



PREDICTING AIRCRAFT AVAILABILITY

GRADUATE RESEARCH PROJECT

Mark A. Chapa, Major, USAF

AFIT-ENS-GRP-13-J-2

**DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY**

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED

The views expressed in this thesis are those of the author and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the United States Government.

AFIT-ENS-GRP-13-J-2

PREDICTING AIRCRAFT AVAILABILITY

GRADUATE RESEARCH PROJECT

Presented to the Faculty

Department of Operational Sciences

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Logistics

Mark A. Chapa, BS

Major, USAF

June 2013

APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED

AFIT-ENS-GRP-13-J-2

PREDICTING AIRCRAFT AVAILABILITY

Mark A. Chapa, BS
Major, USAF

Approved:

Daniel D. Mattioda, Lt Col, USAF, PhD. (Advisor)

Date

Abstract

In today's environment of less manning, older aircraft, and a shrinking budget, it is imperative maintenance leaders utilize all available tactics, techniques and procedures to improve the amount of aircraft available for operations. One of the longstanding measuring sticks to gauge a unit's effectiveness was and still is the Mission Capable (MC) rate. According to AFI 21-103, the MC rate is fully mission capable hours plus partial mission capable hours divided by possessed hours. This formula provides a rate which is a lagging indicator of how well a unit is performing. Although this metric is very valuable, it focuses more on the tactical-level of operations and does not include total aircraft inventory into the equation. There's been a major shift toward utilizing Aircraft Availability (AA) as the measuring stick to gauge how well the "fleet" is performing. Although the concept of AA has been around for quite some time, it has become the reference standard utilized by senior leadership. The ability to predict AA within a fleet has always been a goal of Aircraft Maintenance leaders and is now more important than ever with looming budget cuts across the spectrum of defense.

This graduate research paper focuses on AA and the variables which affect this strategic metric. The research will build upon previous research conducted by Captain Steven Oliver and Captain Frederick Fry in developing an explanatory/predictive model for AA encompassing the variables with the greatest influence upon this dependent variable to include personnel, environment, reliability and maintainability, Operations and Maintenance (O&M), and Aircraft and Logistics Operations.

I dedicate this research to my wife and children. Your patience, love, and understanding enabled me to make the most out of this year at ASAM. I couldn't have made it through without your support.

Acknowledgments

First and foremost, I would like to thank my advisor, Lt Col Dan Mattioda. The expert guidance, genuine feedback and endless patience provided truly enabled this research to come to fruition. I would also like to thank Dr. Weir for providing the pathway to collaborate with AFMC, and assisting with the development of the Aircraft Availability Predictive Tool. Thanks to Mr. Bob McCormick and Mr. Roger Moulder for offering their professional insight and invaluable information, which put the wheels of this research in motion.

I would also like to thank SMSgt John Beal, Mr. Paul Sanzone, and Mr. Paul Deis who provided the backbone to this research, the data. Without their support, there would not have been anything to analyze.

Lastly, I would like to thank all my professors during the ASAM school year. They provided the foundational knowledge that I was able to apply in building this graduate research paper.

Mark A. Chapa

Table of Contents

	Page
Abstract.....	iv
Acknowledgments.....	vi
Table of Contents.....	vii
List of Figures.....	ix
List of Tables.....	x
List of Equations.....	xi
I. Introduction.....	1
Background.....	1
Research Problem.....	4
Research Focus and Objectives.....	5
Investigative Questions.....	5
Methodology.....	6
Data Sources and Analysis.....	6
Assumptions and Limitations.....	7
Implications.....	7
Chapter Summary.....	8
II. Literature Review.....	9
Chapter Overview.....	9
The History of AA.....	9
Previous Research on AA.....	14
Aircraft Availability Forecasting Models.....	23
Chapter Summary.....	26
III. Methodology.....	27
Chapter Overview.....	27
Scope of Data Collection and Research.....	27
Data Sources.....	28
Standardizing the Data.....	35
Correlation of the Data.....	36
Model Building Methodology.....	38
Chapter Summary.....	42

IV. Analysis and Results.....	43
Chapter Overview.....	43
Correlation Analysis Results.....	43
Regression Models.....	47
Validation of the Final Regression Model.....	51
Summary.....	55
V. Conclusions and Recommendations.....	56
Chapter Overview.....	56
Investigative Questions.....	56
Limitations and Significance of the Research.....	59
Recommendations for Action and Future Research.....	60
Summary.....	60
Appendix A.....	61
Appendix B.....	63
Bibliography.....	64
Vita.....	65

List of Figures

	Page
Figure 1: Aircraft Availability Trends	1
Figure 2: Aging Trends of Air Force Aircraft.....	18
Figure 3: Average Age of Air Force Aircraft vs AA.....	19
Figure 4: Requirements, Allocation and Execution of Funds.....	20
Figure 5: Centralized Asset Management Process.....	22
Figure 6: Aircraft Availability Curve.....	23
Figure 7: Scatterplot Matrix	44
Figure 8: Bivariate Analysis of NMCB.....	46
Figure 9: Initial Regression Model Analysis.....	48
Figure 10: Final Regression Model Analysis.....	50
Figure 11: AA Predictive Tool.....	54

List of Tables

	Page
Table 1: Example of B-52 Results	13
Table 2: Potential Factors Affecting the MC Rate.....	15
Table 3: Variable Correlations with AA rates.....	22
Table 4: LIMS-EV Data.....	29
Table 5: Appropriation Data from the Standard Report.....	30
Table 6: CAIG New Data from the Standard Report.....	31
Table 7: CAIG New Data from the OLAP Report.....	33
Table 8: Personnel Data from MilPDS, MPES, and PAS.....	34
Table 9: Variables Used for Correlation Analysis.....	43
Table 10: Multivariate Correlation Results	44
Table 11: Final Regression Model Sensitivity Analysis.....	52

List of Equations

	Page
Equation 1: MC Rate Formula.....	10
Equation 2: AA Rate Formula.....	10
Equation 3: Operational Requirement Formula for AA Standard.....	11
Equation 4: AA Requirement Equation.....	12
Equation 5: Multiple Regression Model.....	38
Equation 6: Initial Regression Model.....	46
Equation 7: Final Regression Model.....	47
Equation 8: Formula for Predicting AA.....	52

PREDICTING AIRCRAFT AVAILABILITY

I. Introduction

Background

In today's environment of less manning, older aircraft, and a shrinking budget, it is imperative maintenance leaders utilize all available tactics, techniques and procedures to improve the amount of aircraft available for operations. One of the longstanding measuring sticks to gauge a unit's effectiveness was and still is the Mission Capable (MC) rate. According to AFI 21-103 (2012:108), the MC rate is fully mission capable hours plus partial mission capable hours divided by possessed hours. This formula provides a rate which is a lagging indicator of how well a unit is performing in Aircraft Maintenance Operations. Although this metric is very valuable, it focuses more on the tactical-level of operations and does not include total aircraft inventory into the equation. Recently, there's been a major shift toward utilizing Aircraft Availability (AA) as the measuring stick to understand how well the "fleet" is performing. Although the concept of AA has been around for quite some time, it has become the reference standard utilized by senior leadership. According to the Maintenance Metrics US Air Force Handbook published by the Air Force Logistics Management Agency (2009:14), maintenance managers will utilize AA as the yardstick to measure the health of the fleet. The formula for AA is MC hours divided by the Total Aircraft Inventory hours (Maintenance Metrics US Air Force, 2009:31). This lagging indicator takes into account the total time possessed minus depot possessed, non-mission capable for maintenance, non-mission capable for supply, non-mission capable for both maintenance and supply and unit

possessed not reported hours (Maintenance Metrics US Air Force, 2009:31). AA has been the push by senior leaders as the indicator to understand how healthy and capable a fleet is in performing their operations. Unfortunately, AA rates have been on the decline. To illustrate this point (Figure 1), John A. Tirpak, Executive Editor from the Air Force Magazine, wrote an article on aircraft availability in 2009 stating the following:

Mission Capable rates for Air Force don't tell the whole story on platform availability. Indeed, when factoring the aircraft that are in depot for routine overhauls as well as those that are assigned for duty, availability numbers for each aircraft type fall precipitously. For example, fighter availability rates are about 58.9 percent today, down from a recent high of 69.2 percent in FY05. Airlift and tanker availability rates hover around 60 percent range, as do those for the special operations and combat search and rescue platforms. But only 44.8 percent of the bomber fleet is ready to go at any time, down from a peak of 57.2 in FY02. The worst availability of any platform belongs to the B-2A, which is available for combat only 36.8 percent of any given time. The most available platform is the MQ-1 Predator, which is ready to go at 80.6 percent of the time (Tirpak, 2009).

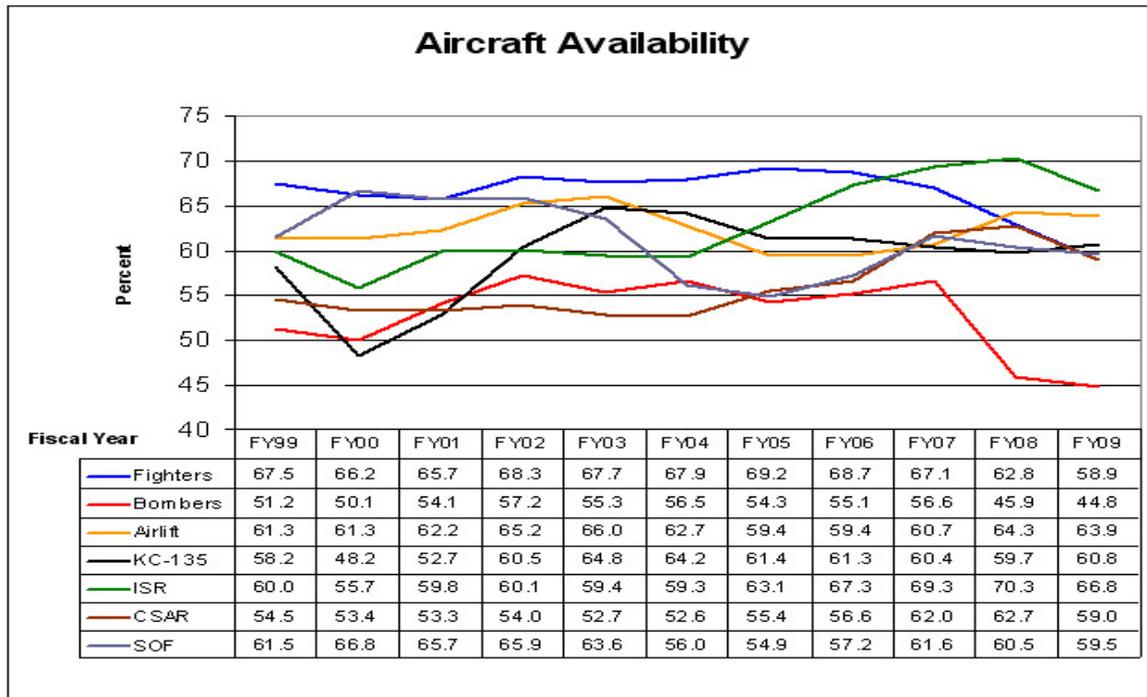


Figure 1. Aircraft Availability Trends (Tirpak, 2009)

Due to the importance of AA, there have been many initiatives to help improve this metric to include the Aircraft Availability Improvement Program (AAIP), a program focused on sharing ideas, best practices, cost reduction and total ownership costs. In addition to the AAIP, there have also been predictive models developed to help ascertain where a particular area of support may need help (O&M budget, initial spares, depot). These mathematical models are also utilized to help predict or forecast where AA rates will be dependent on certain variables. Most of the models developed have used the O&M budget and expenditures as the main variables when predicting AA. The Aircraft Availability Model (AAM) is one such model. The AAM, an analytical model and decision support system, was designed to relate expenditures for the procurement and depot repair of recoverable spares to aircraft availability rates by weapons systems. This model produces curves of cost versus aircraft availability rates for a given aircraft type (O'Malley, 1983). This is an incredible model developed in the early 1980s providing Air Force leaders the capability to forecast aircraft availability rates based on total expenditures for a specific weapons system. Since the creation of the AAM, there have been other models created in hopes of predicting or forecasting AA rates, but most of them have only taken the financial side of operations into account, that is to say the O&M budget. Unfortunately, there are many factors besides just the financial side of the house that affect AA, and need to be taken into account when trying to predict this critical capability. In his 2001 thesis, *Forecasting Readiness*, Captain Steven Oliver identified five potential categories which affect AA; Personnel, Environment, Reliability and Maintainability, Funding and Aircraft and Logistics Operations (Oliver, 2001). Although his work developed explanatory and forecasting models, it focused solely on the F-16

platform and wasn't generalized as a usable model throughout the enterprise. But, his research demonstrated the correlation between these variables and AA and the need to add them to a decision support system.

An update to the AA model incorporating the O&M budget along with the most critical factors which affect AA is sorely needed. This particular subject is of high interest to AMC/A4. In fact, the following is a statement focused on this issue:

“AMC needs to have AFMC provide a MDS by MDS AA forecast that is linked to mission accomplishment. It is imperative that commanders understand what resources are available for mission accomplishment. Therefore, our enterprise must present a fusion of actionable information/analysis at the point of decision.”(AMC/A4, 2012)

Bottom line is the AMC/A4 community is actively pursuing a model which will provide an accurate prediction of AA rates with all the integral variables which affect this strategic metric. This research focuses on the development of an explanatory and predictive model for the Airlift and Tanker community that may provide more insightful and usable information to better allocate resources, people and money to improve our readiness and mission success.

Research Problem

The overall problem is the lack of an AA forecasting model that incorporates all of the critical variables which affect AA. Compounding this problem are the fiscal constraints the Air Force is currently facing, which is requiring leadership to make sound decisions based on actionable information. As stated earlier, there have been many efforts in developing models to predict AA, but the information utilized has been based on expenditures, sustainment budget or spare parts lacking the other critical factors which affect AA. There's also been research on the operations side focusing on personnel,

operations tempo, aircraft usage but most of this research left out the budget side of the house. This research aims at fulfilling these AA forecasting deficiencies and arming the AMC Logistics Directorate with an AA model encompassing the critical correlated variables that affect AA and the potential ability to better assess and predict AA.

Research Focus and Objectives

This research will focus on mobility aircraft specifically the KC-135R active-duty owned aircraft and the corresponding AA rates from the past 10 years. The objective is to identify the critical variables between Personnel, Environment, Reliability and Maintainability, Funding and Aircraft/Logistics Operations and the KC-135R AA rates. Additionally, this research will utilize the identified critical variables and build a multiple linear regression model to quantify and accurately predict the availability of KC-135R aircraft. If successful, this model can be further investigated and utilized for all mobility aircraft.

Investigative Questions

In order to attain the stated objectives of this research, the following questions need to be addressed in an objective manner.

1. What is the current AMC AA standard for the KC-135R?
2. What is the KC-135R AA standard based off of and is it mission linked?
3. What quantifiable correlated variables affect the KC-135R AA rate?
4. Are the KC-135R AA rates influenced by changes in the O&M budget?
5. What model best predicts KC-135R AA and what is the result?

In the process of answering these potential questions, highlighting future study areas and refining the limitations of this research will be addressed.

Methodology

Since this research is building upon previous research conducted by Captain Fry and Captain Oliver, the methodology utilized by both gentlemen will be used for this research and further defined in Chapter III of this paper. Variable correlation and multiple regression analysis will be utilized to investigate the collected data.

Data Sources and Analysis

Personnel data for this research will be retrieved from the Personnel Data Systems, Headquarters Air Force Manpower Data Systems and from AMC Wing Manpower offices. Aircraft reliability and maintainability along with aircraft operations data will be collected from the Air Force's Reliability and Maintainability Information Systems (REMIS) and the Logistics Installation and Mission Support Enterprise View (LIMS-EV) from the year 2002 to 2012 for the KC-135 platform. Supply-related reliability data will be extracted from the Recoverable Consumption Item Requirements System (D041) and all funding data will be retrieved from AFMC and the Air Force Total Ownership Cost (AFTOC) database. Each data set will be analyzed for correlation with AA and an explanatory model for AA will be built utilizing this data by regression analysis, specifically multiple regression analysis. Regression analysis is a mathematical predictive tool used to show a mathematical relationship among a certain set of variables in order to provide a predictive response (Oliver, 2001). Multiple linear regression is used for analysis when higher order terms are believed to be present or when combinations of more than one independent variable are included (McClave, Benson & Sincich, 2009). Since this study will include numerous independent variables, multiple linear regression is the choice of analysis for this research.

Assumptions and Limitations

Due to the amount of aircraft inventory allocated to AMC, this research is limited to only the KC-135R aircraft and only at the base level. Although the scope of this research is limited to only one aircraft, this will provide the basis for future mobility aircraft research. An additional limitation is the time frame for the data collected, which is from 2002 – 2012. The assumptions are data collected is valid and accurate.

Implications

The visionary implication is to provide AMC leadership a tool to utilize in assessing what kind of impact a decrease or increase in the critical variables established will have on aircraft availability. In generic terms, the ability to predict an accurate amount of KC-135R aircraft available due to the amount of budget allocated, personnel assigned, skill level possessed, current environment, reliability and maintainability information and current Aircraft and Logistics Operations data. Once this model is built, the output data can then be utilized to make sound decisions on current and future operations and effective use of resources.

Chapter Summary

In Chapter I, AA was identified as the measuring stick to gauge the effectiveness of a unit and the impact to operations. It was also established that during these fiscally constrained times it is imperative to utilize all the tools available to maximize our resources and an explanatory/predictive model of AA is one of those tools. A wrap up of the chapter was conducted by establishing the objective of this paper, which is to create an AA predictive model incorporating all of the critical variables that affect AA.

The rest of the paper is outlined as follows: Chapter II is a literature review covering AA, the identified variables that affect AA and forecasting models used throughout the years to predict AA. The methodology exercised for this research is discussed in Chapter III, with data analysis and results in Chapter IV. Finally, Chapter V will complete the research with conclusions and recommendations.

II. Literature Review

Chapter Overview

In order to answer the research questions and ultimately reach the objective of developing a predictive AA model with all the critical variables that affect AA, an understanding of AA is required. First, a historical look at AA and AMC's current AA standard for the KC-135 is conducted. Next, a deeper dive into previous research conducted on optimizing AA to include Captain Oliver (2001) and Captain Fry's (2010) thesis on this subject. Lastly, a historical view of AA models utilized throughout the years to include the current models developed to help improve our readiness will wrap up the literature review.

The History of AA

AA is a metric utilized by Air Force leaders to ascertain the health of a particular fleet and the ability to meet the requirements across the spectrum of demands to include training and Combatant Commanders. But, AA has only recently been the metric of choice to understand how well a fleet is performing. The MC rate had been the longstanding measuring stick to gauge a unit's effectiveness, but the MC rate focuses on how well a unit is performing, again more at the tactical level. This rate is a composite metric, that is, a broad indicator of many processes and metrics (AFLMA, 2009:40). Additionally, the MC rate is a maintenance related lagging indicator. Most metrics fall into one of two categories--leading and lagging indicators. Leading indicators show a problem first, as they directly reflect maintenance's capability to provide resources to execute the mission. Lagging indicators show firmly established trends (AFLMA, 2009:

14). A low MC rate may indicate that a unit is affected by many long fixes to their aircraft. It may also indicate poor parts supportability, lack of qualified technicians, or poor job prioritization (AFLMA, 2009:41). Bottom line is the MC rate (Equation 1) is affected by many variables, but what is AA affected by?

$$MC = ((FMC \text{ hours} + PMC \text{ Hours}) / (Possessed \text{ Hours})) \times 100 \quad (1)$$

The AA rate (Equation 2) is a flying-related metric and is the cornerstone for maintenance metrics measuring the maintenance group's ability to supply sufficient amount of aircraft to accomplish the mission (ALFMA, 2009:31).

$$AA = (MC \text{ Hours}) / (TAI \text{ Hours}) \times 100 \quad (2)$$

In the end, the biggest difference between the AA rate and the MC rate is the denominator within the formula. The AA rate takes into account the total aircraft inventory hours accrued for the assessed period, whereas the MC rate only takes into account the possessed hours accrued for the assessed period. The AA rate formula takes into account the total aircraft inventory giving you a strategic view of all the assessed aircraft, but keep in mind the numerator within the AA rate formula is still MC hours. So in saying this, it can be deducted that what affects the MC rate must affect the AA rate. In other words, when tactics, techniques and procedures (TTP) have been developed and published within maintenance pamphlets and publications to articulate what processes or variables a maintenance leader should be looking at when their MC rate is low, then we

should be utilizing the same variables and TTPs when the AA rate is below standards to analyze why the rate is below standard.

In 2009 HAF/A4L initiated an AA Standards Integrated Project Team that worked with the Air Force Logistics Management Agency in a mission to establish and institutionalize a repeatable and defensible process by which lead commands will be required to develop AA standards that are linked to operational requirements (Waller, 2010). The project team developed an operational requirement equation (Equation 3) with three primary components; contingency hours, training hours and secondary requirements which is composed of ground requirements, spare requirements, alert requirements, and reserve requirements (Waller, 2010).

$$\left[\frac{(So)}{Fdays \times Tu \times (1-a)} \right] + \left[\frac{(St)}{Fdays \times Tu \times (1-a)} \right] + G + S + A + R = OR \quad (3)$$

So – Sorties required; contingency

St – Sorties required; training

F – Days available to fly

Tu – Turn rate

a – Attrition rate

G – Ground schedule requirements

S – Spare requirements

A – Alert requirements

R – Reserve and Guard requirements

OR – Operational Requirements

The contingency component is the total number of sorties projected divided by the number of flying days. For most units the operational flying day variable is 365 days. This represents the 24 hours, 7 day a week operational tempo seen in contingency operations. If the time window requirement is less than one year, the fly days need to

reflect the total days for the period in question. For AMC or AFSOC, the flying day denominator used is 1 day. This is due to the fact that AMC and AFSOC determines a daily fixed aircraft requirement for both contingency missions and training sorties versus number of sorties or flying hours. For current operational norms, when one aircraft equals one sortie (mission), Turn rates (T_u) are set to 1 and Attrition (a) is set to 0. This converts sorties per day to aircraft per day (Waller, 2010).

The training component is the total number of sorties projected divided by the established scheduling parameters of the parent MAJCOM. The flying hour programs of the various commands establish the requirements for flying days, programmed average sortie duration, turn patterns of aircraft and the training attrition rate. The calculation of these variables will give the daily aircraft requirements to meet the training programs. As with the operational component, most units establish a total number of flying days for the year, otherwise the fly days need to reflect the total days for the period in question. For AMC or AFSOC, the flying day denominator used is 1 day. As stated before, this is due to the fact that AMC and AFSOC determines a daily fixed aircraft requirement for both contingency missions and training sorties versus number of sorties or flying hours (Waller, 2010).

The last component of the equation takes into account the ground requirements, spares needed, alert requirements and the aircraft needed for the reserve component of an active/reserve associated unit. These three components summed together quantify the operational requirements within a unit into an amount of aircraft needed to conduct operations. The operational requirement is then inputted into the AA requirement equation (Equation 4). The OR number is divided by the Total Active Inventory for the

specific MDS of interest. This will provide the required AA standard for the specified time period (Waller, 2010).

$$\frac{OR}{TAI} = AA \text{ std} \quad (4)$$

An example of this is the B-52 operational requirements (Table 1). Combining the three components of the operational requirements equation resulted in 44 aircraft required for operations. The TAI of the B-52 fleet is 76 aircraft. Dividing the operational requirement (44 aircraft) by the TAI (76 aircraft) results in the AA requirement, which is 57.7 percent.

Table 1. Example of B-52 Results (Waller, 2010)

		B-52H
Tail Req contingency ¹	AT _o	
Flying Sorties contingency ²	S _o	676
Flying Hours contingency	FH _o	
ASD contingency	ASD _o	0
# Flying days contingency	F _{dayo}	365
Turn Rate contingency	T _u	1
Attrition Rate contingency	a	0
Tail Req trng	AT _t	
Flying Sorties trng	S	3332
Flying Hours trng	FH _t	
ASD training	ASD _t	6.2
# of Flying days training	F _{dayt}	242
Turn rate training	T _u	1.00
Attrition rate	a	0.12
Acft req for other events	G	9
Req Acft Spares	S	9
Req Acft Alert	A	0
Req Acft for ARC	R	8.25
OR =		44
Total Active Inventory	TAI	76
AA_{std} = OR/TAI =		57.7%

The AA standard equation discussed above has become a requirement for each MAJCOM to utilize in developing their respective AA standards for each MDS they possess (AFI 21-103, 2012:10).

The current AA standard for the KC-135 is 83.7 percent, which equates to 347 aircraft required for operations out of 414 total aircraft in the inventory (AMC/A4M).

The attainable AA rate for the KC-135 is currently 72.1 percent, which equates to 298 aircraft and approximately 49 aircraft short of operational requirements (AMC/A4M). Due to the importance of AA, AMC initiated an Aircraft Availability Improvement Program (AAIP) with many initiatives to improve the AA rate and provide the required amount of aircraft for operations.

Determining the health of the fleet and ascertaining a unit's capabilities has always been a goal of leadership, whether that was through the MC rate or more currently the strategic view of the AA rate. Throughout the past 20 years, there has been much research analyzing what factors affect the AA rate and that analysis is the foundation to this research.

Previous Research on AA

Before the AA rate was chosen as the metric of choice, Captain Steven Oliver analyzed what factors affect the MC rate. The premise behind his research was the MC rate was a great indicator of readiness and the MC rates had fallen from all-time highs at the onset of the 1990s to an average of 10 percent drop across MDS by 1999 (Oliver, 2001). The framework was to investigate what variables affect the MC rate and create a multiple linear regression model to develop explanatory and predictive models that provide more insightful forecasts (Oliver, 2001). He developed six categories with numerous sub-categories that he conducted correlation analysis to ascertain the critical variables that affect the MC rate. The six overarching categories were personnel, environment, reliability and maintainability, funding, aircraft operations and logistics operations (Table 2).

Table 2. Potential Factors Affecting the MC Rate (Oliver, 2001)

Personnel	Environment	Reliability & Maintainability	Funding	Aircraft Operations	Logistics Operations
Personnel assigned or authorized	OPSTEMPO factors	TNMCM hours	Replenishment spares funding	Aircraft utilization rates	TNMCS hours
Personnel in each skill-level (1, 3, 5, 7, 9 and 0)	PERSTEMPO factors	Maintenance downtime/reliability	Repair funding	Possessed hours	Base repair cycle time
Personnel in each grade (E1-E9)	Number of deployments	Mean time between failures/mean time to repair	General support funding	Average sortie duration	Order and ship time
F-16 maintenance personnel in various Air Force specialty codes (AFSC)	Policy changes	Code 3 breaks	Contractor logistics support funding	Flying hours	Level of serviceable inventory
F-16 maintenance personnel by skill-level per AFSC	Contingencies	8-hour fix rate	Mission support funding	Sorties	Level of unserviceable inventory
F-16 maintenance personnel by grade per AFSC	Vanishing Vendors	Reparable item failures	O&M funding	Flying scheduling effectiveness	Supply reliability
Retention rates for F-16 maintenance personnel	Weather	Cannibalization hours/actions	Initial spares funding	Type mission (DACT, CAP, and so forth)	Supply downtime
Personnel per aircraft ratios	Aircraft age	Repair actions/hours	Acquisition logistics funding	Over-Gs	Depot repair cycle time
Maintenance officers assigned or authorized	Aircraft mission (training, test, combat)	Maintenance man-hours		Airframe hours	Maintenance scheduling effectiveness

Personnel

Captain Oliver identified the numerous changes within our force structure from the build-up of the 1980s to the drawdown of our forces after the fall of the Berlin wall and the victory in the Persian Gulf War. In addition to the reduction in force, a decline in retention rates, increased operations tempo and changes in the Air Force Specialty Code shred-out for maintenance personnel, all had major impacts to the amount of 3-levels, 5-levels and 7-levels across all flight-lines. He concluded that in the maintenance arena, changes in manning levels, experience (skill level and rank), morale and retention were related to changes in MC rates. Captain Oliver also deducted that some of these factors are easily quantified (manning levels and number of NCOs) while others are not (maintenance experience and morale). With respect to the quantifiable variables, several studies have indicated manning levels in the enlisted maintenance career fields

(2AXXX and 2WXXX) appear to be negatively correlated to the MC rate (Oliver, 2001).

Environment

One of the most used clichés in the past 15 years is, “doing less with more.” As the Air Force has drawn down its forces, operation tempo has increased and this has had a dramatic effect on the defense environment. Captain Oliver concluded through his research that some of these effects can be seen as decreased aircraft reliability and maintainability and spare parts level, increased maintenance man-hours and deployments, and reduced retention and morale (Oliver, 2001). The Operations Tempo (OPSTEMPO) and Personnel Tempo (PERSTEMPO) have only increased since 2001 with Operations ENDURING FREEDOM and IRAQI FREEDOM.

Reliability

Reliability is the probability that an item will perform its intended function under stated conditions for either a specified interval or over its useful life (DoD, 2005). In 2001 when Captain Oliver conducted his research, the average age of our fleet was 20 years old with 40 percent of the fleet 25 years or older. As these aircraft age and their operating conditions change, the reliability of their systems and components begins to decrease and costs start to increase (Oliver, 2001). More breaks require more maintenance actions taken to bring an aircraft back to MC status. This problem has only been compounded as our fleet on average has gotten older. As of 2011, the average age of the Air Force fleet was over 27 years old (USAF, 2012). Figure 2 depicts this aging trend over the past 20 plus years. Captain Oliver also pointed out the additional man-hours required to keep these aging aircraft airworthy such as special inspections and

Time Compliance Technical Orders (TCTO) have only grown exponentially as our fleet has aged. These additional man-hours are making up more and more of the TNMCM time. Figure 3 provides a snapshot of the upward trend of our aging aircraft and AA over that time period.

	ACTIVE AIR FORCE	AIR FORCE RESERVE	AIR NATIONAL GUARD	PERCENT OF AIRCRAFT 9 YEARS OR OLDER
1987	15.5	17.5	17.4	78.8
1988	15.9	17.1	17.3	70.9
1989	16.5	15.5	16.8	71.1
1990	16.9	16.5	16.1	71.7
1991	17.4	15.8	15.2	70.4
1992	17.6	15.5	14.7	68.9
1993	17.7	16.5	14.6	68.5
1994	17.7	18.1	15.1	67.1
1995	17.8	18.4	15.9	67.0
1996	17.9	20.6	16.6	69.0
1997	18.8	21.5	17.7	73.1
1998	19.7	22.0	18.7	76.5
1999	20.5	22.9	19.7	80.3
2000	21.2	23.8	20.6	84.3
2001	21.9	24.8	21.4	85.8
2002	22.2	25.6	22.5	86.3
2003	22.7	26.3	23.2	88.7
2004	22.8	26.8	23.7	89.8
2005	22.8	27.5	24.5	89.5
2006	24.1	31.1	22.5	99.5
2007	23.9	30.9	22.4	99.3
2008	23.1	28.1	23.1	84.5
2009	22.6	28.5	23.5	86.7
2010	23.0	29.8	24.6	86.6
2011	23.6	32.4	26.4	83.5

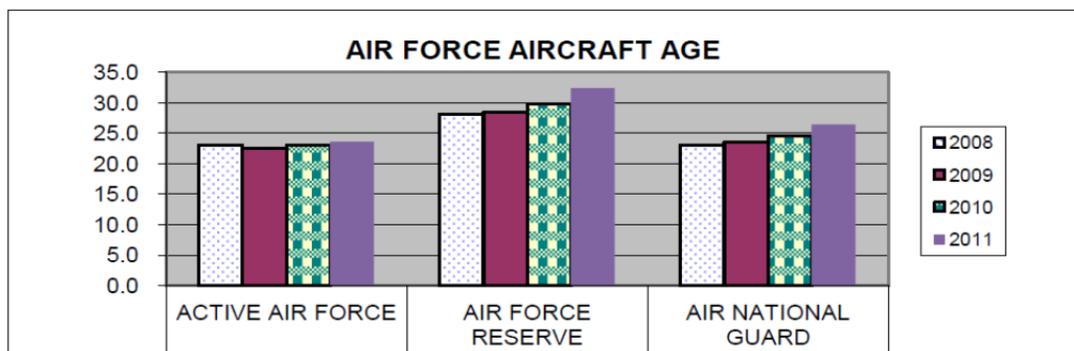


Figure 2. Aging Trends of Air Force Aircraft (AF/A8, 2012)

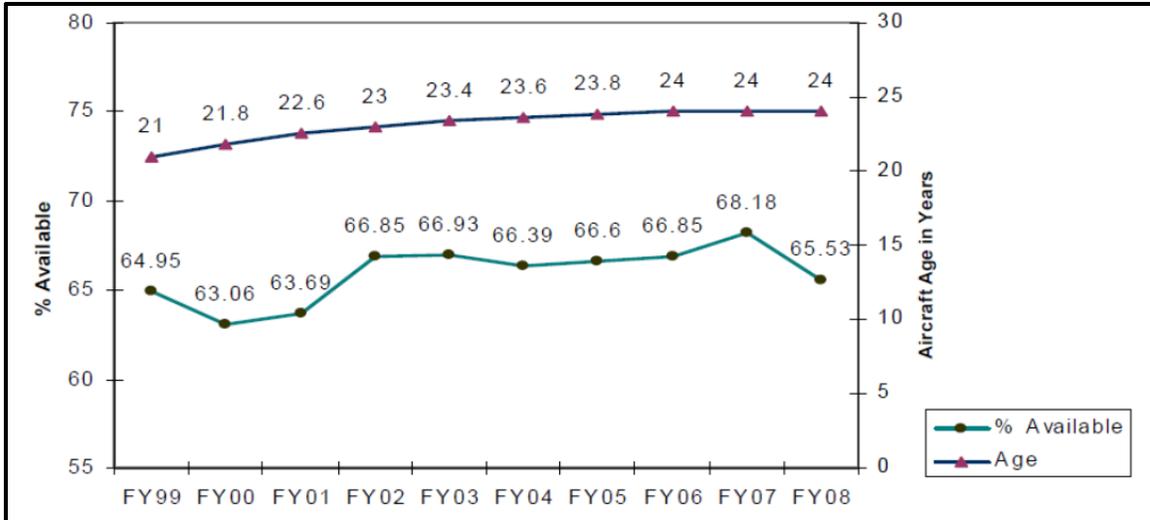


Figure 3. Average Age of Air Force Aircraft vs. AA (SAF/FMB, 2009)

Funding

The common characteristic amongst all research conducted on MC rates/AA rates have been funding. Without the funding required for spares, equipment, depot, upgrades and reparable parts operations would cease to exist. In his in-depth research, Captain Oliver discovered that a study conducted by the Dynamic Research Corporation (DRC) concluded that if funding for spare parts is even marginally less than the requirement it will have a negative impact on aircraft availability (Oliver, 2001). While the relationship between funding and AA rates might not always be easily identified, previous research has proven that a reduction in funding or reallocation of funds has an impact on AA rates. An example of this is the RAND study Captain Fry (2010) utilized in his research of AA rates. It was discovered that aircraft maintained by Contracted Logistic Services (CLS) contractors have a higher amount of fixed costs than organically repaired aircraft, and a result of this is CLS programs are less affected by funding instability compared to organically repaired aircraft (Fry, 2010).

Another possible impact funding has on AA is the process how funds are allocated to Weapons System Sustainment. Prior to 2008, the Air Force replicated the process to determine weapon system sustainment requirements, allocate resources, and execute funds across each of the 10 MAJCOMS (including the Guard and Reserves) through stove-piped business areas (Fry, 2010). Each MAJCOM created their budget and program objective memorandum (POM) inputs based on those requirements and submitted them to Air Staff (Figure 4). At this stage, requirements usually exceeded the resources available so resources were allocated on a “percent funded” basis (McKown, 2009). After enactment of funds, Air Staff sent funds to the MAJCOMS for execution. Finally, the MAJCOMS provided funds to the appropriate AFMC product and logistics centers for every program they operated on an expense-by-expense basis for execution. Additionally, product and logistics centers, depots, and supply operations exchanged funds within AFMC. As a result, over two million transactions occurred every year between AFMC’s supply and maintenance activities alone (Naguy and Keck, 2007).

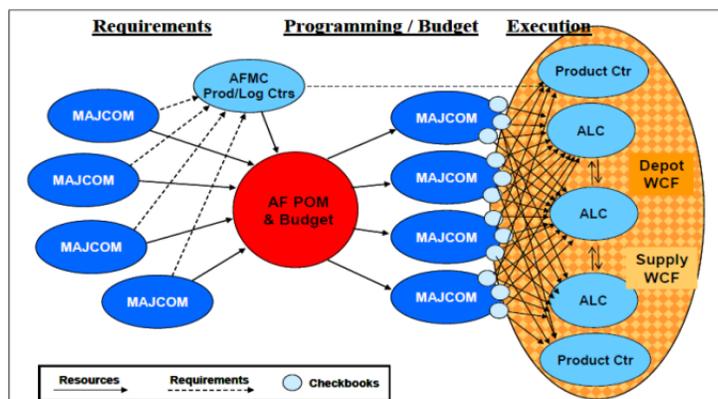


Figure 4: Requirements, Allocation and Execution of Funds (Fry, 2010)

This process proved to be very inefficient due to the labor intensive, parallel activities which were stove-piped in each MAJCOM. This process lacked the holistic

view that each MDS requires for fleet management and induced a non-homogeneous perspective of requirements and allocation of funds. Finally, due to the different procedures used and subsequent inconsistencies inherent in the requirements determination and resource allocation process, there was not a feasible way to determine the impact of funding reductions on aircraft availability. This shortcoming meant that Air Force leaders were unable to know if the needs of the warfighter were going to be met in an environment of constrained resources (Fry, 2010).

In an effort to improve AA, focus on AF-level planning for supply and maintenance, and reduce maintenance downtime AF/A4 developed eLog21 in 2003 (AFMC/A4). The only issue to seeing the full effects of eLog21 was the stove-piped, compartmentalized way of determining requirements, resourcing allocations and executing the funds to meet those requirements. To improve this process, the centralized asset management (CAM) was created and AFMC was designated Executive Agent for this account (AFMC/A4). CAM is based off of four pillars; centralized funding, centralized requirements determination, integrated wholesales supply and depot maintenance, and performance based logistics. CAM is a combination of A4 and FMB with A4 responsible for the weapons system sustainment requirements, POM, performance based outcomes, and Consolidated Air Force Data Exchange system and FMB responsible for the financial management of the requirements (AFMC/A4). CAM provides the structure required to provide a holistic view of managing weapons systems and allow for optimization at the USAF level (Figure 5). With the critical importance of AA, CAM links AA with AFMC metrics through performance based outcomes.

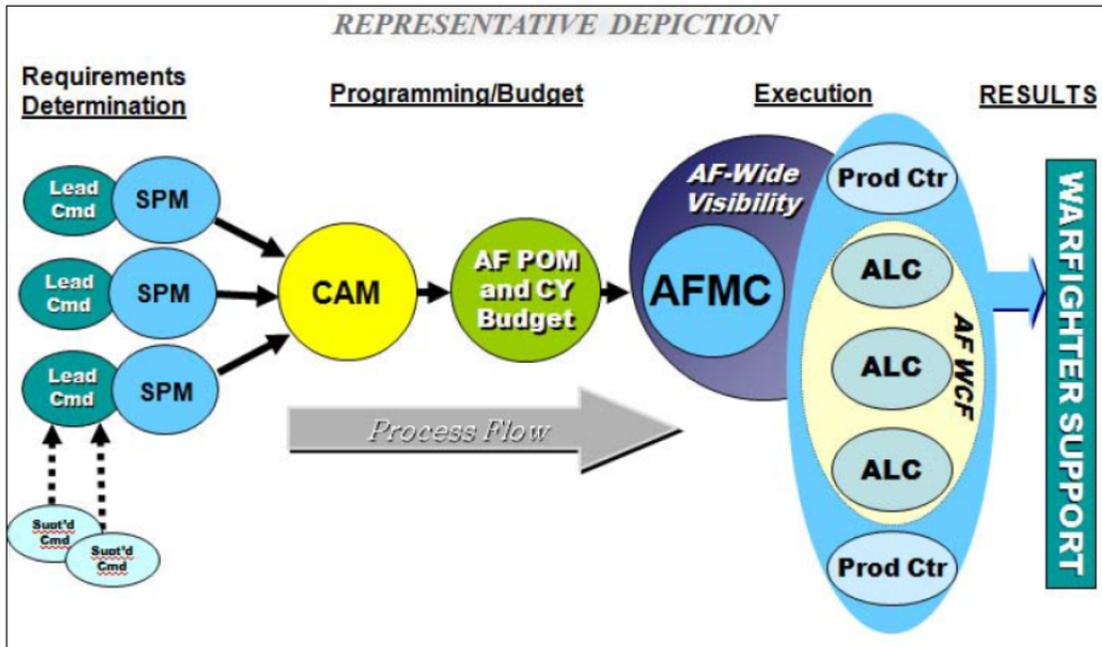


Figure 5. Centralized Asset Management Process (AFMC/A4)

Aircraft Operations

Captain Fry discovered through his research that an increase in the number of sorties is positively correlated to MC rates, but that an increase in the number of sorties combined with an increase in the number of cannibalizations is negatively correlated to MC rates (Fry, 2010).

Logistics Operations

There are many variables within the logistics arena that can possibly affect AA such as Total Non-Mission Capable Supply (TNMCS), depot repair time, supply reliability and maintenance scheduling effectiveness. But, previous research by Captain Oliver and Captain Fry identified a few of these variables have a direct correlation to the AA rate. Captain Fry showed that awaiting parts discrepancies and a shortage of spare parts have a negative correlation to AA rates. It was also discovered by the GAO that

MC rates increase as consumables or repairable parts orders are filled within one or two days (Fry, 2010).

As stated at the beginning of this chapter, Captain Oliver and Captain Fry’s analysis of the MC/AA rate is the framework for this research and the six categories of personnel, environment, reliability & maintainability, funding, aircraft operations and logistics operations are the independent variables we will examine in creating our forecasting AA model. Table 3 shows a snapshot of the AA correlated variables.

Table 3. Variable Correlation with AA Rates (Fry, 2010)

Category	Variable	Correlation	Author
Personnel	Ratio of 3-levels to 5-levels	Negative	Oliver, 2001
	Ratio of 3-levels to 7-levels	Negative	Oliver, 2001
	Total # of Inexperienced Maintainers by Rank or Skill Level	Negative	Oliver, 2001
	Maintainers Per Aircraft	Positive	Oliver, 2001
	Total # of Maintainers	Positive	Oliver, 2001
	Overall Reenlistment Rate	Positive	Oliver, 2001
	Reenlistment Rate of First-Term Airmen	Positive	Oliver, 2001
	Reenlistment Rate of Career Airmen	Positive	Oliver, 2001
	Reenlistment Rate of Eligible Crew Chiefs	Positive	Oliver, 2001
	Crew Chief Manning Levels	Positive	Huseroft, 2004
	Percentage of 7-level Maintainers	Positive	Chimka and Nachtmann, 2007
Percentage of 9-level Maintainers	Positive	Chimka and Nachtmann, 2007	
Environment	Average # of Possessed Aircraft	Positive	Gilliland, 1990
	Aircraft Age	Mixed (Bathub Curve)	GAO, 2003
	Transition to Combat Wing Structure in 2002	Positive	Barthol, 2005
Reliability & Maintainability	Cannibalization Rate	Negative	Gilliland, 1990; Moore, 1998; Oliver, 2001
	Awaiting Maintenance Discrepancies	Negative	Gilliland, 1990
Funding	8-Hour Fix Rate	Positive	Oliver, 2001
	CLS supported	Positive	RAND, 2009
Aircraft Operations	Sorties	Mixed	Moore, 1998;
	Awaiting Parts Discrepancies	Negative	Gilliland, 1990
Logistics Operations	% of Requests for Consumables Filled in 1-2 days	Positive	Moore, 1998

With the historical aspect of AA and previous research conducted on AA rates complete, the previous and current AA rate models utilized within the Air Force are reviewed.

Aircraft Availability Forecasting Models

Aircraft Availability Model

One of the first models developed was the Aircraft Availability Model (AAM) that was created in 1983. It is an analytical model and decision support system that relates expenditures for the procurement and depot repair of recoverable spares to aircraft availability rates by weapons system (O'Malley, 1983). The AAM produces curves of cost versus availability rate for each aircraft type (Figure 6).

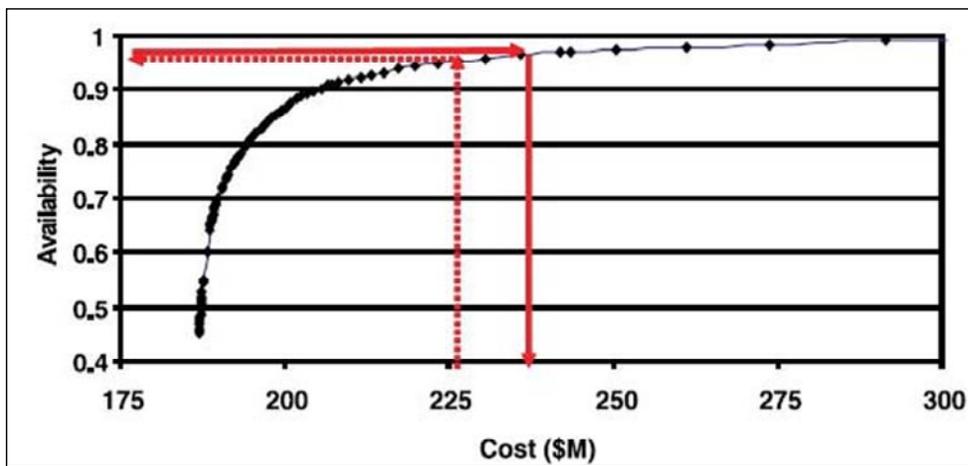


Figure 6. Aircraft Availability Curve (Fry, 2010)

However, the AAM does not take any variable outside of TNMCS as a consideration into the equation. It's utilized by the Air Force Logistics community to determine the amount of spare parts needed with the funding available and still meet a certain level of aircraft availability (Fry, 2010). Although it is a great model in determining the repairable parts needed for each weapons system, it's not a complete decision support system in terms of determining AA.

Funding/Availability Multi-Method Allocator for Spares

In 2001, the Air Force started to utilize the Funding/Availability Multi-Method Allocator for Spares (FAMMAS) as a way to forecast MC rates for each of the weapons systems. Employing time-series forecasting methods, FAMMAS uses the last 3 years of historical TNMCS and Total Non-Mission Capable Maintenance (TNMCM) data combined with past, present, and future spares funding to forecast MC rates (Fry, 2010). While it produces useful results, time-series models like FAMMAS do not provide insight into potential cause-and-effect relationships that may be exploited to affect MC rates. FAMMAS produces its forecasts by simply projecting data trends, not by using explanatory models (Fry, 2010). As discussed earlier in the chapter, Captain Oliver discovered there are more variables that have a correlation with the AA rate besides funding and TNMCS and TNMCM rates such as number of personnel assigned and skill levels. Therefore, FAMMAS is not an effective tool to use for policy or resource decisions because of the limited scope of variables used in the model and because the relationships between the variables are largely unknown (Oliver, 2001).

Mobility Aircraft Availability Forecasting Simulation Model

In 2005, AMC/A4 Directorate of Logistics contracted Northrup Grumman and Wright State University to build an AA forecasting model that could be used within AMC. They developed the Mobility Aircraft Availability Forecasting Simulation Model (MAAF). MAAF is an object-oriented modeling and simulation tool that is purportedly capable of predicting AA rates, providing “what if” analysis, and offering insight into problems that may affect AA (Fry, 2010). Although the model proved to be a useful

prototype in laboratory conditions, AMC determined the model was not ready for implementation in real-world operations (Fry, 2010).

There are other models utilized within the logistics community such as the Logistics Composite Model (LCOM), and the Aircraft Sustainability Model (ASM) but their main objective is readiness and not AA. Since this research sole focus is to analyze the variables that impact AA and create a forecasting AA model with those critical variables, it is prudent to leave those models out of this research.

Chapter Summary

In this chapter, a historical look at AA and AMC's current AA standard for the KC-135 was discussed. Previous research conducted on optimizing AA to include Captain Oliver and Captain Fry's thesis on this subject was highlighted. Lastly, a literature review with a historical view of AA models utilized throughout the years to include the current models developed to help improve our readiness. This literature review provides the foundation for this research and answering the research questions, ultimately reaching the objective of developing a predictive AA model with all the critical variables that affect AA.

III. Methodology

Chapter Overview

Many variables affect the AA rate as shown in the literature review. Thus, the research goal for this research is to identify these critical variables and add them into an explanatory/predictive AA model. In order to achieve this goal, data must be collected on these variables, a process developed to identify the variable's criticality and then utilize these variables in building a multiple linear regression model. Chapter III describes this process. First, explanation of the scope of data collection and research is discussed. After the scope of data and research is discussed, acknowledging and understanding the applications/systems utilized to collect the data takes place. From this point, describing the method used to standardize the data for comparison is provided. After the standardization method, expounding upon the method of correlation analysis to determine criticality is highlighted. Lastly, a thorough explanation of multiple regression application and the creation of an aircraft availability predictive tool caps off the methodology section.

Scope of Data Collection and Research

Previous research conducted on AA has been at the fleet level encompassing all the aircraft within a specific MDS. An example of this is research that covered all F-16s within the Air Force (Oliver, 2001). Research was also conducted at the fleet level, and included multiple MDS such as the A-10, B-52, and F-15, but only included active-duty aircraft (Fry, 2010). This was due to the scope of the Centralized Asset Management's mission only extends to the Active Duty Air Force; it does not manage the O&M funds for weapon systems that operate in AFRC or ANG (Fry, 2010).

The scope of this research follows Oliver (2001) and Fry's (2010) scope of research to a certain extent. As with Oliver's (2001) research, this research focuses on only one aircraft, the KC-135R. And as with Fry's (2010) research, this research only focuses on active duty aircraft. But, this research will not examine the entire fleet of KC-135s across the Air Force; rather it will focus at the base level of operations with Fairchild AFB as the hub of the research. The theoretical premise behind focusing at the tactical level of operations is there are many factors that take place at the base level that have a major impact on AA, which may be covered up by analyzing the entire fleet within the Air Force. A hypothetical example of this are the decisions made for the flying schedule. These decisions are greatly influenced by the environment of operations (training, personnel, experience, etc...) and executing that flying schedule has an impact on AA, and that impact can be analyzed through the flying schedule effectiveness (FSE) rate. The strategic analysis of AA can possibly dilute the critical variables of AA, and not portray the actual impact of these variables. A formal study conducted by AFLMA analyzing the declining Total Not Mission Capable for Maintenance (TNMCM) rates on the C-5 showed a misalignment of goals between the MXGs and the MAJCOM (Air, 2010). The end result of the study was the decisions made at the tactical level for operational effectiveness had an impact on strategic readiness (Air, 2010).

The data for this study ranges from 2002 – 2012 encompassing variables from personnel, funding, reliability, aircraft and logistics operations. This timeframe was selected due to the enduring changes in operations since 9/11 and the strategic focus on AA during this time.

Data Sources

Data for the KC-135R at Fairchild AFB during the period of 2002 – 2012 was ascertained from five main sources; Logistic, Installation & Mission Support – Enterprise View (LIMS-EV), Air Force Total Ownership Cost (AFTOC), Military Personnel Data System (MilPDS), Manpower Programming and Execution System (MPES), and the Personnel Accounting Symbol (PAS) system. Data from each one of these systems was collected covering the selected timeframe to provide a plethora of possible variables that correlate with AA, and supply the vast amount of data needed to build a multiple linear regression model. Most of the variables collected have already been established as contributors to AA by previous research aforementioned in the literature review. A thorough understanding of these systems provides the background needed for a repeatable and comprehensive methodology.

LIMS-EV

LIMS-EV provides one central, standardized point of access to analytical information across all A4/7 resources and process areas (LIMS-EV, 2013). It is made up of a host of different capabilities spanning from Executive, Logistics Readiness, Requirements, Maintenance Repair and Overhaul, and Mission Support capabilities (LIMS-EV, 2013). In order to gain access to LIMS-EV, a request must be sent and permissions granted by HAF A4/7, then an individual can access up to 18 different capabilities within this resource.

To gain the amount of information needed for this research, the Weapons System View capability from LIMS-EV was utilized. It provides a historical or snapshot type of report covering aircraft, missiles, or mine resistant ambush protected (MRAP) categories

offering metrics ranging from availability, status, debrief, and utilization with over 90 subcategories. The Weapons System View allows for search by CAF/MAF, mission area, specific MDS or down to the block configuration of the MDS (LIMS-EV, 2013). It also offers the capability of selecting the theater, command, base or drilling down to the group/squadron level. These reports can range from a year, quarter, month and down to daily status. For the purpose of this research, a historical report was conducted with the KC-135R from Fairchild AFB, 92 ARW on a monthly basis from 2002 – 2012. The metrics attained were from the categories of availability, status, debrief, and utilization. Overall 20 different variables were chosen to analyze for correlation with AA. A snapshot of those variables is provided in Table 4.

Table 4. LIMS-EV Data

Date	Command	Base	Nam	MD	Wing/Gro	Mission	A Available	Available	Depot (%)	UPNR (N)	UPNR (%)	TAI (N)	MC (%)				
Jan 2002	AMC	FAIRCHILD	KC-135		92nd Air R	Tanker	35.30	64.18%	27.54%	0.10	0.18%	55.00	89.15%				
Oct 2002	AMC	FAIRCHILD	KC-135		92nd Air R	Tanker	34.38	62.50%	27.11%	0.09	0.17%	55.00	84.94%				
Nov 2002	AMC	FAIRCHILD	KC-135		92nd Air R	Tanker	36.91	67.11%	23.18%	0.33	0.60%	55.00	86.29%				
Dec 2002	AMC	FAIRCHILD	KC-135		92nd Air R	Tanker	37.51	68.20%	23.35%	0.86	1.56%	55.00	90.47%				
NMCB (%)	NMCM (%)	NMCS (%)	MMH / FH	Hours	Flo	Sorties	Fic	Sorties	Scl	ASD (H)	Flying	hou	USE / FH	(I	Sorties / T	USE / Sorti	FSE (%)
3.98%	4.86%	2.02%	7.89	1,281.70	249.00	249.00	5.15	23.30	38.03	4.53	7.39	100.00%					
5.60%	5.31%	4.15%	9.50	1,072.70	209.00	209.00	5.13	19.50	34.08	3.80	6.64	100.00%					
4.83%	6.82%	2.06%	9.15	1,032.50	203.00	203.00	5.09	18.77	31.36	3.69	6.17	100.00%					
2.17%	4.23%	3.12%	7.17	1,231.50	210.00	210.00	5.86	22.39	38.30	3.82	6.53	100.00%					

AFTOC

AFTOC is a net enabled decision support system that turns data into information. It provides visibility into the costs of owning and operating infrastructure by providing routine and timely visibility into almost all unclassified Air Force costs to include major Air Force systems, MAJCOMs, Air Force Appropriations, Logistics and Programmatic data (AFTOC, 2013). In order to attain the critical funding data for the multiple linear regression model, AFTOC was the primary source for this information.

In order to attain access to the AFTOC database, a request must be sent to the AFTOC managers and permission granted. Once permission is granted, an individual has four methods to access data; standard reports, online analytical processing (OLAP), account tool, and the weapons system cost retrieval system (WSCRs). For the purpose of this study, standard reports and OLAP is highlighted.

The standard reports capability has five different formats; appropriations, cost analysis improvement group (CAIG), CAIG new, commodities and indirect. The appropriations report identifies direct costs in the form of obligations and budget authority for weapons systems developed, procured, and operated by the Air Force (AFTOC, 2013). The limitation to the appropriations format within the standard report is inability to drill down to the base level and only a 4-year historical look back. Table 5 highlights the data pulled from the appropriations format of the standard report.

Table 5. Appropriation Data from the Standard Report

Appropriation KG-135R All Cmd Direct Obs		Air Force Total Ownership Cost For Official Use Only				
Analyst Notes	Release Notes	2008	2009	2010	2011	2012
RD&E	3600	25,888,935	25,303,931	32,145,605	41,661,618	24,123,823
	Total	25,888,935	25,303,931	32,145,605	41,661,618	24,123,823
Procurement	3010	104,850,706	106,729,451	100,217,907	19,312,746	21,195,176
	Modifications	5,319,421	3,220,595	1,686,906		
	Initial Spares and Repair	2,536,129	7,161,476	86,807		
	Misc Production Charges	1,281,074	1,361,818			
	Post Production Charges		11,124			
	Total	113,067,329	118,487,964	101,991,620	19,312,746	21,200,432
	Elect & Telecom Equip	114,731				5,255
O&M	3400	114,731	39,865,696	42,182,009	39,565,264	36,220,521
	Civilian Personnel	89,524,306	73,969,559	82,161,703	88,572,357	54,291,663
	DLRs	24,894,346	39,592,342	43,879,482	38,623,640	20,923,362
	Consumables	578,005,107	328,394,619	425,894,111	606,136,149	412,042,120
	AV Fuel	327,057,643	276,450,070	334,914,838	292,882,192	334,701,819
	Depot Maintenance	10,084,721	20,071,427	10,288,022	12,436,494	11,294,560
	Sustaining Engineering	10,468,049	5,988,681	6,112,919	5,276,606	10,212,757
	Software Maintenance	23,236,323	24,590,093	16,504,743	19,198,628	26,761,769
	Contract Services	63,905,756	64,621,826	62,854,477	58,623,741	66,908,192
	Other					
	Total	1,164,065,116	872,534,312	1,024,822,304	1,171,320,971	963,256,764
	Civilian Personnel	9,111,814	10,771,438	11,363,931	15,363,754	22,205,048
	DLRs	2,602,248	3,887,603	4,338,894	4,711,497	3,383,309
	Consumables	747,723	1,092,576	1,479,003	1,497,221	1,211,181
	AV Fuel	3,910,784	3,603,314	4,531,052	5,943,131	6,556,101
	Depot Maintenance	107,453	0	0	6,000	
	Software Maintenance	94,986	123,484			
	Contract Services	19,874	49,718	101,478	93,447	152,406
	Other	7,772,795	8,805,326	8,114,014	9,538,488	12,850,355
	Total	24,366,778	28,333,457	29,938,372	37,153,838	46,358,401
	Civilian Personnel	124,983,009	119,458,485	126,166,163	125,482,221	120,781,690
	DLRs	18,347,731	16,907,986	21,852,981	17,471,201	14,450,888
	Consumables	10,358,724	8,488,989	8,968,631	8,023,814	6,129,296
	AV Fuel	112,480,745	94,283,751	118,303,238	158,253,920	161,943,528
	Depot Maintenance	72,535,025	89,086,382	128,974,470	156,028,038	138,208,805
	Sustaining Engineering	1,205,541	856,000	5,665,008	1,581,426	1,366,896
	Other	8,287,516	9,617,885	9,433,897	10,581,485	9,050,569
	Contract Services		8,982	66,147	73,224	150,395
	Total	348,198,291	338,708,370	419,450,635	477,495,329	452,080,066
	Civilian Personnel	240,554,953	237,995,695	264,271,121	254,713,706	253,923,648
	DLRs	36,969,374	46,068,553	39,194,812	26,954,676	26,960,607
	Consumables	17,226,126	20,178,451	16,784,680	14,079,229	13,517,378
	AV Fuel	245,689,951	188,440,816	240,580,876	434,759,817	419,151,077
	Depot Maintenance	137,210,962	214,647,305	316,197,031	275,661,455	303,404,564
	Sustaining Engineering	3,324,486	2,882,989	7,764,368	5,487,372	9,561,300
	Contract Services	1,514,848	1,476,025	-438,835	31,524	
	Other	38,903,930	33,035,739	34,986,252	39,974,518	30,882,022
	Total	721,394,638	744,725,563	919,340,304	1,051,702,296	1,057,490,566
	DLRs	2,160				
	Consumables	315,702	1,389,637	1,305,943	1,419,972	617,826
	Other	295,697	211,141	205,380	280,470	107,514
	Total	603,549	1,600,777	1,511,323	1,700,441	625,339
	Consumables	290,207	2,680,902	970,254	740,507	730,338
	Other	72,878	82,835	95,077	-224,731	-461,127
	Total	363,084	2,763,737	1,065,331	519,776	269,211
MIIPers	3500	237,738,465	261,177,179	276,702,463	296,053,149	317,411,449
	Enlisted	117,038,063	129,146,422	132,384,216	131,436,861	132,118,026
	Officer	354,776,528	390,279,601	409,086,679	427,526,011	449,629,478
	Total	354,776,528	390,279,601	409,086,679	427,526,011	449,629,478
	Enlisted	39,072,557	59,017,994	60,849,793	76,949,341	79,949,493
	Officer	18,092,299	26,068,636	25,657,501	29,415,793	28,541,243
	Total	55,164,856	85,086,630	86,506,294	104,475,234	104,488,737
	Enlisted	129,176,989	138,572,713	160,351,057	149,366,147	153,062,341
	Officer	61,110,038	65,430,582	75,169,481	69,764,900	69,651,045
	Total	190,287,028	204,003,295	235,520,538	219,131,048	222,713,387
Grand Total		3,000,210,862	2,811,821,637	3,261,368,005	3,552,000,508	3,342,047,160

The CAIG new format within the standard report, which has the same capabilities as the original CAIG format except for a different format established in 2008, offers the capability of drilling down to the base level and the ability to pull historical data as far back as 1997. The limitation with the CAIG new format is it only pulls data 1 year for each report. Although this limitation was time consuming, the CAIG new report was utilized to pull historical funding data for the KC-135R at Fairchild AFB from 2002 – 2012. In order to pull the report desired for this study, the direct obligations, aircraft, KC-135R, AMC, and each fiscal year from 2002 – 2012 were selected from the drop-down menus. Table 6 is a snapshot of some of the data attained from this report.

Table 6. CAIG New Data from the Standard Report

CAIG New FY2002 KC-135R AMC Direct Obs Financial View		Air Force Total Ownership Cost								
Release Version: FY2012Q4V1		For Official Use Only								
Analyst Notes		Release Notes		Commodities			A/C Engine			
CAIG New First Level	All Base	ANDERSEN AFB (GUAM) MAJCOM OTHER UNITS	ANDREWS AFB (MD) MAJCOM HQ	BANGOR ANG BASE (ME) MAJCOM OTHER UNITS	BEALE AFB (CA) MAJCOM OTHER UNITS	CHARLESTON AFB (SC) 21st AF 437th AW	ELMENDORF AFB (AK) MAJCOM OTHER UNITS	FAIRCHILD AFB (WA) 15th AF 92nd ARW		
1.0 Unit Personnel	210,092,594					10,059		23,775,237		
2.0 Unit Operations	178,533,014	161,473	30,649,614	444,567	927,054			13,841,260		
3.0 Maintenance	228,991,334	55,932		150,614			13,184	3,121,661		
4.0 Sustaining Support	19,047,802							238,244		
5.0 Continuing System Improvements	2,281,955									
6.0 Indirect Support	17,049,181							1,821,765		
Total	655,995,879	217,406	30,649,614	595,182	927,054	10,059	13,184	42,798,168		
1.0 Unit Personnel	210,092,594					10,059		23,775,237		
2.1 Operating Material	122,217,726	144,286	64,738	69,032				11,838,020		
2.2 Support Services	11,433,343	17,188		375,535	8,090			107,655		
2.3 TDY	44,881,945		30,584,876		918,964			1,894,586		
2.0 Unit Operations	178,533,014	161,473	30,649,614	444,567	927,054			13,841,260		
3.1 Organizational Maintenance & Support	43,621,911	55,932		150,614			13,184	3,121,661		
3.3 Depot Maintenance - Overhaul/Rework	185,369,423									
3.0 Maintenance	228,991,334	55,932		150,614			13,184	3,121,661		
4.1 System Specific Training	7,795,491							211,484		
4.3 Operating Equipment Replacement	127,106							26,759		
4.4 Sustaining Engineering & Prog Mgmt	11,125,204									
4.0 Sustaining Support	19,047,802							238,244		
5.2 Software Maintenance & Modifications	2,281,955									
5.0 Continuing System Improvements	2,281,955									
6.1 Installation Support	15,234,701							1,567,778		
6.2 Personnel Support	1,814,480							253,987		
6.0 Indirect Support	17,049,181							1,821,765		
Total	655,995,879	217,406	30,649,614	595,182	927,054	10,059	13,184	42,798,168		

1.1.1 Pilot	38,867,881					10,059		4,457,493
1.1.2 Aircrew	21,248,901							2,004,036
1.1.3 Crew Technician	5,551,868							716,921
1.1.4 Command & Control	9,782,382							911,865
1.1 Operations Personnel	75,451,033					10,059		8,090,314
1.2.1 Organizational	72,110,819							8,461,263
1.2.2 Intermediate	34,185,301							4,152,585
1.2.3 Ordnance	57,089							
1.2.4 Other Maintenance	41,358							
1.2 Maintenance Personnel	106,394,568							12,613,848
1.3.1 Unit Staff	5,726,931							733,816
1.3.2 Security	8,733,189							792,017
1.3.4 Other Support	13,786,873							1,545,242
1.3 Other Direct Support Personnel	28,246,993							3,071,075
1.0 Unit Personnel	210,092,594					10,059		23,775,237
2.1.1 Energy (Fuel, POL, Electricity)	112,666,780		64,738	3,413				10,584,677
2.1.3 Other Operational Material	9,550,946	144,286		65,619				1,254,343
2.1 Operating Material	122,217,726	144,286	64,738	69,032				11,839,020
2.2.1 Purchased Services	5,407,695	17,188		305,272				70,134
2.2.2 Transportation	140,117			70,263	8,090			724
2.2.3 Other	5,885,531							36,797
2.2 Support Services	11,433,343	17,188		375,535	8,090			107,655
2.3 TDY	44,881,945		30,584,876				918,964	1,894,586
2.0 Unit Operations	178,533,014	161,473	30,649,614	444,567	927,054			13,841,260
3.1.2 Repair Parts	11,940,405	54,242		64,237			11,514	1,105,629
3.1.3 Depot Level Repairables (DLR)	31,681,506	1,690		86,378			1,670	2,016,032
3.1 Organizational Maintenance & Support	43,621,911	55,932		150,614			13,184	3,121,661
3.3.1 Aircraft Overhaul/Rework Depot Repair	182,607,073							
3.3.3 Engine Overhaul/Rework Depot Repair	2,589,981							
3.3.4 Other Overhaul/Rework Depot Repair	172,369							
3.3 Depot Maintenance - Overhaul/Rework	185,369,423							
3.0 Maintenance	228,991,334	55,932		150,614			13,184	3,121,661
4.1.1 Non-Operator Training	2,088,614							201,884
4.1.2 Operator Training	9,601							9,601
4.1.3 Simulator Operations	5,697,276							
4.1 System Specific Training	7,795,491							211,484
4.3 Operating Equipment Replacement	127,106							26,759
4.4 Sustaining Engineering & Prog Mgmt	11,125,204							
4.0 Sustaining Support	19,047,802							238,244
5.2.1 Software Maint & Mod (Government)	2,281,955							
5.2 Software Maintenance & Modifications	2,281,955							
5.0 Continuing System Improvements	2,281,955							
6.1.1 Base Operating Support	15,142,010							1,567,778
6.1.2 Real Property Maintenance	92,692							
6.1 Installation Support	15,234,701							1,567,778
6.2.3 Medical Support	1,814,480							253,987
6.2 Personnel Support	1,814,480							253,987
6.0 Indirect Support	17,049,181							1,821,765
Total	655,995,879	217,406	30,649,614	595,182	927,054	10,059	13,184	42,798,168

The OLAP report is based off a multi-dimension database that organizes the data into a specialized structure to facilitate rapid analysis. It allows the user to look at the data at either a highly detailed level of summary or a highly summarized level, and the ability to use different combinations of detail in each dimension (AFTOC, 2013). It offers the ability for a user to drill down to the program element codes (PEC) or the responsibility codes. A user has the ability to compare costs for a specific MDS across commands that fly that MDS. OLAP also offers the ability to compare military and civilian costs for an aircraft or per flying hour basis (AFTOC, 2013). Those features, just to name a few, combined with the ability to create a pivot table to arrange and display the data offer the user a lot of flexibility. The user can either utilize a predefined pivot table created by the AFTOC team, which is saved on the program's "S" drive, or the user can

create a pivot table from scratch. Once the user has established what type of pivot table required, the OLAP capability offers multiple connections to specific data such as appropriations, CAIG New, GSA Fuel, Engines, or Indirect Costs. For the purpose of this study, the CAIG New format was selected to retrieve historical costs data. Table 7 provides an overview of the data collected through the OLAP report.

Table 7. CAIG New Data from the OLAP Report

Direct Obs	Column Labels										
Row Labels	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
ANM	139,961,249	144,641,824	160,614,921	182,461,798	184,187,439	180,178,504	251,252,629	198,910,416	240,830,822	333,582,885	264,875,355
FAIRCHILD AFB (WA)	139,961,249	144,641,824	160,614,921	182,461,798	184,187,439	180,178,504	251,252,629	198,910,416	240,830,822	333,582,885	264,875,355
KC-135R/T	139,961,249	144,641,824	160,614,921	182,461,798	184,187,439	180,178,504	251,252,629	198,910,416	240,830,822	333,582,885	264,875,355
AVFUEL	40,217,700	41,669,335	49,978,989	70,946,372	90,340,731	87,046,551	152,536,280	90,414,523	119,758,258	205,522,585	131,718,896
Civ Personnel	585,379	846,156	1,827,251	2,776,318	1,879,232	1,573,822	1,796,467	2,701,678	3,104,226	2,280,219	2,341,133
Communications	553	1,756	-122,906	110,340	68,987	32,181	34,176	12,684	6,545	28,725	180,978
Contract Services	198,378	273,130	316,029	4,052,912	6,022,200	7,567,917	10,017,268	8,054,686			
DLR-Flying	7,571,137	7,488,592	6,839,556	8,790,532	4,153,700	8,046,883	10,143,101	8,626,363	11,530,544	6,271,708	11,635,740
DLR-Nonflying			1,250		20,817	2,706	7,200	27,173	1,265		
Education & Training	32,722	14,789	15,668	10,106							
Equip/Fac Lease & Rental	9,391				750	1,020					
IT & Software	102,246	305,413		71,535			87,606	152,690		103,795	
Maint, Repair, Minor Cons					19,950			29,401			
Mil Personnel	77,367,458	83,374,414	89,262,293	85,126,068	73,090,378	68,680,892	68,645,951	79,257,319	87,104,662	97,574,441	101,392,789
Misc Expense	31,045	1,916	-107,148	25,957	92,722	28,528	5,523	14,386	9,477,393	11,009,882	6,939,098
Other Services								17,970	14,378	78,605	12,820
Printing			2,125								
Purchased Equip			3,565	3,505	626	419		185,400	312,511	51,395	
Purchased Equip Maint	14,400				678	215,861	155,649	147,839	180,348	121,470	192,260
Supplies	8,080,662	8,008,142	8,988,927	8,590,696	6,328,307	5,175,224	6,387,121	7,612,813	7,377,159	7,881,408	7,745,483
TDY	5,747,981	2,657,936	3,609,325	1,957,458	2,167,510	1,806,354	1,431,828	1,653,969	1,958,454	2,649,642	2,701,912
Transportation	2,198	244			851	146	4,459				820
Vehicle Rental								1,524	5,080	9,011	13,425
Grand Total	139,961,249	144,641,824	160,614,921	182,461,798	184,187,439	180,178,504	251,252,629	198,910,416	240,830,822	333,582,885	264,875,355

The standard report and the OLAP report were the only two reports utilized to attain funding/costs data for this research. The appropriations format and the CAIG new format were both utilized within the standard and OLAP reports. The remaining formats from both reports were not utilized and will not be expounded upon for the purposes of this research.

MilPDS, MPES, PAS

The personnel data was attained from the last three resources utilized, MilPDS, MPES and PAS. A request was sent to HAF/A1 for access into the personnel system in order to attain information from Fairchild AFB from 2002 – 2012. The response from HAF/A1 was a copious amount of data in a report covering authorized and assigned

personnel with a skill-level breakout by month for Fairchild AFB during the period of 2002 – 2012. The data pulled from MilPDS provided the accurate number of assigned personnel for Fairchild AFB during the time period. The data pulled from MPES provided the correct number of authorized personnel during the time period, and the data pulled from PAS provided organizational data to identify the aircraft maintenance organizations tied to Fairchild AFB during the time period (HAF/A1P, 2013). Table 8 showcases some of the data attained from the report.

Table 8. Personnel Data from MilPDS, MPES and PAS

month	id	pas nr	org nbr	org name	org type	location	AFSC	AFSC Desc	Skl lvl	Auth	Asgd
200210	FGFH	0092	MAINTENANCE	GP	FAIRCHILD	20C		LOGISTICS COMMANDER		2	2
200210	FGFH	0092	MAINTENANCE	GP	FAIRCHILD	21A		AIRCRAFT MAINTENANCE		1	0
200210	FGFH	0092	MAINTENANCE	GP	FAIRCHILD	33S		COMMUNICATIONS AND INFORMATION		1	0
200210	FGFH	0092	MAINTENANCE	GP	FAIRCHILD	2A5X1		AIRLIFT/SPECIAL MISSION AIRCRAFT MAINTENANCE	7	1	1
200210	FGFH	0092	MAINTENANCE	GP	FAIRCHILD	2A5X3		MOBILITY AIR FORCES ELECTRONIC WARFARE SYSTEMS	7	0	0
200210	FGFH	0092	MAINTENANCE	GP	FAIRCHILD	2A6X0		SYSTEMS (CEM)	9	1	0
200210	FGFH	0092	MAINTENANCE	GP	FAIRCHILD	2A6X2		AEROSP GROUND EQUIP	5	0	1
200210	FGFH	0092	MAINTENANCE	GP	FAIRCHILD	2A6X2		AEROSP GROUND EQUIP	7	1	0
200210	FGFH	0092	MAINTENANCE	GP	FAIRCHILD	2A7X1		ACFT METALS TECHNOLOGY	7	1	0
200210	FGFH	0092	MAINTENANCE	GP	FAIRCHILD	2A7X3		ACFT STRUCTURAL MAINT	7	0	1
200210	FGFH	0092	MAINTENANCE	GP	FAIRCHILD	3A0X1		KNOWLEDGE OPERATIONS MGT	7	1	1
200210	FGFH	0092	MAINTENANCE	GP	FAIRCHILD	6F0X1		FINANCIAL MGT AND COMPTROLLER	7	1	0
200210	FGFH	0092	MAINTENANCE	GP	FAIRCHILD	6F0X1		FINANCIAL MGT AND COMPTROLLER	5	0	1
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	21A		AIRCRAFT MAINTENANCE		1	5
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	21B		OPERATIONS MAINTENANCE		1	0
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	21S		SUPPLY		0	1
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A4X1		ACFT G AND C	7	0	2
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A4X1		ACFT G AND C	3	0	1
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A4X1		ACFT G AND C	5	0	1
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A4X2		ACFT C AND N SYS	7	0	2
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A4X2		ACFT C AND N SYS	5	0	3
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A5X0		AEROSPACE MAINTENANCE (CEM)	9	0	2
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A5X1		AIRLIFT/SPECIAL MISSION AIRCRAFT MAINTENANCE	5	18	0
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A5X1		AIRLIFT/SPECIAL MISSION AIRCRAFT MAINTENANCE	7	9	8
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A5X1J		AEROSPACE MAINTENANCE C-5/C-9/C-12/C-17/C-20/C-21/C-22/C-26/C-27/C-130/C-141/T-39/T-43	5	0	1
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A5X1L		AEROSPACE MAINTENANCE C-135/C-18/E-3/E-4/KC10/VC25/VC137	5	0	9
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A5X3		MOBILITY AIR FORCES ELECTRONIC WARFARE SYSTEMS	7	1	0
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A5X3		MOBILITY AIR FORCES ELECTRONIC WARFARE SYSTEMS	5	6	0
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A6X1		AEROSPACE PROPULSION	7	1	0
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A6X1		AEROSPACE PROPULSION	5	5	0
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A6X1A		AEROSPACE PROPULSION JET ENGINES	5	0	2
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A6X1A		AEROSPACE PROPULSION JET ENGINES	7	0	4
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A6X2		AEROSP GROUND EQUIP	7	0	1
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A6X5		ACFT HYDRAULIC SYSTEMS	7	1	3
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A6X5		ACFT HYDRAULIC SYSTEMS	5	1	0
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A6X6		ACFT ELECT AND ENVIR SYSTEMS	7	0	2
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2A6X6		ACFT ELECT AND ENVIR SYSTEMS	5	2	2
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2R0X1		MAINTENANCE MANAGEMENT ANALYSIS	7	4	3
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2R0X1		MAINTENANCE MANAGEMENT ANALYSIS	5	6	2
200210	FHCQ	0092	MAINTENANCE OPS	SQ	FAIRCHILD	2R0X1		MAINTENANCE MANAGEMENT ANALYSIS	3	2	7

The reports obtained from these five sources of LIMS-EV, AFTOC, MilPDS, MPES, and PAS provide the data needed for the dependent variable of AA, and the independent variables that have a strong correlation with AA. In order to define what

variables will be used for the multiple linear regression model, first the data must be manipulated to standardize comparison across the different spectrums.

Standardizing the Data

To ensure standard comparison, the data is manipulated in order to be in the same format. Due to limitations on some of the reports obtained, the range of data will be from a fiscal year not a calendar year. The range of data is from October 2002 – September 2012. The format for this research is all data must be in a monthly rate, percentage or dollar format for comparison. Unfortunately, some of the data is not in this format and standardization is required. The next section identifies the standardization process for each group of data.

LIMS-EV

The data obtained from the LIMS-EV was already in the desired format for comparison with other variables. The data range was from a fiscal year and then broken down to monthly rates or percentages for each category requested.

AFTOC

The data obtained from AFTOC was formatted in a fiscal year, but was limited to a yearly breakout. In order to ensure a logical comparison between costs and AA, which is in a monthly format, each cost category for every year was broken down to 12 monthly data points simply by dividing the gross amount in each cost category by 12. This allows a correlation comparison by month between the costs categories and the monthly AA rates obtained from LIMS-EV. For example, the data obtained from the CAIG new report for Fairchild AFB during FY2012 was \$149,876,321. In order to compare this amount to the Fairchild FY2012 monthly AA rates, this amount was divided by 12 to

establish a monthly costs of \$12,489,693. This process was done for each cost category in each of the fiscal years examined.

MilPDS, MPES, and PAS

The personnel report obtained for Fairchild AFB during 2001 – 2012 was in a monthly format, but needed to be manipulated in order to get a percentage for each month. The personnel report had two different overall data points; monthly assigned vs. authorized for the entire MXG, and a monthly skill level assigned vs. authorized for each AFSC during the examined time period. Both of these overall data points were manipulated in order to obtain monthly percentages. For example, the overall assigned for October, 2012 within the Fairchild AFB MXG was 839. The overall authorized for the same time period was 914. In order to get a percentage of assigned personnel for October 2012 within the Fairchild AFB MXG, the assigned personnel of 839 was divided by the authorized personnel of 914 for an assigned personnel percentage of 91.7% during October, 2012. This process was conducted for each month of the examined time period. This same process was conducted for the monthly skill-level percentage of assigned vs. authorized for each AFSC at Fairchild AFB during 2002 – 2012.

Now that all the data obtained is in a standard format of a monthly rate, percentage or dollar amount for each fiscal year examined, each variable must be correlated with AA to determine the criticality of the variable and its inclusion to the multiple linear regression model.

Correlation of the Data

In order to determine the criticality of these variables, determination of a relationship between the dependent variable (AA) and the independent variables (data

collected) must be established. Correlation is used to measure the linear relationship between two variables; x (dependent variable) and y (independent variable). A numerical descriptive measure of the linear association between x and y is provided by the coefficient of correlation, r (McClave, Benson, Sinich, 2009). The coefficient of correlation, r , is a measure of strength of the linear relationship and is computed on a scale of -1 and +1. A value of r near 0 indicates little or no linear relationship between x and y . In contrast, a value close to -1 or +1 indicates a strong relationship between x and y (McClave, Benson, Sinich, 2009). Due to vast amount of data, JMP® version 10 software was utilized to determine the coefficient of correlation between the dependent variable x and each of the independent variables y . For the purpose of this research, a coefficient of .5 or more and -.5 or less is considered a critical variable and is added as an independent variable for the multiple regression model.

As stated in the textbook, *Statistics for Business and Economics*, “multicollinearity can exist between two or more of the independent variables used in a regression model” (McClave et al., 2009:713). Multicollinearity happens when two or more of the independent variables are contributing information to the prediction of the dependent variable, but some of the information is overlapping because of the multicollinearity of the independent variables. Some multicollinearity can be expected with numerous variables, but severe multicollinearity can cause misleading regression results (McClave et al., 2009). In order to identify and discard any variables with severe multicollinearity, the JMP® software is utilized to determine variance inflation factors (VIF) scores on the independent variables. As a rule of thumb, VIF scores less than 5 to 10 are generally acceptable. For the purpose of this research, a VIF score of 5 or less is

considered acceptable. If a VIF score of more than 5 occurs in 2 or more independent variables, each independent variable with the high VIF score is removed individually and the regression equation with the highest R^2 is kept. Finally, once correlation is completed and the critical independent variables are identified, building the multiple linear regression model is the next step.

Model Building Methodology

The crux of this research is more than one independent variable has an impact on AA, and with multiple independent variables present, the complexity of an explanatory or predictive model is amplified. Probabilistic models that include more than one independent variable are called multiple regression models (McClave et al., 2009). The general form (Equation 5) of the these models is

$$Y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_kx_k + \varepsilon \quad (5)$$

Where:

Y = dependent variable
x₁, x₂, ... x_k = independent variables
β₀ = the intercept
β₁, β₂, ... β_k = the population coefficients
ε = the random error component

Note: “The symbols $x_1, x_2, \dots x_k$ may represent higher-order terms for quantitative predictors or terms that represent qualitative predictors” (McClave, et al., 2009:626).

Once a multiple regression model is built, analyzing the model is a six-step process according to McClave et al. (2009), the steps are as follows:

Step 1: Hypothesize the deterministic component of the model. This component relates the mean, $E(y)$, to the independent variables $x_1, x_2, \dots x_k$. This involves the choice of the independent variables to be included in the model.

Step2: Use the sample data to estimate the unknown model parameters $\beta_0, \beta_1, \beta_2, \dots \beta_k$ in the model.

Step 3: Specify the probability distribution of the random error term, ϵ , and estimate the standard deviation of this distribution, σ .

Step 4: Check that the assumptions on ϵ are satisfied, and make model modifications if necessary.

Step 5: Statistically evaluate the usefulness of the model.

Step 6: When satisfied that the model is useful, use it for prediction, estimation, and other purposes.

The model built for this research only includes *quantitative* independent variables and according to authors McClave et al. (2009), is called a first order model. The method of fitting first-order models and multiple regression models is identical to that of fitting a simple straight line model; the method of least squares. The main difference though is the estimates of the coefficients $\beta_0, \beta_1, \dots, \beta_k$ are obtained using matrices and matrix algebra (McClave et al., 2009). Vice using matrix algebra to establish the least ordered squares, the output of the JMP® software is utilized to determine our mean square for error (MSE). The goal of this research is to build a model that can provide predictions on AA with the smallest value of MSE as possible. The MSE helps identify the utility of the model.

The model building process begins with only the independent variables deemed critical in our correlation analysis. Part of the model building process uses stepwise regression. Due to the sheer amount of independent variables, this process is utilized by the JMP® software. Stepwise regression results in a model containing only those terms with *t*-values that are significant at the specified α level. Thus, only several of the initial independent variables remain (McClave, et al., 2009). Since there is probability of errors being made, such as including unimportant variables in the model (Type I errors) and

omitting some important variables (Type II errors), it's recognized this is only an objective variable screening process and is treated as such (McClave, et al., 2009).

Step 4 of analyzing a multiple regression model is to check that the assumptions on “ ε ” are satisfied and make model modifications as needed. The assumptions for random error “ ε ” have a probability distribution with the following properties (McClave, et al., 2009:626):

1. Mean equal to 0
2. Variance equal to σ^2
3. Normal distribution
4. Random errors are independent (in a probabilistic sense).

Residual analysis steps from McClave et al. (2009) are used to check for assumptions and to improve the model. This process starts by plotting the residuals against each of the independent variables about a mean line of zero. The goal is to look for a curvilinear trend. This shape indicates a need for a second order term. Next, examination of outliers is required. If an observation is determined to be an error, outside 3-standard deviations, then it needs to be fixed or removed. Following the examination of outliers, a frequency distribution is plotted using a histogram checking for obvious departures from normality. Lastly, plotting the residuals against the predicted values of y observing for patterns that may indicate the variance is not constant (McClave et al. 2009).

McClave et al. (2009), elaborate in order to test the utility of a multiple regression model, a global test, one that encompasses all the β parameters is needed. One such test is the multiple coefficient of determination of R^2 , which is explained variability divided by total variability. Thus, $R^2 = 0$ implies a complete lack of fit of the model to the data, and $R^2 = 1$ implies a perfect fit with the model passing through every data point. In

general, the larger the value of R^2 , the better the model fits the data (McClave et al., 2009). In order to reach a desired usefulness of the AA model built, a R^2 value of .80 or higher is a goal of this research. Despite the R^2 utility, it is only sample statistics. An additional method is to conduct a test of hypothesis involving all the β parameters (except β_0). This method is an F -statistic, which is as follows:

$$H_0: \beta_1 = \beta_2 = \dots = \beta_k = 0 \text{ (terms with } 0 \text{ are unimportant to predicting } y\text{)}$$

$$H_a: \text{At least one model term is useful for predicting } y$$

The MSE, R^2 and F -statistic will be used to determine the merit of the model and aid in the model building. The final explanatory model will include only those variables deemed to have an important relationship to AA, and have a low MSE, a R^2 of .80 or above and a rejection of the null hypothesis.

Lastly, a test of the model takes place to evaluate its ability for prediction. As with Oliver (2001) and Fry (2010), 20 percent of the initial data is set aside and not used to build the regression model, but rather used to test the final regression model. The confidence intervals for AA from the final explanatory model (without the 20 percent of data) are benchmarked to measure the test data. Using this procedure for model validation allows the evaluation of the model's usefulness when new data from outside the original sample is used for prediction.

From this point, a tool is created from the final multiple regression model formula to help maintenance leaders predict AA from the critical variables identified. This tool will help maintenance leaders ascertain what rates or percentages of the critical variables the unit must attain in order to achieve an AA goal.

Chapter Summary

In this chapter, explanation of the scope of data collection and research was discussed. In addition to the scope of data collection and research overview, understanding the applications/systems utilized to collect the data followed. From there, describing the method used to standardize the data for comparison was provided. After the standardization method, expounding on the methodology of correlation analysis to determine criticality was highlighted. Lastly, a thorough explanation of the multiple regression model and the process utilized to build an AA explanatory model was examined. Analysis and results of the data is discussed in the next chapter.

IV. Analysis and Results

Chapter Overview

Utilizing the methodology discussed in Chapter III, analysis and results of the KC-135R data from Fairchild AFB during FY 2002 – 2012 is discussed in this chapter. First, results from the correlation analysis are explained. After correlation analysis, regression models are created utilizing the critical variables identified and the results of developing the final regression model is discussed. The last aspects of this chapter are the results of validating the final regression model utilizing the test data from FY2010 – 2012, and creating a tool for maintenance leadership to utilize in predicting aircraft availability through the critical variables identified from the final regression model.

Correlation Analysis Results

Overall 35 different KC-135R variables were utilized for correlation analysis from the data collected during the period of FY2002 – 2012 at Fairchild AFB. Table 9 illustrates all the variables used for correlation analysis. Unfortunately, some of the previously determined critical variables in LIMS-EV such as the repeat/recur rate and 12-hour fix rate did not have any data during the time period specified and were not included in this analysis. These variables were selected due to their availability and applicability from the sources utilized.

Table 9. Variables Used for Correlation Analysis

Available (N)	Available (%)	Depot (%)	UPNR (N)	UPNR (%)
TAI (N)	MC (%)	NMCB (%)	NMCM (%)	NMCS (%)
MMH / FH (Unit) (N)	Hours Flown (H)	Sorties Flown (N)	Sorties Scheduled (N)	ASD (H)
Flying hours / TAI by Month (H)	USE / FH (H)	Sorties / TAI by Month (N)	USE / Sortie (N)	FSE (%)
Costs	Assigned/Authorized	Crew Chief	Cann Rate Hours (%)	Cann Rate Sorties (%)
Cann Hours (H)	Canns (N)	MTBF-1 (Inherent) (H)	MTBF-2 (Induced) (H)	MTBM-6 (No Defect) (H)
MTBM Total (H)	Failures - 1 (Inherent) (N)	Failures - 2 (Induced) (N)	Total Actions (N)	TMMHs (H)

As stated in the methodology section, the variables greater than .5 or less than -.5 would be considered critical variables and added to the regression model. The critical variables identified from this analysis are as follows: Depot %, MC Rate, NMCM Rate, Assigned/Authorized %, and Crew Chief %. Additionally, to ensure none of the variables that could be used as explanatory variables in the regression model were possibly left out, a bivariate analysis was conducted on each of the variables. Figure 8 illustrates an example. Bivariate analysis results are found in Appendix A.

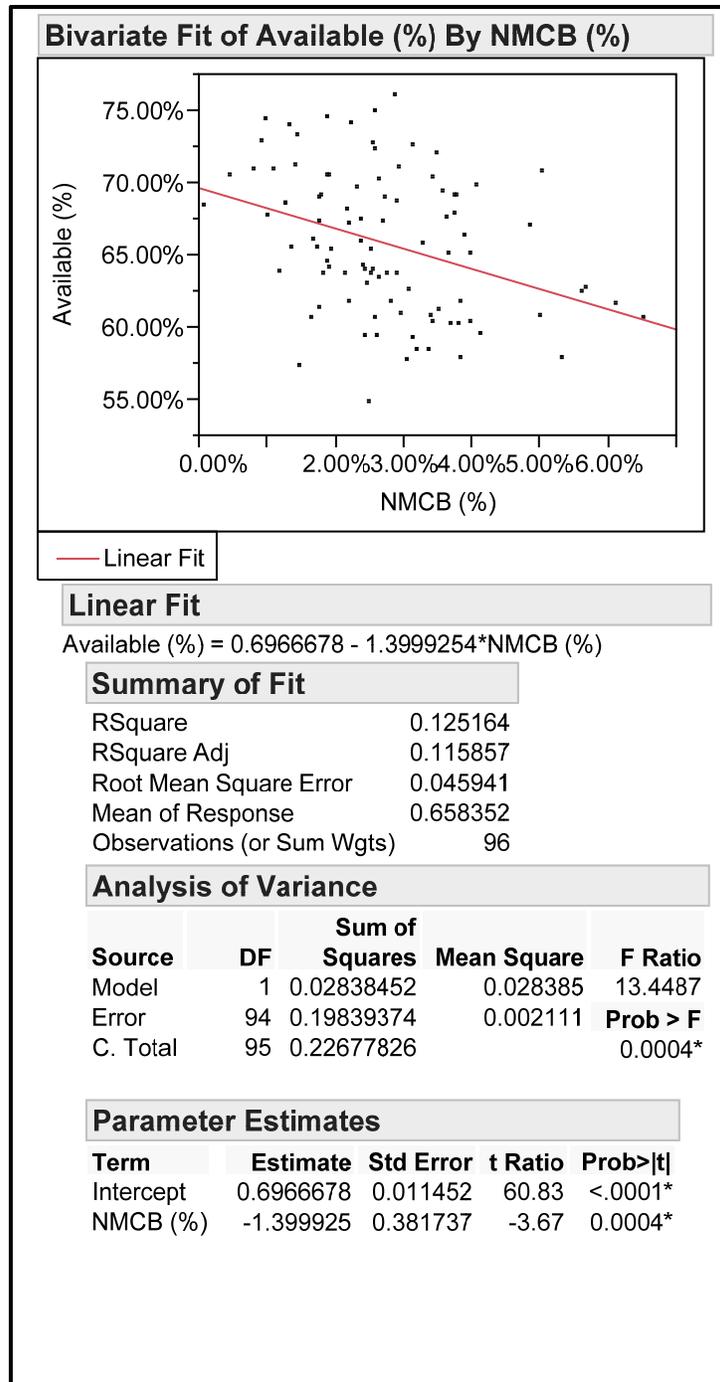


Figure 8. Bivariate Analysis of NMCB

Due to the relatively strong R^2 value and the low Prob > F value indicating a possible explanatory variable, five more variables were added as independent variables for the regression model. The following variables were those selected from the bivariate

analysis: NMCB Rate, Total Actions, Sorties Flown, Sorties Scheduled, and MTBM-6 (no defects).

Regression Models

The initial regression model evaluated contained one dependent variable, Availability %, and ten independent variables as mentioned in the previous section. As stated in the methodology section, a model with a low MSE, a R^2 greater than .80, rejects the null hypothesis, and has a VIF score of less than 5 is the ideal model to utilize for this research. Equation 6 depicts the initial regression model created.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} \quad (6)$$

Predicted Y: Aircraft Availability

Independent Variables (Effects): $X_1 = Depot \%$
 $X_2 = MC Rate$
 $X_3 = NMCB Rate$
 $X_4 = NMCM Rate$
 $X_5 = Sorties Flown$
 $X_6 = Sorties Scheduled$
 $X_7 = Assign/Authorized Rate$
 $X_8 = Crew Chiefs Assigned/Authorized Rate$
 $X_9 = MTBM-6 (No Defects)$
 $X_{10} = Total Number of Actions$

The initial regression model was run utilizing JMP® software incorporating 96 months of data for each of the variables. The data utilized was for Fairchild AFB from FY2002 – 2010. The result was a R^2 of .978512 and an MSE of .007527, but there was strong indication of multicollinearity due to high VIF scores. Additionally some of the P-values of the individual variables were higher than .05 indicating insignificance towards a relationship with the dependent variable of AA. Figure 9 shows the results of the initial regression model.

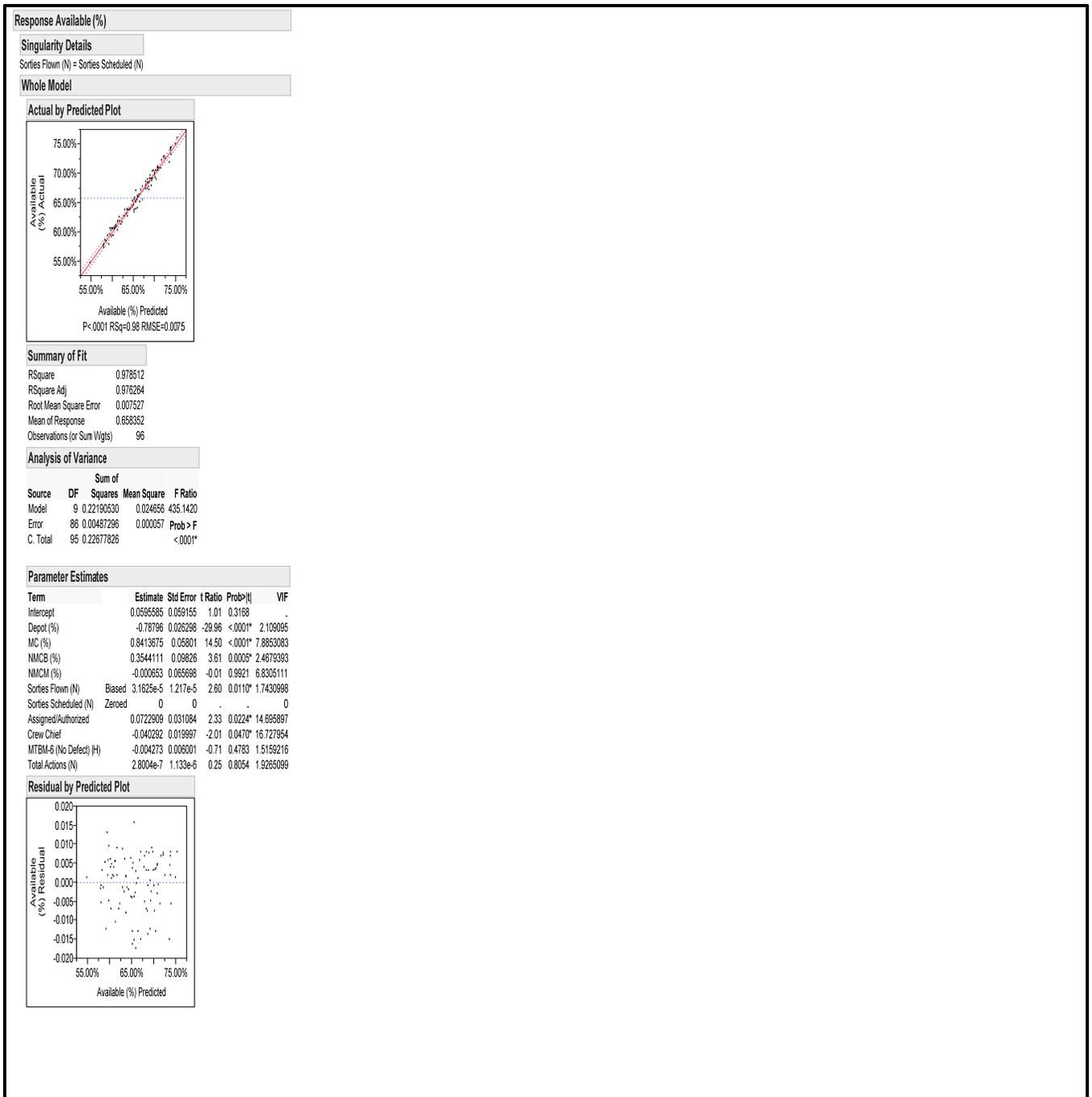


Figure 9. Initial Regression Model Analysis

The following variables were removed from the initial regression model due to high P-values: Total Actions (.8054), MTBM-6 (.4783), and NMCM (.9921).

Additionally, the following variables had VIF scores higher than 5 and were removed

individually, while the model was run again after each removal until the VIF scores were below 5 and the model with the best R^2 was kept for further evaluation: MC Rate (7.89), Sorties Scheduled (zeroed), Assigned/Authorized (14.70), and Crew Chiefs (16.73) were the variables removed due to high VIF scores. The model was run multiple times to determine the best fit, and eventually the final regression model utilized for evaluation contained four independent variables. During the course of multiple runs, one of the initial variables removed, NMCM, was reinstated due to the strong fit with the final regression model. Equation 7 illustrates the final regression model.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \quad (7)$$

Predicted Y: Aircraft Availability

Independent Variables (Effects): $X_1 = \text{Depot \%}$
 $X_2 = \text{MC Rate}$
 $X_3 = \text{NMCM Rate}$
 $X_4 = \text{Sorties Flown}$

The final model had a R^2 of .97412 and a MSE of .008031. All the VIF scores were below 5 and the P-values were also all below .05. Additionally, the effects test revealed an F-statistic for each variable above zero, ultimately rejecting the null hypothesis.

Figure 10 reveals the analysis of the final regression model.

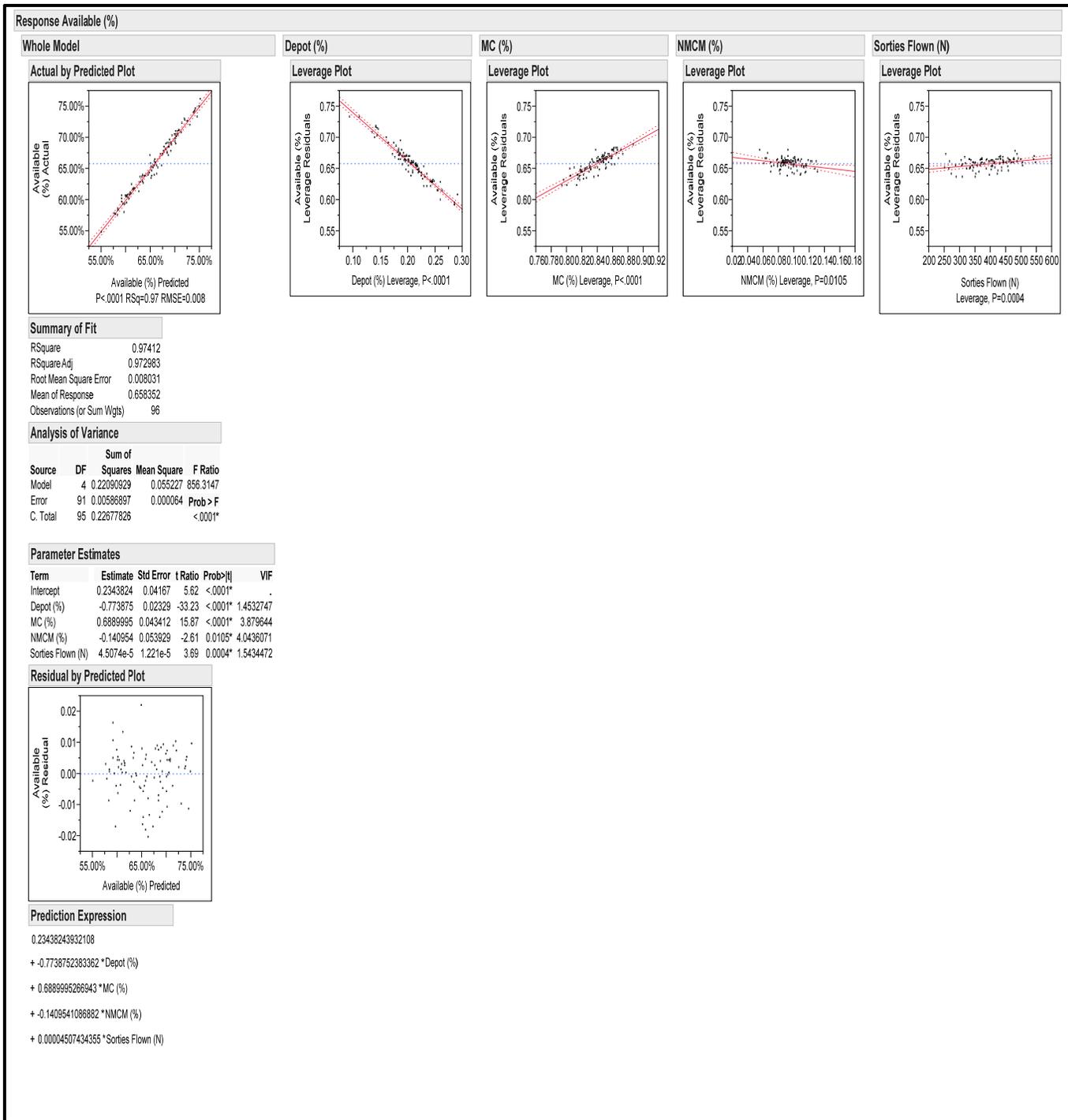


Figure 10. Final Regression Model Analysis

The final regression model's R^2 of .97412 is unusually high. An R^2 of 1 indicates that a regression line perfectly fits the data, and in the case of this final regression model

only .03 of the dependent variable's variation can't be explained by the independent variables. The contributing factors to such a high R^2 are the independent variables that showed a strong correlation with the dependent variable, AA, and were utilized in the final regression model. The two biggest contributors to the high R^2 are Depot % and MC Rate. The Depot % of a unit plays a critical role into how many aircraft will be available for operations, and the MC Rate is part of the AA formula. Some of the data utilized to determine the MC Rate is also utilized to determine the AA rate. Due to their close relationship with AA, these two independent variables caused the R^2 to be unusually high. It was determined to keep these two independent variables in the final regression model, not due to the high R^2 , but rather to quantify how much these independent variables influence the AA rate and provide useful information when analyzing these key metrics.

The final regression model was then evaluated for the random error term ϵ , step 4 of the regression model analysis stated in the methodology section. A thorough examination revealed a standard deviation of .0080 and all data points were within three-standard deviations from the mean, as seen in the figure above. Additionally, there was no evidence of curve-linear trends and all data portrayed normal distribution. Since the final regression model passed the first four steps of the regression model analysis, the model was tested for usefulness by predicting the test data.

Validation of the Final Regression Model

To test the usefulness and to validate the model, 24 months of data (20 percent) was set aside to utilize as test data for the final regression model. This test data was for Fairchild AFB from FY2010 – 2012. The test data was added to the existing data that

was used to build the regression models. Once the test data was added, the final regression model was run in JMP® and the Predicted Availability rates along with Individual Confidence Intervals was selected as an option from the program. This process generated individual prediction intervals along with a prediction Availability rate for the dependent variable at each of the 24-month periods. Theoretically, the final regression model should have been able to predict AA rates within the prediction intervals (at 95% confidence) 95% of the time. If the actual Availability rate for the selected month is within the predicted confidence interval, then the model has predicted the Availability rate correctly. The test results from this analysis are displayed in Table 11.

Table 11. Final Regression Model Sensitivity Analysis

Date	Lower 95% Confidence Interval (%)	Actual Available (%)	Predicted Available (%)	Upper 95% Confidence Interval (%)	Absolute Percentage Error
Oct-10	59.61%	61.30%	61.25%	62.89%	0.05
Dec-10	59.14%	61.40%	60.79%	62.43%	0.61
Jan-11	58.10%	59.70%	59.75%	61.41%	0.05
Feb-11	55.18%	58.00%	56.83%	58.47%	1.17
Mar-11	59.30%	61.00%	60.94%	62.58%	0.06
Apr-11	60.30%	62.90%	61.97%	63.64%	0.93
May-11	65.71%	66.60%	67.37%	69.03%	0.77
Jun-11	65.83%	67.00%	67.50%	69.17%	0.50
Jul-11	65.07%	65.00%	66.76%	68.46%	1.76
Aug-11	74.78%	76.80%	76.44%	78.11%	0.34
Sep-11	73.81%	75.30%	75.47%	77.13%	0.17
Oct-11	73.27%	75.20%	74.92%	76.56%	0.28
Nov-11	74.69%	76.90%	76.33%	77.97%	0.57
Dec-11	74.66%	77.10%	76.32%	77.98%	0.78
Jan-12	70.08%	72.30%	71.75%	73.43%	0.55
Feb-12	72.36%	74.40%	74.07%	75.77%	0.33
Mar-12	74.67%	76.30%	76.33%	77.99%	0.03
Apr-12	74.81%	77.80%	76.46%	78.12%	1.34
May-12	69.60%	72.30%	71.24%	72.88%	1.06
Jun-12	70.57%	73.10%	72.20%	73.83%	0.90
Jul-12	69.10%	71.90%	70.73%	72.36%	1.17
Aug-12	66.72%	68.20%	68.35%	69.99%	0.15
Sep-12	67.66%	68.90%	69.31%	70.97%	0.41
					MAPE = 0.5825

Empirical results show the final regression model was able to predict the Availability rate 24 out of the 24 months or 100% of the time, which is well within the confidence interval level. The final model also had a fairly low Mean Absolute Percentage Error (MAPE) of only .5825; this is the average difference of the actual

Availability rate and the predicted Availability rate for the 24-month period. Additionally, the prediction confidence intervals had an average range of only 3.17%, which is a relatively small window to predict within when considering the prediction of a strategic metric such as AA that has so many different variables.

From this final regression model, a tool was created to help predict aircraft availability utilizing the regression model formula. This formula contains the four critical variables identified in the regression model along with the beta values for each independent variable in order to predict AA within a 95% confidence interval as shown from the test data. Equation 8 highlights this formula.

$$Y = .2344 + -.7739X_1 + .6890X_2 + -.1410X_3 + .00004X_4 \quad (8)$$

Predicted Y: Aircraft Availability

Independent Variables (Effects): $X_1 = \text{Depot \%}$
 $X_2 = \text{MC Rate}$
 $X_3 = \text{NMCM Rate}$
 $X_4 = \text{Sorties Flown}$

From this formula, the AA predictive tool was created from Excel. To build this predictive AA tool, a modified version of linear programming was utilized. First the AA rate, also known as the objective function, was subject to the independent variables and their beta values, which are constant. The constraints of this formula are the rates or numbers of the independent variables, which are then, multiplied in a linear fashion with the beta values of the independent variables. The end product is the AA rate determined by the rates or numbers of the independent variables. Upper and lower bounds were inserted into the formula, but play no bearing since the formula is not optimized utilizing Solver in Excel. The reason Solver isn't utilized is due to the software tries to optimize

only one or two of the independent variables and leaves the other variables at zero, which isn't realistic or possible.

In this tool, one constraint (rate/number) can be changed at a time, or a combination of the constraints can be changed to include all four constraints at once. Due to the strong relationship of Depot % and MC Rate to AA, a change of 1.5% in each of these rates will change the AA rate by 1%. A change of 7% in the NMCM rate results in a 1% change in the AA rate, and a change of 250 in Sorties Flown results in a 1% change in the AA rate. A change in all four independent variable's rates/numbers has the biggest impact on the AA rate. A change in the Depot % and the MC Rate has the biggest return on investment. In the end, this tool predicts what the AA rate will be from what the independent variables rates/numbers are. Ultimately, maintenance leaders can insert applicable rates/numbers for the independent variables to determine what rate or sorties flown the unit would need to attain in order to achieve a certain AA goal or standard. Figure 11 illustrates the AA predictive tool.

<i>Aircraft Availability Predictive Tool</i>	
Depot %	0.13
MC Rate	0.9
NMCM Rate	0.05
Sorties Flown	500
AA Rate	0.77

Rules of Thumb for determining AA rate from the independent variables
** A change of 1.5% in Depot % equals a 1% change in AA Rate*
** A change of 1.5% in MC Rate equals a 1% change in AA Rate*
** A change of 7% in NMCM Rate equals a 1% change in AA Rate*
** A change of 250 in Sorties Flown equals a 1% change in AA Rate*
*** Changing all four variables at once has the biggest impact to AA rate*
*** Changing Depot % and MC Rate has the biggest return on investment*

Figure 11. AA Predictive Tool

Theoretically, this AA predictive tool has the potential for maintenance leaders to utilize as a mechanism for predicting AA, but there are many factors that must be examined and explained about this research, which takes place in Chapter V.

Chapter Summary

Analysis and the results of the data collected were discussed in this chapter. First, an in-depth look into correlation analysis was reviewed. This process was utilized to identify the critical variables with a potential relationship with AA. Next, an overview of the initial regression model built and the process used to simplify and strengthen the model into the final regression model was illustrated. Finally, validation and usefulness of the final regression model was examined utilizing the test data set aside from FY2010 – 2012, and a predictive tool was created utilizing the final multiple regression formula. Chapter V answers the research questions, address limitations and implications of the final regression model, and highlights suggestions for further actions and research on this topic.

V. Conclusions and Recommendations

Chapter Overview

In this final chapter, the first area discussed is answering the investigative questions that were raised in Chapter I. Next, an introspective review of the limitations and significance of this research and the final regression model and predictive tool is discussed. Finally, suggestions on future actions and research of this topic are highlighted.

Investigative Questions

1. What is the current AMC AA standard for the KC-135R?

The AMC AA standard for the KC-135R is currently 83.7%. This information was attained from AMC/A4 along with other vital information concerning fleet availability. Currently, the attainable KC-135R AA rate is 72.1%, which equates to 299 aircraft from a total inventory of 414. To attain the AMC AA standard, 347 aircraft must be mission capable and available for operations. Due to this shortage, AMC/A4 has launched many initiatives within their AA improvement program to aid in reaching the AA standard. The goal of this research was to provide some more insight into what variables affect AA and provide a tool to help decision makers focus their efforts when determining what actions are needed to improve the AA rate.

2. What is the KC-135R AA standard based off of and is it mission linked?

The answer to this investigative question was found during literature review of Major Waller's research of AA and operational requirements. The KC-135R AA standard, along with all other aircraft, is based off of operational requirements set forth

by AFI 21-103, *Equipment Inventory, Status, and Utilization Reporting*. As discussed in Chapter II, the operational requirement is derived from many factors that are included in the operational requirement equation that ultimately defines how many aircraft are required from the total inventory to meet operations. Due to the relatively new existence of the AA standard within AFI 21-103, many personnel are not aware of this process and understand how the AA standard is linked with operational requirements. This equation within AFI 21-103 legitimizes the AA standard and provides the basis for trade-offs between operational requirements and maintenance capability.

3. What quantifiable correlated variables affect the KC-135R AA rate?

Out of the 130 months of base-level data pulled from the five different sources, 35 different variables were established to determine what variables affect the KC-135R rate. Utilizing the methodology discussed in Chapter III, 10 independent variables were identified as variables that affect the AA rate. During the strengthening and simplification process for the multiple regression analysis, four independent variables were identified as the most critical variables that affect the KC-135R AA rate. As previously mentioned in Chapter IV, those variables are Depot %, MC Rate, NMCM Rate and Sorties Flown. Many of these variables are already known as critical variables, but this research quantifies how strong of a relationship they have with AA.

Although the analysis shows a strong relationship between the independent and dependent variables, the limitations of this research must be restated that the research was scoped down to only one base, Fairchild AFB, and bounded to the data available from the sources chosen and the time frame selected. There were many metrics that could have

possibly demonstrated a relationship with AA that were not available due to limited or zero information available for the base or time frame selected.

4. Are the KC-135R AA rates influenced by changes in the O&M budget?

As it has been stated many times before, “money is the bottom line, and it makes the world go around.” Unfortunately from this research, the budget/costs associated with Fairchild AFB during the timeframe of FY2002 – 2012 did not show a correlation with the KC-135R AA rate. This was largely due to the fact the budget/costs data was only available in yearly increments. The data was manipulated in order to correlate the data with AA and this limitation created equal parts of the budget/costs across all 12 data points within a year. This unrealistically kept the budget/costs constant as changes occurred to the AA rate. This was the method chosen in order to utilize the budget/costs data and not diminish the remaining 34 variables utilized for this research. This was a huge limitation to this research and is discussed further in this chapter. The O&M budget plays a vital role in the amount of aircraft available, but the key is to figure how much of an influence and what are the trade-offs. Unfortunately this research was not able to reveal that key and unlock the answer.

5. What model best predicts KC-135R AA and what is the result?

The final regression model demonstrated the strongest relationship with the remaining four independent variables to AA. This model clearly showed the ability to predict AA rates with a small mean absolute percentage error between the actual rate and the predicted rate in addition to predicting the AA rate 100% of the time within a relatively small window of ± 3.17 . As stated previously, this model has its limitations due to the fact the data was only pulled from one base and was not all inclusive. The

result is a model and a predictive tool that has the potential to aid maintenance decision makers on what areas to best concentrate on in order to improve aircraft availability in order to meet operational requirements.

Limitations and Significance of the Research

As just previously mentioned, this research was scoped down to the tactical level of assessing AA, and is only an accurate portrayal of Fairchild AFB. The final regression model can't be utilized across all platforms or even across other KC-135R bases expecting accurate results. Additionally, this research was limited to the data available/extracted and surely there are other credible variables that could influence AA. Lastly, the O&M budget was manipulated in a way that didn't allow for accurate correlation analysis with AA. With that being stated, this research does offer the methodology for any base to duplicate and create a final multiple regression model and predictive AA tool utilizing the data from that base. This methodology reveals tactics, techniques and procedures utilized at the base level and enables that data to play a critical part of identifying the exact variables that affect AA at that specific base vice possibly being overshadowed at the MAJCOM or fleet level.

As aforementioned, the critical variables of Depot %, MC Rate, NMCM Rate and Sorties Flown identified in the final regression model are already known as key variables of AA, but this research demonstrates they're the most critical variables and quantifies by how much. Lastly, this research offers Fairchild AFB leadership a predictive AA tool that can be utilized as decision support system to ascertain where resources should be focused to increase aircraft availability in order to meet operational requirements.

Recommendations for Action and Future Research

The primary recommendation for action is for AMC to collaborate with AFMC and HAF/FM to establish a methodology to accurately determine O&M budget and costs at the base level on a monthly basis. This would enable a realistic and precise correlation analysis with AA and provide the needed insight of how much the O&M budget influences AA.

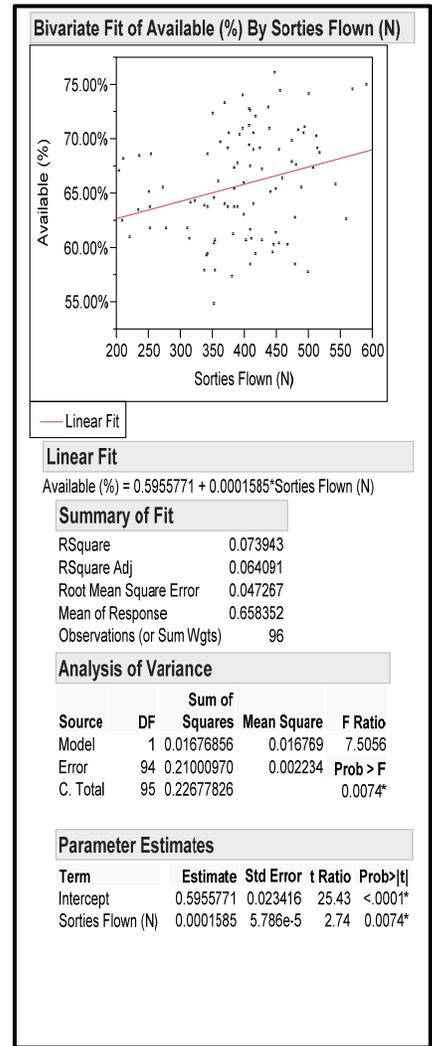
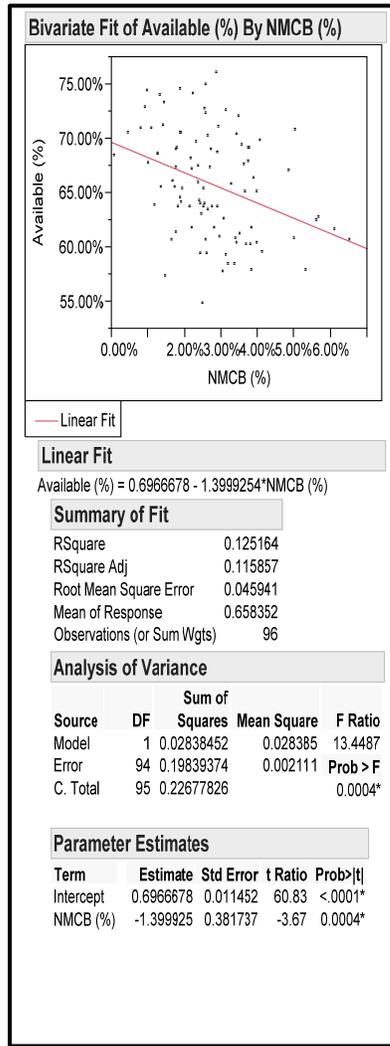
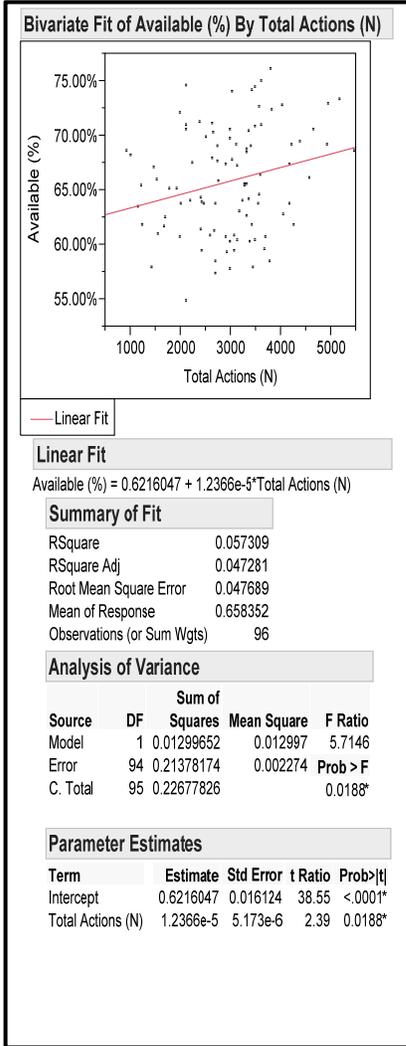
Additionally, implement and evaluate the usability of this final regression model and predictive AA tool at Fairchild AFB. If the test drive proves valuable and meets the user's needs then use this research as the methodology to create a multiple regression model and predictive AA tool at other KC-135R bases.

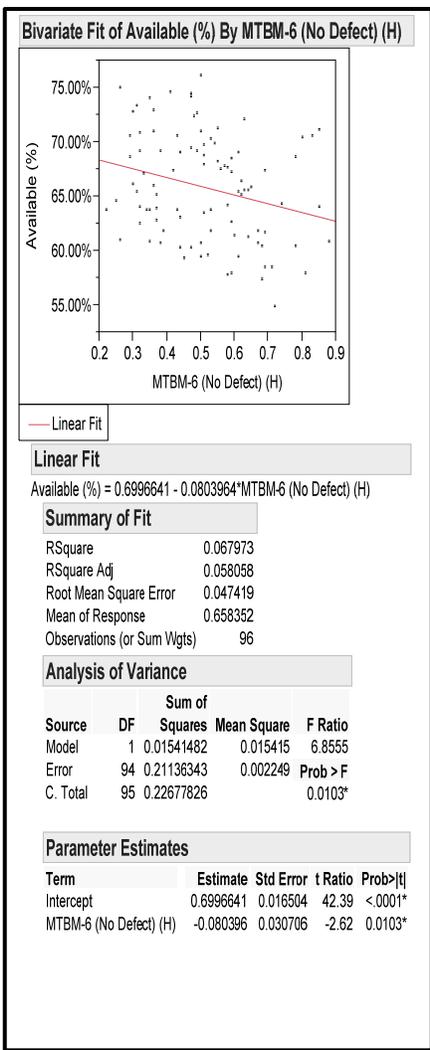
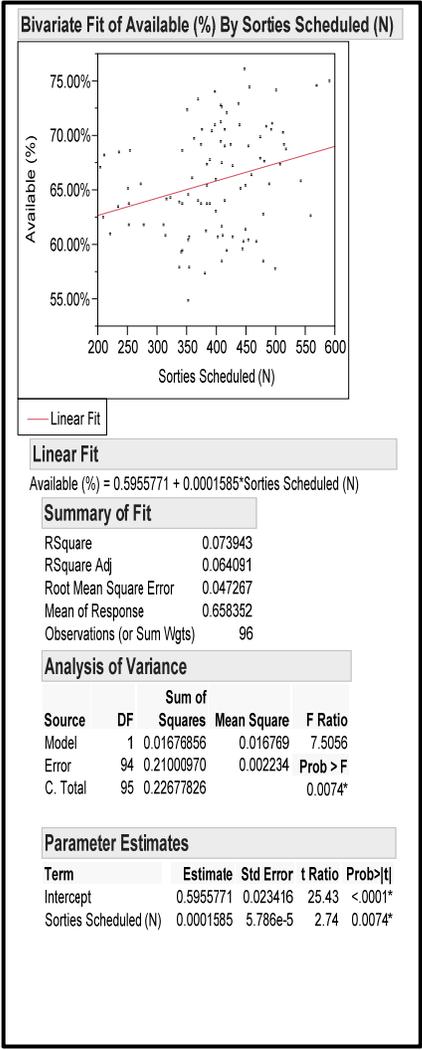
Lastly, expound this research to strategic airlift bases within AMC. Use this methodology to create multiple regression models and predictive AA tools at the base level of those assets. This could provide another credible source of information for decision makers to effectively and efficiently utilize their resources to accomplish the mission.

Summary

In today's environment of less manning, older aircraft, and a shrinking budget, maintenance leaders must utilize all available tactics, techniques and procedures to improve the amount of aircraft available for operations. This research solidifies and quantifies how important the basic variables of Depot%, MC Rate, NMCM Rate and Sorties Flown play a pivotal role in the strategic metric of AA, and arms maintenance leaders with another tool to improve the operations of their units.

Appendix A: Results of Bivariate Analysis





Appendix B: Quad Chart



Predicting Aircraft Availability



Maj Mark Chapa
Advisor: Lt Col Dan Mattioda
Sponsor: Col Mary Ann Hixon
 Advanced Study of Air Mobility (ASAM)
 Air Force Institute of Technology

Introduction

In today's environment of less manning, older aircraft, and a shrinking budget, it is imperative maintenance leaders utilize all available tactics, techniques and procedures to improve the amount of aircraft available for operations. One of the longstanding measuring sticks to gauge a unit's effectiveness was and still is the Mission Capable (MC) rate. But, there's been a major shift toward utilizing Aircraft Availability (AA) as the measuring stick to gauge how well the "fleet" is performing. Although the concept of AA has been around for quite some time, it has become the reference standard utilized by senior leadership. The ability to predict AA within a fleet has always been a goal of Aircraft Maintenance leaders and is now more important than ever with looming budget cuts across the spectrum of defense.

Motivation

An update to the AA model incorporating the most critical factors which affect AA is sorely needed in the Airlift and Tanker community.

Available (N)	Available (%)	Depot (%)	UPNR (N)
TAI (N)	MC (%)	NMCB (%)	NMCM (%)
MMH / FH (Unit) (N)	Hours Flown (H)	Sorties Flown (N)	Sorties Scheduled (N)
Flying hours / TAI by Month (H)	USE / FH (H)	Sorties / TAI by Month (N)	USE / Sortie (N)
Costs	Assigned/Authorized	Crew Chief	Cann Rate Hours (%)
Cann Hours (H)	Canns (N)	MTBF-1 (Inherent) (H)	MTBF-2 (Induced) (H)
MTBM Total (H)	Failures - 1 (Inherent) (N)	Failures - 2 (Induced) (N)	Total Actions (N)
			MTBM-6 (No Defect) (H)
			TMMHs (H)

$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$

Predicted Y: Aircraft Availability

Independent Variables (Effects):

- $X_1 = \text{Depot \%}$
- $X_2 = \text{MC Rate}$
- $X_3 = \text{NMCM Rate}$
- $X_4 = \text{Sorties Flown}$

Aircraft Availability Predictive Tool	
Depot %	0.13
MC Rate	0.9
NMCM Rate	0.05
Sorties Flown	500
AA Rate	0.77

Application

Offers leadership a predictive AA tool that can be utilized as a decision support system to ascertain where resources should be focused to increase aircraft availability in order to meet operational requirements.

Impacts/Contributions

The critical variables of Depot %, MC Rate, NMCM Rate and Sorties Flown identified in the final regression model are already known as key variables of AA, but this research demonstrates they're the most critical variables and quantifies by how much.

Collaboration

HAF/A1, AFMC/A4, AMC/A4

Rules of Thumb for determining AA rate from the independent variables

- * A change of 1.5% in Depot % equals a 1% change in AA Rate
- * A change of 1.5% in MC Rate equals a 1% change in AA Rate
- * A change of 7% in NMCM Rate equals a 1% change in AA Rate
- * A change of 250 in Sorties Flown equals a 1% change in AA Rate
- ** Changing all four variables at once has the biggest impact to AA rate
- ** Changing Depot % and MC Rate has the biggest return on investment



Bibliography

- Air Force Instruction 21-103 *Equipment Inventory, Status, and Utilization Reporting*, (January, 2012)
- Air Force Journal of Logistics *Aligning Maintenance Metrics; Improving C-5 TNMCM*, Volume XXXII, Number 1, (March, 2010)
- Air Force Logistics Management Agency *Maintenance Metrics US Air Force*, (March, 2009)
- Fry, Frederick G. "Optimizing Aircraft Availability: Where to Spend Your Next O&M Dollar," AFIT Thesis AFIT/GCA/ENV/10M-03, (March, 2010)
- LIMS-EV, http://www.acq.osd.mil/log/mpp/cbm+/Briefings/LIMS-EV_OSD_CBMPPlus_AG_Brief.pdf (March, 2013)
- McClave, John T. and others. *Statistics for Business and Economics*. Massachusetts: Pearson Education, 2009.
- Oliver, Steven A. "Forecasting Readiness: Using Regression to Predict Mission Capability of Air Force F-16 Aircraft," AFIT Thesis AFIT/GLM/ENS/01M-18, (March, 2001)
- O'Malley, T.J. "The Aircraft Availability Model: Conceptual Framework and Mathematics," Logistics Management Institute, (June, 1983)
- USAF "Statistical Digest FY11," Deputy Assistant Secretary; Cost and Economics, (2012)
- Waller, Brian "Aircraft Availability Standards Methodology," AFLMA/LM200928700 (July, 2010)

Vita

Major Mark A. Chapa graduated from Pasadena High School, Pasadena Texas in 1989. He enlisted in the Air Force as a Tactical Aircraft Maintenance Technician in August of 1990, and his first assignment was RAF Lakenheath, UK where he maintained the F-111F and the F-15E aircraft until 1996. After his tour in the UK, he was reassigned to Mountain Home AFB, Idaho as a Repair and Reclamation Journeyman where he maintained F-15C/E, KC-135R, B-1B, and F-16 aircraft. During his time at Mountain Home, Major Chapa completed his Bachelor of Science in Professional Aeronautics through Embry-Riddle Aeronautical University and was commissioned through Officer Training School at Maxwell AFB, Alabama in August of 2001.

After earning his commission, he was assigned to the 3rd Fighter Wing at Elmendorf AFB, Alaska where he was a Flight Commander and Assistant Officer in Charge of the 12th Aircraft Maintenance Unit where he directed maintenance operations in support of NORAD's commitment to the defense of the Alaskan Region. After his assignment to Alaska, he was selected as the Detachment 5 Commander, 373rd Training Squadron, Charleston AFB providing initial skills and advanced C-17 aircraft maintenance training across 5 MAJCOMs, the United Kingdom and Australia. Upon completion of his detachment commander tour, he was assigned to the 437th Airlift Wing where he led flight line production of 25 C-17 aircraft in support of worldwide missions to include Operations Iraqi and Enduring Freedom. In 2008, Major Chapa was selected for assignment to the 5th Bomb Wing as a Maintenance Operations Officer where he was instrumental in numerous Nuclear Operational Readiness and Surety Inspections

resulting in the wing earning the highest possible ratings. In May of 2012, he entered the Advance Study of Air Mobility program as an Intermediate Development Education student. Upon graduation, Major Chapa will be assigned as the 376th Expeditionary Aircraft Maintenance Squadron Commander, Manas AB, Kyrgyzstan.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 074-0188

The public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of the collection of information, including suggestions for reducing this burden to Department of Defense, Washington Headquarters Services, Directorate for Information Operations and Reports (0704-0188), 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to any penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.

PLEASE DO NOT RETURN YOUR FORM TO THE ABOVE ADDRESS.

1. REPORT DATE (DD-MM-YYYY) 14-06-2013			2. REPORT TYPE Master's Graduate Research Project			3. DATES COVERED (From - To) 21 May 2012 – 14 June 2013		
4. TITLE AND SUBTITLE Predicting Aircraft Availability					5a. CONTRACT NUMBER			
					5b. GRANT NUMBER			
					5c. PROGRAM ELEMENT NUMBER			
6. AUTHOR(S) Chapa, Mark A., Major, USAF					5d. PROJECT NUMBER N/A			
					5e. TASK NUMBER			
					5f. WORK UNIT NUMBER			
7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S) Air Force Institute of Technology Graduate School of Engineering and Management 2950 Hobson Way WPAFB OH 45433-8865					8. PERFORMING ORGANIZATION REPORT NUMBER AFIT-ENS-GRP-13-J-2			
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Colonel Mary Ann Hixon 402 Scott Drive, Unit 2A2 Scott AFB, Illinois 62225 (618) 229-2063; DSN 779-2063; mary.hixon@us.af.mil					10. SPONSOR/MONITOR'S ACRONYM(S) AMC/A4P			
					11. SPONSOR/MONITOR'S REPORT NUMBER(S)			
12. DISTRIBUTION/AVAILABILITY STATEMENT APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED								
13. SUPPLEMENTARY NOTES								
14. ABSTRACT In today's environment of less manning, older aircraft, and a shrinking budget, it is imperative maintenance leaders utilize all available tactics, techniques and procedures to improve the amount of aircraft available for operations. One of the longstanding measuring sticks to gauge a unit's effectiveness was and still is the Mission Capable (MC) rate. According to AFI 21-103, the MC rate is fully mission capable hours plus partial mission capable hours divided by possessed hours. This formula provides a rate which is a lagging indicator of how well a unit is performing. Although this metric is very valuable, it focuses more on the tactical-level of operations and does not include total aircraft inventory into the equation. There's been a major shift toward utilizing Aircraft Availability (AA) as the measuring stick to gauge how well the "fleet" is performing. The ability to predict AA within a fleet has always been a goal of Aircraft Maintenance leaders and is now more important than ever with looming budget cuts across the spectrum of defense. This graduate research paper focuses on developing an explanatory/predictive model for AA encompassing the variables with the greatest influence upon this dependent variable.								
15. SUBJECT TERMS Aircraft Availability, Multiple Regression, Correlating Variables, Forecasting Models, KC-135R								
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON			
a. REPORT	b. ABSTRACT	c. THIS PAGE			19b. TELEPHONE NUMBER (Include area code)			
U	U	U	UU	79	Lt Col Dan Mattioda, Ph.D. (AFIT/ENS) (937) 255-6565, x 4510 (daniel.mattioda@afit.edu)			