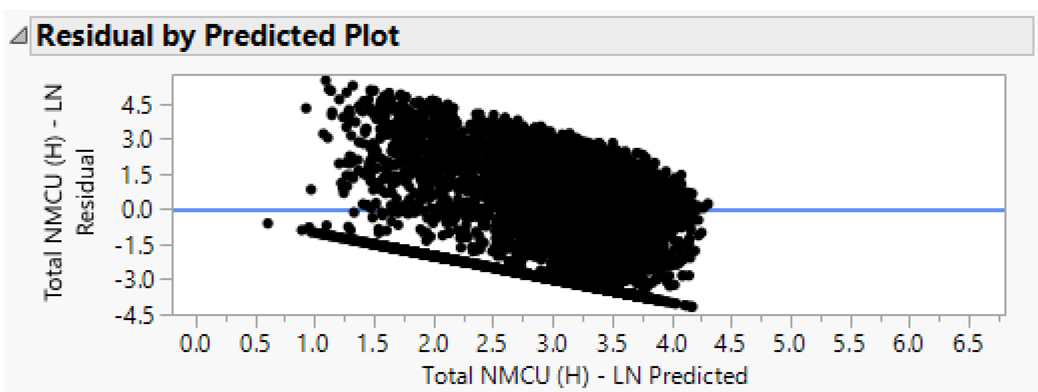

Figure 8: Biased Residual by Predicted Plot

Fletcher, Mackenzie and Villouta (2005), detailed a method to deal with the biasing effect of a large quantity of zero values. An indicator variable assigns a value of 1 when NMCU time did not occur and 0 if NMCU time did occur. This allowed each portion of the regression to be analyzed separately and effectively account for the biasing effect of the large number of zeros.

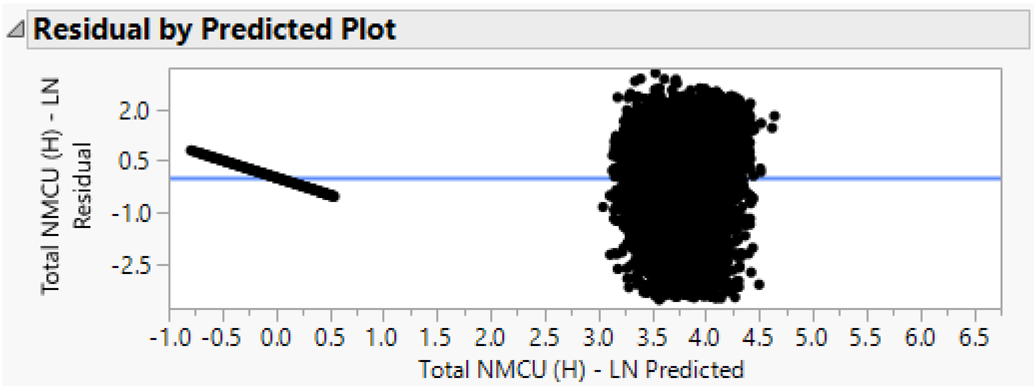

Figure 9: Unbiased Residual by Predicted Plot

The resulting model, including the binary indicator variable, is described by the prediction equation in Figure 10.

Prediction Expression

-27.66607388

+ -3.884257777 • On/Off

+ Match(Command)

"AETC"	⇒	-0.304757774
"AFMC"	⇒	0.0716085931
"AFRC"	⇒	0.065341007
"AMC"	⇒	-0.063331078
"ANG"	⇒	0.0041234626
"PACAF"	⇒	0.0131631731
"USAFE"	⇒	0.2138526164
else	⇒	.

+ 0.1128623598 • Age (Months) - LN

+ -0.063553459 • Sorties (N) - LN

+ -0.116755791 • ASD (H) - LN

+ 0.2281271588 • Mean Temp (°F) - LN

+ -0.391960367 • Mean Temp Diff (°F) - LN

+ 0.1346239675 • Mean Windspeed (kts) - LN

+ 4.5912227454 • Mean Pressure (mbs) - LN

+ -0.01988662 • Mean Precip Freq (%) - LN

+ -0.015052536 • Mean Humidity (%) - LN

Figure 10: Prediction Equation - First Model

Summary of Fit	
RSquare	0.601122
RSquare Adj	0.600568
Root Mean Square Error	1.152269
Mean of Response	3.091407
Observations (or Sum Wgts)	11536

AICc	BIC
36026.87	36159.16

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	16	23048.651	1440.54	1084.970
Error	11519	15294.057	1.33	Prob > F
C. Total	11535	38342.708		<.0001*

Figure 11: Summary of Fit - First Model

After correcting for bias, the model's adjusted R^2 increased from .18 to .6, meaning the model explains 60% of the variation in the data. Furthermore, the root mean squared error (RMSE) of the data is 1.15, representing the square root of the sum of the squared differences between the actual and predicted values, a measure of model accuracy.

Table 2: Parameter Estimates - First Model

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-27.66607	6.505	-4.25	<.0001*
Command[AETC]	-0.304758	0.039656	-7.69	<.0001*
Command[AFMC]	0.0716086	0.057355	1.25	0.2119
Command[AFRC]	0.065341	0.045613	1.43	0.1520
Command[AMC]	-0.063331	0.03528	-1.80	0.0727
Command[ANG]	0.0041235	0.045036	0.09	0.9271
Command[PACAF]	0.0131632	0.14766	0.09	0.9290
Age (Months) - LN	0.1128624	0.010502	10.75	<.0001*
Sorties (N) - LN	-0.063553	0.009985	-6.37	<.0001*
ASD (H) - LN	-0.116756	0.02594	-4.50	<.0001*
Mean Temp (°F) - LN	0.2281272	0.049856	4.58	<.0001*
Mean Temp Diff (°F) - LN	-0.39196	0.164219	-2.39	0.0170*
Mean Windspeed (kts) - LN	0.134624	0.049601	2.71	0.0067*
Mean Pressure (mbs) - LN	4.5912227	0.903712	5.08	<.0001*
Mean Precip Freq (%) - LN	-0.019887	0.016804	-1.18	0.2367
Mean Humidity (%) - LN	-0.015053	0.022571	-0.67	0.5049

However, as shown in Table 2, many variables do not have effects which are statistically different from zero, including all commands other than AETC, mean precipitation frequency and mean humidity. These variables were then removed for successive runs. The next model is described by the prediction equation shown in Figure 12.

Prediction Expression

-11.10706903

+ 0.0938667037 • Age (Months) - LN

+ -0.074991646 • Sorties (N) - LN

+ -0.084837441 • ASD (H) - LN

+ 0.1610011652 • Mean Temp (°F) - LN

+ -1.011150103 • Mean Temp Diff (°F) - LN

+ 0.0685685369 • Mean Windspeed (kts) - LN

+ 2.5987744222 • Mean Pressure (mbs) - LN

+ -3.884102804 • On/Off

Figure 12: Prediction Equation – Second Model

Summary of Fit

RSquare	0.60189
RSquare Adj	0.601626
Root Mean Square Error	1.159401
Mean of Response	3.087215
Observations (or Sum Wgts)	12090

AICc	BIC
37897.25	37971.23

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	8	24551.846	3068.98	2283.112
Error	12081	16239.398	1.34	Prob > F
C. Total	12089	40791.244		<.0001*

Figure 13: Summary of Fit - Second Model

Removing insignificant variables increased the adjusted R^2 value slightly, to .601, and slightly increased RMSE, to 1.159. Next, we once again examine the parameter estimates to determine if all variables are significant.

Table 3: Parameter Estimates – Second Model

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-11.10707	4.817757	-2.31	0.0212*
Age (Months) - LN	0.0938667	0.010088	9.30	<.0001*
Sorties (N) - LN	-0.074992	0.009547	-7.85	<.0001*
ASD (H) - LN	-0.084837	0.025065	-3.38	0.0007*
Mean Temp (°F) - LN	0.1610012	0.042826	3.76	0.0002*
Mean Temp Diff (°F) - LN	-1.01115	0.13369	-7.56	<.0001*
Mean Windspeed (kts) - LN	0.0685685	0.035931	1.91	0.0564
Mean Pressure (mbs) - LN	2.5987744	0.644418	4.03	<.0001*

In this model, mean wind speed is also insignificant. This variable is removed in successive runs, as shown in Figure 14.

Prediction Expression

-6.383507728

+ 0.0933360738 • Age (Months) - LN

+ -0.076356772 • Sorties (N) - LN

+ -0.09016701 • ASD (H) - LN

+ 0.1598496697 • Mean Temp (°F) - LN

+ -1.103949911 • Mean Temp Diff (°F) - LN

+ 1.9873681598 • Mean Pressure (mbs) - LN

+ -3.883987325 • On/Off

Figure 14: Prediction Expression – Third Model

Summary of Fit

RSquare	0.60177
RSquare Adj	0.601539
Root Mean Square Error	1.159527
Mean of Response	3.087215
Observations (or Sum Wgts)	12090

AICc	BIC
37898.89	37965.47

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	7	24546.951	3506.71	2608.180
Error	12082	16244.293	1.34	Prob > F
C. Total	12089	40791.244		<.0001*

Figure 15: Summary of Fit - Third Model

The third model also shows incremental increases in adjusted R^2 and incremental increases in RMSE.

Table 4: Parameter Estimates - Third Model

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-6.383508	4.133728	-1.54	0.1226
Age (Months) - LN	0.0933361	0.010085	9.25	<.0001*
Sorties (N) - LN	-0.076357	0.009521	-8.02	<.0001*
ASD (H) - LN	-0.090167	0.024912	-3.62	0.0003*
Mean Temp (°F) - LN	0.1598497	0.042826	3.73	0.0002*
Mean Temp Diff (°F) - LN	-1.10395	0.124546	-8.86	<.0001*
Mean Pressure (mbs) - LN	1.9873682	0.559191	3.55	0.0004*

Finally, all variables included in the model are significant. While it appears as though the intercept is not significant, this simply means that the intercept of the linear equation is not statistically different from zero, not that the model is incorrect. This is explained by the fact that the intercept is the representation of the output should all the independent variables have a value of 0. In this case, mean temperature, mean temperature difference and mean pressure will never be zero, by definition. For this reason, the intercept will not be statistically different from zero.

The next step is to identify whether the data has any outliers which are exerting an outsized influence on the fit of the model. Using a table of the studentized residuals of the model, we look for any values with an absolute value greater than 3, which are defined as extreme outliers.

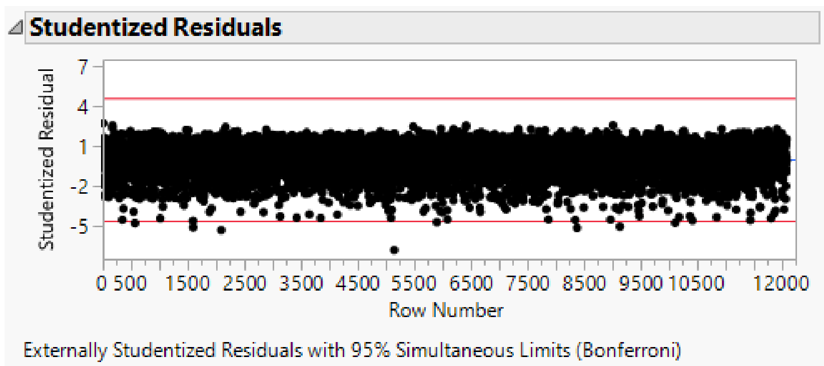

Figure 16: Studentized Residuals Showing Outliers

111 outliers were identified, generally correlating to extreme weather, high operations tempo or another exceptionally unusual value in one of the independent variables.

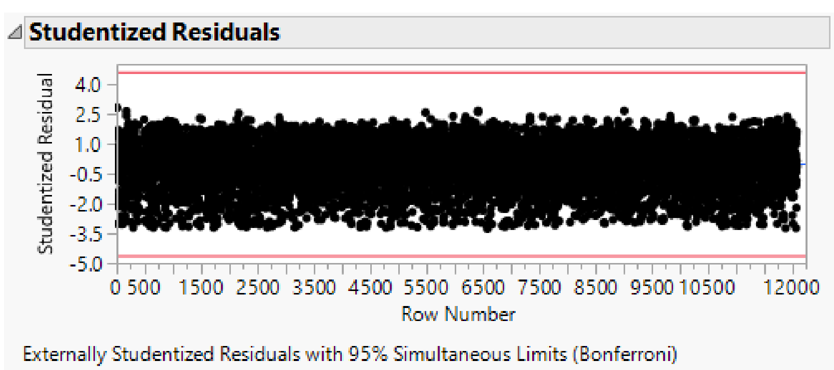

Figure 17: Studentized Residuals with Outliers Removed

After removing the outliers, the model is run a final time.

Prediction Expression

-6.553489311

+ 0.0911267174 • Age (Months) - LN

+ -0.092096291 • Sorties (N) - LN

+ -0.083341353 • ASD (H) - LN

+ 0.1277367379 • Mean Temp (°F) - LN

+ -1.072453958 • Mean Temp Diff (°F) - LN

+ 2.0266215566 • Mean Pressure (mbs) - LN

+ -3.953497403 • On/Off

Figure 18: Prediction Expression - Final Model

Summary of Fit

RSquare	0.640948
RSquare Adj	0.640738
Root Mean Square Error	1.084472
Mean of Response	3.120788
Observations (or Sum Wgts)	11982

AICc	BIC
35956.77	36023.27

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	7	25138.605	3591.23	3053.561
Error	11974	14082.370	1.18	Prob > F
C. Total	11981	39220.976		<.0001*

Figure 19: Summary of Fit - Final Model

After removing outliers from the data set, the adjusted R^2 value increases to .64, which is a good fit (USAF Scientific Advisory Board, 2011).

Table 5: Parameter Estimates – Final Model

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-6.553489	3.881437	-1.69	0.0914
Age (Months) - LN	0.0911267	0.009465	9.63	<.0001*
Sorties (N) - LN	-0.092096	0.008967	-10.27	<.0001*
ASD (H) - LN	-0.083341	0.023409	-3.56	0.0004*
Mean Temp (°F) - LN	0.1277367	0.040256	3.17	0.0015*
Mean Temp Diff (°F) - LN	-1.072454	0.117053	-9.16	<.0001*
Mean Pressure (mbs) - LN	2.0266216	0.525033	3.86	0.0001*

After running the final model, it is possible to examine the effects of the variables remaining in the model. Age has an estimated β value of .09. This means that for each 1% increase in the age of the aircraft, the not mission capable time increases by .09%. This is not a strong effect, but it is statistically significant. Sorties and average sortie duration appears to be a somewhat perverse result. Both variables have negative estimated β values of .09 and .08 respectively, meaning that as sorties and average sortie duration increase by 1%, not mission capable time decreases by .09% and .08%. At first glance, this result does not make sense, as increased usage should increase not mission capable time. However, by definition, if an aircraft is available for and flying sorties, it is less likely to experience not mission capable time, this relationship makes sense within the context of the model. Mean temperature also conforms to expectations. The model predicts that as mean temperature increases by 1%, unscheduled not mission capable time increases by .12%. This result is validated by the Arrhenius equation, which directly links increased temperature to increased speed of chemical reactions, such as corrosion. The negative coefficient associated with mean temperature difference also conforms to the Arrhenius equation, as cooling should mitigate the effects of elevated temperature. The greater the degree to which the environment is subjected to cooling, the greater the arresting effect is likely to be. Finally, the mean pressure coefficient appears to have the greatest effect. This is likely due to several effects being contained within a single predictor variable. First, pressure is a rough correlation to altitude, as stated in Chapter III. By definition, locations at high altitude are further away from a coastline which brings with it increased levels of chlorides. Second, as shown in the correlation matrix, lower atmospheric pressure has a moderate correlation with a higher mean temperature difference, which has its own arresting effect. Third, higher elevations tend to have lower relative humidities, which is also correlated with a lower rate of corrosion. It is for all of these reasons that the USAF's Aerospace Maintenance and Regeneration Group (AMARG) "The Boneyard" is located at high altitude, as the conditions retard corrosion.

In order to be confident in the results of the model, the model must be demonstrated to meet the assumptions for linear regression: absence of multicollinearity, normally distributed residuals, and homoscedasticity. Multicollinearity can be assessed by examining the correlation matrix.

Table 6: Correlation of Estimates

Correlation of Estimates

Corr

	Intercept	Age (Months) - LN	Sorties (N) - LN	ASD (H) - LN	Mean Temp (°F) - LN	Mean Temp Diff (°F) - LN	Mean Pressure (mbs) - LN	On/Off
Intercept	1.0000	0.1795	-0.0254	0.0279	0.0208	-0.6196	-0.9947	0.0058
Age (Months) - LN	0.1795	1.0000	0.0322	0.0917	-0.0254	-0.0146	-0.1997	0.0285
Sorties (N) - LN	-0.0254	0.0322	1.0000	-0.0538	-0.0069	-0.0929	0.0325	0.4326
ASD (H) - LN	0.0279	0.0917	-0.0538	1.0000	0.0798	0.0329	-0.0431	0.1769
Mean Temp (°F) - LN	0.0208	-0.0254	-0.0069	0.0798	1.0000	-0.1678	-0.0463	0.0185
Mean Temp Diff (°F) - LN	-0.6196	-0.0146	-0.0929	0.0329	-0.1678	1.0000	0.5447	-0.0164
Mean Pressure (mbs) - LN	-0.9947	-0.1997	0.0325	-0.0431	-0.0463	0.5447	1.0000	-0.0101
On/Off	0.0058	0.0285	0.4326	0.1769	0.0185	-0.0164	-0.0101	1.0000

Correlation values with an absolute value greater than .6 can be considered problematic. According to the correlation matrix, the model does not appear to suffer from multicollinearity. Only two values exceed the .6 threshold: correlation between mean temperature difference and mean pressure. However, each of these results is predictable, since neither value will ever reach zero. The next closest correlation values are between the indicator variable and sorties at .43, and mean pressure and mean temperature difference. The indicator variable, as it is designed to indicate when not mission capable time is present, will by definition be somewhat linked to number of sorties, as a sortie is less likely to occur when there is unscheduled not mission capable time. Furthermore, mean pressure and mean temperature difference are also related by definition.

Linear regression assumes that the residuals are approximately normal. This is the central assumption of linear regression, as it is imperative that a linear relationship exists. This condition can be checked with a normal QQ plot.

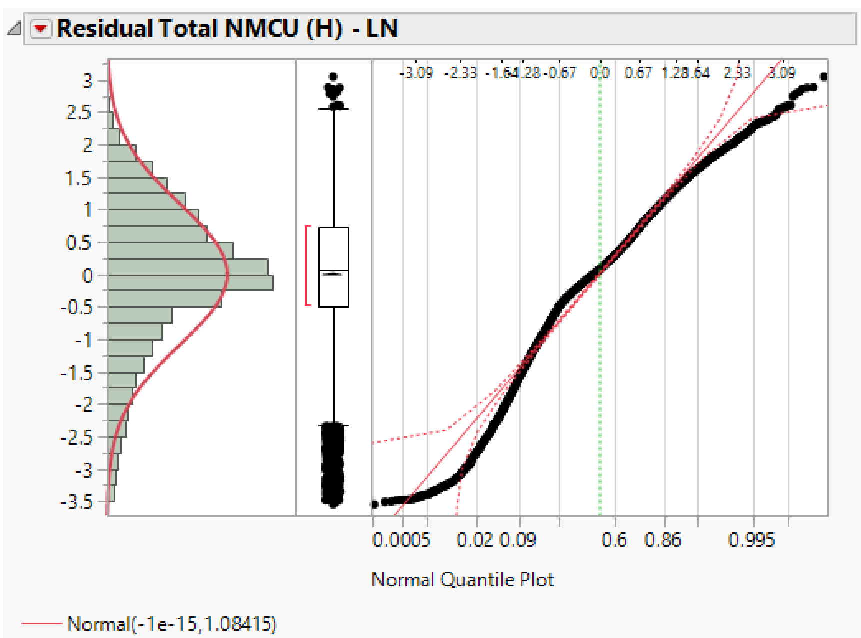

Figure 20: Residual Normal Quantile Plot

As shown in Figure 8 above, the residuals are roughly normal, but not perfectly. This is reflective of the imperfect fit of the model to the data.

Investigative Questions Answered

1. Does the age of the airframe affect the amount of not mission capable time in a particular month? If so, to what degree?

Yes, it appears that airframe age has a small, but statistically significant effect upon unscheduled not mission capable time. For every 1% increase in aircraft age, unscheduled not mission capable time increases by .09%. Therefore, we can reject the null hypothesis that age does not have a statistically significant effect on monthly unscheduled not mission capable time.

2. Does the Major Command (MAJCOM) operating the aircraft affect the occurrence of not mission capable time?

No, the regression model found that the effect of MAJCOM on unscheduled not mission capable time was not statistically different from zero. Therefore, we fail to reject the null hypothesis that the effect of a particular command is statistically different from zero.

3. Do the various atmospheric weather conditions experienced on the ground at the operating location have an effect on not mission capable time? If so, to what degree?

Yes, mean temperature, mean temperature difference and mean atmospheric pressure all have an effect upon unscheduled not mission capable time. Therefore, we reject the null hypothesis that weather effects are not statistically different from zero.

Summary

This section summarized the results of the multiple regression models and summarized and provided reasonable explanations for each predicted effect. The next chapter will provide conclusions, recommendations and suggest future research.

V. Conclusions and Recommendations

Chapter Overview

This chapter describes the findings of the regression model in detail. The significance of research section will provide applications and likely uses of the data contained in this research. Finally, recommendations will suggest future research in order to build upon the foundation established in this research.

Conclusions of Research

The regression model seems to suggest that age has a small but marked effect on the amount of unscheduled NMC time that a C-130J can be expected to experience. Furthermore, as constructed, sorties and average sortie duration can be expected to have a slight negative correlation to unscheduled not mission capable time, if only because reality dictates it as such. This is not to suggest that flying more and longer sorties decreases unscheduled not mission capable time.

Command does not appear to have a statistically significant effect upon unscheduled not mission capable time. This appears to validate the conclusions in Dixon (2005). Furthermore, this would suggest that MAJCOMs experience aircraft wear and tear, corrosion and flight stresses at roughly the same rate.

The regression model found that many weather variables as presented were not statistically different from zero, such as relative humidity and windspeed. However, other variables may have acted as a proxy variables to absorb some of the effects. Further research must be conducted to identify the causal relationships.

Significance of Research

The most immediate implication of this research would seem to indicate that aircraft, when possible, should be based in dry, high altitude locations away from city centers, assuming the Air Force's goal is to reduce atmospheric corrosion. However, this is a speculative statement without evidence to validate the assumption that corrosion was the primary driver of unscheduled not mission capable time.

Given that scheduled maintenance is relatively more predictable and programmable, total system maintenance costs should be somewhat easier to forecast. With this information, Air Force planners and acquisition professionals can determine the best decision regarding whether to repair, replace or overhaul Air Force aircraft.

Recommendations for Future Research

This is a foundational study, and as such, the information provided is not of sufficient granularity to make operational decisions. Further research must be conducted into the root causes of each of the various effects, as well as mitigating actions and circumstances. Furthermore, each MAJCOM must be interviewed regarding maintenance practices and documentation to ensure LIMS-EV data is correct and reliable. Absent information regarding the standard operating procedures for coding an aircraft NMC, reliable conclusions cannot be drawn. Additionally, other MDSs must be subjected to the same analysis in order to ensure the outcomes are transferrable outside of the narrow example of the C-130J fleet. Additional studies must also be completed using the same set of dependent variables upon cost and total maintenance man hours in order to compare and contrast.

Summary

This research used multiple regression analysis to identify whether age, MAJCOM and ambient operating location weather had any effect upon unscheduled not mission capable time. The results seem to indicate that age and weather each have a small but statistically significant effect upon the independent variable, while MAJCOM does not. Given these insights, the Air Force must take further steps to identify and leverage knowledge about the various drivers of age-related wear.

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14. ABSTRACT
As a result of increasing system complexity and cost, new aircraft acquisition, upgrade and repair timelines continue to lengthen. As a result, aircraft are kept in service longer than originally intended. Therefore, age-related wear continues to play a large part in determining mission-capable status, and therefore, aircraft availability (AA) rates. Combined with decreasing fleet sizes and manpower resource pools, each aircraft declared not mission capable (NMC) exerts an out-sized influence upon fleet AA rates. This research used multiple regression analysis to identify and quantify the effects of age, Major Command (MAJCOM) and operating location ambient weather on unscheduled not mission capable time. The research found that age and ambient weather have a small but statistically significant effect upon unscheduled not mission capable time, while MAJCOM does not appear to have a statistically significant effect. The research serves as a foundational study to identify and propose new and more in-depth research into the root causes of the identified effects.

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