EXPLAINING WEAPON SYSTEM SUSTAINMENT'S IMPACT TO AIRCRAFT AVAILABILITY

THESIS

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Abstract

This research focused on understanding the phenomena behind the cost growth of Weapon System Sustainment (WSS) and the simultaneous degradation in USAF aircraft system availability. The primary modelling technique used was Ordinary Least Squares (OLS) while incorporating temporal effect. Other studies have looked at cost factors related to the Flying Hour Program, flying conditions and age. This study found empirical relationships between each of the four WSS business processes and the lead time in months it takes to realize improvements in system aircraft availability.

Acknowledgments

I dedicate this research to my wife and children. Your incredible patience, love and monumental support made this research and my time at AFIT possible.

I also want to thank my instructors and advisor, for their patience, encouragement and the intellectual foundation they provided me to take on this research.

Michael D. Ingram

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EXPLAINING WEAPON SYSTEM SUSTAINMENT'S IMPACT TO AIRCRAFT AVAILABILITY

I. Introduction

General Issue

Available and mission ready aircraft are the lifeblood to United States Air Force (USAF) operations. The USAF's ability to sustain aircraft in a usable state drives its ability to meet its mission: to fly, fight and win. The USAF capabilities required by combatant commanders are made up of both functionally ready aircraft and trained aircrews. The Air Force Division for Current Operations (HQ AF/A3O-AT, 2011) outlines aircrew training in the following way. Aircrew training is accomplished through peacetime flying where specific training objectives are met (HQ AF/A3O-AT, 2011). This training requirement drives a constant annual demand for peacetime flying hours by all aircrews (HQ AF/A3O-AT, 2011). This annual demand for peacetime flying is necessary to ensure aircrews are able to safely operate aircraft while sufficiently performing core tasks. (HQ AF/A3O-AT, 2011). The USAF must closely monitor the serviceable state of aircraft as peace time training levies significant stress on the very aircraft and equipment expected to be operationally ready to deploy and meet combatant commander requirements. In order to reconcile serviceability and readiness, the USAF establishes and monitors standards for a metric known as Aircraft Availability (AA) (HQ AF/A4LM, 2020). Furthermore, the USAF spends billions of dollars annually on Weapon System Sustainment (WSS) activities to sustain AA in the presence of the non-stop stress of daily flying operations (HQ AF/A4P; 2018). These WSS activities are intended to improve reliability, procure technical data and execute major maintenance activities

(AFMC/A4F, 2015). WSS activities are determined by system program managers with input from applicable Major Commands (MAJCOM) and fund's managers. (AFMC/A4F, 2015).

Recently, the USAF has struggled to fix a downward trend in operationally available aircraft across all aircraft fleets going back to at least 2012 (Losey ,2019). Data from the USAF's Logistics Information Management System – Enterprise View (LIMS-EV) supports this finding. Figure (1) shows the percent of AA to fly in January 2010 was roughly 65% this same rate was recorded at 58% in Oct 2019 (LIMS-EV, 2020).

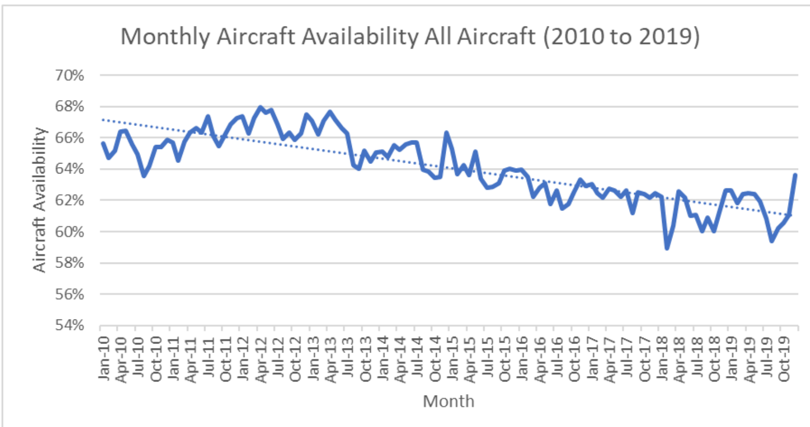

Figure 1: Monthly AA of All USAF Aircraft (2010 to 2019) (LIMS-EV, 2020)

Problem Statement

Balancing the resource needs to conduct flying operations and meet aircraft readiness requirements poses a significant challenge that is not new to the USAF. Historically, researchers and analysists have attributed the primary culprit of decay in AA and the rise in aircraft sustainment requirements to age (Hildebrandt & Sze, 1990; Stoll & Davis, 1993; Pyles, 1999; CBO, 2001; Greenfield & Persselin, 2002; Pyles, 2003; Dixon, 2005). Others have associated major changes in USAF organizational structure as both the cause and remedy to the underlying issues ailing AA (Creech, 1983; Oliver 2001). While other researchers have indicated environmental conditions as a driver in maintenance actions (Gill, 2019; GAO, 2003). Gill (2019) found temperature and atmospheric pressure as drivers in Non-Mission Capable Time (NMC). The United States Government Accountability Office (GAO) found the presence of electrolytes (i.e. salt) ultraviolet exposure, temperature, oxygen levels as significant drivers that increase maintenance cost across the Department of Defense (DoD) in the form of corrosion control (GAO, 2003). Other researchers have looked at the funding of aircraft spares, maintenance manning and Depot Possession Rates (Depot %) as potential factors in driving AA (Fry, 2010; Chapa, 2013). Another study on support equipment purchases failed to find significant relationships between AA and equipment levels (Leighton, 2017). Unfortunately, these studies offer USAF leaders little constructive insight on how to managerially control or reverse this negative AA trend. To exacerbate these concerns, Figure (2) shows an unsettling trend of projected cost growth in WSS from $16.6 Billion in Fiscal Year (FY) 2017 to $20.4, Billion in FY 2024 (Base Year 2019 dollars) (HQ AF/A4P; 2018).

FY20 Presidential Budget Request (PBR) (Base Year 2019)			
FY	**WSS Requirement in (Billions of $)**	**TAI**	**WSS Requirement Per Aircraft (in Millions $)**
FY17	$16.60	6,657	$2.49
FY18	$17.11	6,536	$2.62
FY19	$17.32	6,662	$2.60
FY20	$18.85	6,745	$2.80
FY21	$19.26	6,731	$2.86
FY22	$19.88	6,836	$2.91
FY23	$19.77	6,916	$2.86
FY24	$20.49	6,996	$2.93

Figure 2: FY20 WSS Presidential Budget Request (HAF/A4P, 2018)

This phenomena of increased spending on major aircraft sustainment activities and the decrease in AA is troubling. Previous research has insufficiently shown a relationship in at least two controllable USAF resource categories, aircraft parts and support equipment. Given the undesirable AA rates and rising sustainment costs, there has never been a more urgent time to understand the effects of USAF sustainment activities on AA. Focusing on WSS impacts to AA may provide valuable information to USAF decision makers on the value of WSS.

Research Question

The purpose of this research is to explore the impact of WSS activities on AA. Focusing on WSS's impact to AA may provide key USAF decision makers valuable insight on how to positively affect AA. Specifically, this research intends to answer the following questions:

1. How much variability in AA can be attributed to historical WSS funding?
2. What is the lead time in realizing AA benefits from each WSS business process?
3. What impact does each WSS activity have on AA?

Background

In order to fully understand the importance of AA to the USAF, it is important to understand how AA is consumed and measured. The USAF Headquarters Maintenance Division (HQ AF/A4LM) has a systematic process in identifying how much AA is needed to meet the needs of the USAF. This process begins with the establishment of the Operational Requirement (OR) for each aircraft fleet (HQ AF/A4LM, 2020). The OR is derived from the number of sorties required to adequately train aircrews, the number of aircrews, days available to fly and other factors related to aircraft alert requirements. Formulas 1 provides the formula used to calculate OR.

$$\boldsymbol{OR} = \left[\frac{\boldsymbol{S_o}}{\boldsymbol{F_{do}}}\right] + \left[\frac{(\boldsymbol{S_t})}{\boldsymbol{F_{dt}} \times \boldsymbol{T_u} \times (\boldsymbol{1} - \boldsymbol{a})}\right] + \boldsymbol{G} + \boldsymbol{S} + \boldsymbol{A} + \boldsymbol{R} \tag{1}$$

A: Number of Aircraft required for Alert Status
a: Attrition rate (expected rate of mission losses for a given year
F_{do}: Days available to fly during a given Fiscal Year
F_{dt}: Contingency and training flying days
G: number of required aircraft required for executing ground training
R: Number of Aircraft required to meet reserve/guard units flying requirements who fly active unit possessed aircraft
S: Number of required Spare Aircraft
S_o: Sorties needed to complete all aircrew contingency training
S_t: Number of sorties required to complete training mission requirements
T_u: Turn Rate (total sorties / flying period)
(HQ AF/A4LM, 2020)

The USAF then finds the ratio of the OR and the total number of aircraft the USAF is actively flying in that fleet. This total is called the Total Active Inventory (TAI). This ratio is the Aircraft Availability Standard (AA_{std}). Formula (2) provides the exact formula for calculating AA_{std}.

$$\boldsymbol{AA_{std}} = \frac{\boldsymbol{OR}}{\boldsymbol{TAI}} \tag{2}$$

(HQ AF/A4LM, 2020)

Availability, is defined as the probability of a system being in a usable state at some point in the future (Ebeling, 2009). The USAF simply measures historical availability to monitor fleet health (LIMS-EV, 2020). AA_h allows the USAF to gauge if aircraft supply and maintenance activities are adequately providing flying units the necessary aircraft to meet mission requirements (HQ AF/A4LM, 2020). AA_h is calculated by measuring the total number of hours that assigned aircraft could perform at least one of its functional requirements over total hours (HQ AF/A4LM, 2020).

$$AA_h = \frac{uptime}{uptime+downtime} \quad (3)$$

(Ebeling, 2009)

AA_h uses the hours of uptime and downtime that have already occurred, making the USAF's measure of AA a lagging indicator. Figure (3) provides a comparison of four different airframes compared to the median AA standard the USAF has established for each. The four fleets shown in Figure 3 clearly show that AA is truly an issue the USAF must correct.

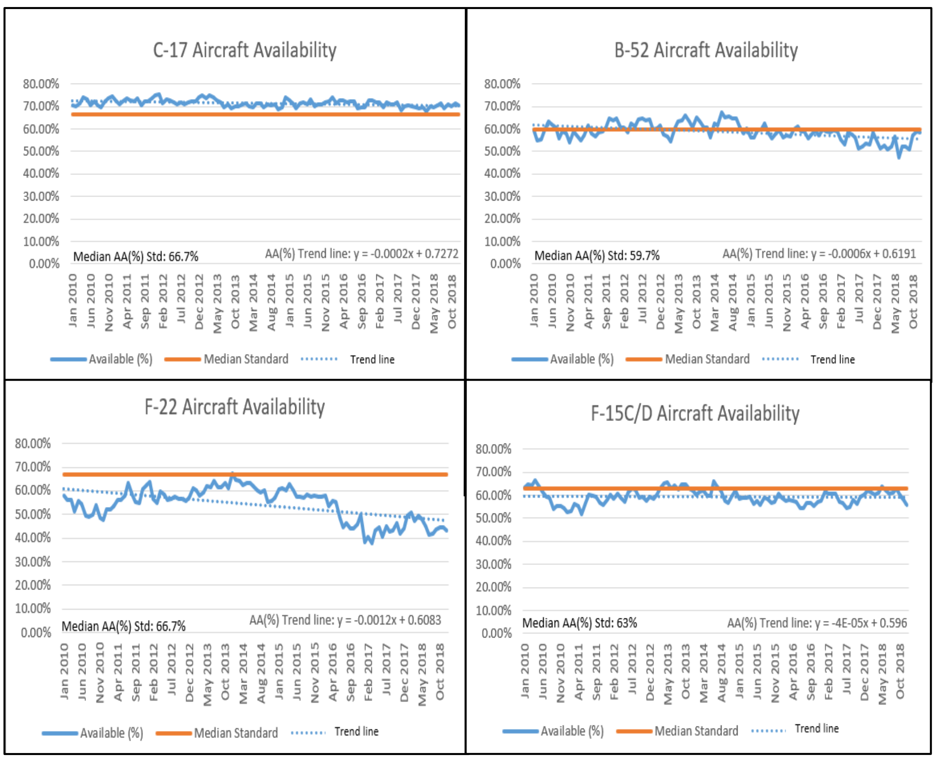

Figure 3: Jan 2010 – Oct 2018 Monthly AA compared to AA_{std} (LIMS-EV, 2020)

Each of these airframes are inherently different in fleet size, assigned locations and MAJCOMs (LIMS-EV, 2020), yet all four airframes have an AA rate that is negatively trending. Three of the four airframes are consistently failing to meet the standards levied upon them as determined in the prior formulas.

WSS is specifically designed to sustain the health of the fleet in the presence of environmental and operational elements that negatively affect AA. With such an important role, WSS activities require careful planning, adequate funding and timely execution. Fry (2010) studied aircraft sustainment in depth and made the following points. Prior to 2008, management of WSS planning and execution activities were dispersed across the USAF's 10 MAJCOMs (Fry, 2010). This method of WSS management was highly inefficient and disorganized. The USAF recognized several shortcomings in managing WSS processes in a decentralized manner and established the Centralized Asset Management (CAM) office in 2008 in order to centralize and integrate the cumbersome processes behind sustainment requirements determination and resource allocation (Fry, 2010).

The CAM office manages WSS actions by breaking them into three major areas called business processes. These business processes are the Flying Hour Program (FHP), new support equipment and Weapon System Sustainment (WSS) (AFMC/A4, 2015). The FHP provides the immediate resources needed for aircrews to stay ready; this includes, consumable and depot repairable aircraft parts and Aviation Petroleum, Oils and Lubricants (AVPOL) (AFMC/A4, 2015). New support equipment supports procurement of required Operations & Maintenance (O&M) Support Equipment (AFMC/A4, 2015). WSS funding is intended to meet sustainment requirements forecasted by weapon system engineers (AFMC/A4, 2015). These weapon system engineering requirements are focused on reliability, inspection and aircraft structural integrity policies (AFMC/A4, 2015).

In order to effectively manage requirements from these widely diverse policy areas, WSS is further broken into four business processes. Those business processes are Depot Purchased Equipment Maintenance (DPEM), Sustaining Engineering (SE), Contractor Logistics Support (CLS) and Technical Orders (TO) (AFMC/A4, 2015). The DPEM process provides major maintenance activities like Programmed Depot Maintenance (PDM) and engine overhauls (AFMC/A4, 2015). The SE process provides engineering reviews and activities to assess and resolve technical and supportability deficiencies in fielded systems (AFMC/A4, 2015). The CLS process manages all contracted sustainment activities. Finally, the TO process is responsible for procuring needed technical data on aircraft systems (AFMC/A4F, 2015).

Methodology Overview

In order to evaluate the impact of WSS on AA, empirically modelling was conducted using CLS, DPEM, SE and TO as the independent variables and AA as the dependent variable. In addition to this, the study incorporated lags to measure the lead time needed to realize the benefits to AA. In order to empirically model the four variables against AA and incorporate lead time this research employed Ordinary Least Squares (OLS) regression while incorporating temporal effects. In order to control for extraneous factors outside of WSS, a single weapon system was selected to conduct the research.

The literature review and methodology provides a deeper explanation on the specifics and sound justification for the singular weapon system focus.

Assumptions/Limitations

This research is intended to develop an explanatory model showing the relationship between WSS and AA. It is not intended to be predictive in nature. Therefore, this study excludes trend and seasonal decomposition, smoothing and other forecasting related methods. Additionally, the CAM office stood up in 2008. Due to the time needed to transition to the procedures under CAM, data prior to 2010 is not adequately reliable. Furthermore, this study began in 2019, therefore 2019 data was incomplete and not mature enough to be included. Given these two factors the study is limited to data between 2010 and 2018.

Implications

The Air Force Logistics, Engineering and Force Protection Directorate (HAF/A4) makes decisions on WSS annually (AFMC/A4F, 2015). The impact of this is highly significant in that it will inform HAF/A4 senior leader decision making on an estimated annual $16 Billion dollar portfolio. Furthermore, the implications of this research is to provide a foundation for future research that further enables improved analysis of the support functions used to keep USAF aircraft ready.

Preview

In order to dive deeper into how sustainment activities impact AA, this paper is structured in the following manner: 1) background and review of applicable literature and studies, 2) methodology and data 3) results and 4) conclusion and future research.

II. Literature Review

It is paramount that the empirical model accounts for the effects of the relevant variables associated with AA. The research conducted prior to this study greatly assisted in identifying those relevant variables outside of WSS. The literature on aviation maintenance sustainment and system availability is robust. The areas that have been thoroughly researched and are relevant to this research are broken down into the following categories 1) sustainment and support 2) reliability theory 3) learning curve theory.

Sustainment and Support

Pyles (1999) researched the effects of aircraft age on maintenance and material costs for the purpose of improving forecasts of maintenance workloads, material consumption and the related costs. A historical look at KC-135, Boeing 727, 737, McDonnel Douglas DC-9 and DC-10 over a 40-year period showed a nine-fold increase in workload for heavy depot maintenance and aircraft engine support (Pyles, 1999). A study conducted by the Congressional Budget Office (CBO) using historical Future Year Defense Program (FYDP) data for F-15, F/A-18, CH53 and P-3 aircraft found an estimated 1 to 2.5 years in aircraft age produces a one percent increase in operations and support cost (CBO, 2001). A later study tested the hypothesis that aircraft complexity exacerbates the effect that age has on required maintenance growth and was unable to statistically prove such relationship (Pyles, 2003).

Oliver (2001) modelled aircraft maintenance technicians' skill levels, retention of maintenance personnel, aircraft fix rates, operational tempo (OPT), spare parts issues and system reliability and maintainability to predict F-16 Mission Capable (MC) rates. Oliver found reliability and maintainability related variables Total Non-Mission Capable due to Maintenance (TNMCM) hours and cannibalization hours had the strongest effect on F-16 MC rates (Oliver, 2001).

Fry (2010) studied the impact of aircraft spares funding and the effect of assigned maintenance technicians' skill on AA. Fry (2010) used a ratio of assigned inexperienced technicians (1, 3 and 5 skill level) to experienced technicians (7, 9 and 0 skill level). Fry (2010) found mixed reviews on maintenance skill levels indicating that certain A-10, F-16 and KC-135 units responded negatively to higher levels of inexperienced technicians. Meanwhile different A-10 units and B-2 units responded positively to higher levels of inexperienced technicians. Fry (2010) also studied the use of Element of Expense Investment Code (EEIC) 644 funds which cover Material Support Division (MSD) costs for repairable parts in order to study spare parts resourcing impacts on AA. In which case the AA rates of only 2 aircraft fleets out of 18 studied could be empirically linked to spare parts funding (Fry, 2010).

Jones et al. (2014) studied the variability in the proportions of Operations and Support (O&S) costs across the Department of Defense (DoD) weapon system categories. They also found that proportions vary widely and that a previously used heuristic of 70:30 is inaccurate (70% of total life cycle costs are attributed to sustainment and 30% attributed to acquisition). Jones et al. (2014) found that the mean proportion of O&S costs to total life cycle costs by weapon system category can fluctuate from 15% to 71%.

The Air Force Resource Division (AF/A4P) developed a theoretical model for overall USAF readiness called the “Five Levers of Readiness” (HQ AF/A3, 2018). AF/A3 (2018) found that the FHP, WSS, Critical Skills Availability (CSA), Training Resource Availability (TRA) and Operations and Personnel Tempo (OPT) each effect readiness. CSA refers to the availability of skilled technicians, and TRA refers to the availability of all aircrew training resources to include aircraft ranges and flying simulators (HQ AF/A3, 2018). OPT deals with equipment availability due to deployments and exercises (HQ AF/A3, 2018).

Gill (2019) researched the impacts of age and weather conditions on C-130J Non-Mission Capable (NMC) rates. Gill (2019) found that age, increases unscheduled NMC time by in C-130Js. Additionally, Gill (2019) found that temperature and atmospheric pressure also impact unscheduled NMC time.

Reliability Theory

Ebeling (2009) provides a great break down of the major concepts involved in Reliability Theory, which are outlined in the following paragraphs in this section. Reliability is the probability a system will not fail over a given period of time and Mean Time Between Failure (MTBF) is a common measure of Reliability (Ebeling, 2009). Maintainability is the probability that a system will be repaired within a given amount of time and is often measured by the Mean Time To Repair (MTTR) (Ebeling, 2009). Additionally, Mean Time Between Maintenance (MTBM) is often used as a metric to measure maintainability as it incorporates both scheduled and unscheduled maintenance (Ebeling, 2009). Ebeling (2009) uses MTTR and MTBF to calculate Operational

Availability (A_o) and Inherent Availability (A_i) represented in Formula (4) and (5). Rather than measuring past system performance A_o, and A_i measure the probability of a system functioning at some point in the future (Ebeling, 2009).

$$A_O = \frac{MTBM}{MTBM + MDT} \tag{4}$$

(Ebeling, 2009)

$$A_i = \frac{MTBF}{MTBF + MTTR} \tag{5}$$

(Ebeling, 2009)

The importance of these formulas is that future availability can be measured in multiple different ways and is contingent upon repair times, decisions on scheduled and unscheduled maintenance and overall system reliability. Furthermore, the age of the system plays a role in Reliability Theory. This can be seen when the hazard rate of a system is measured. The hazard rate is the probability of a failure occurring in the next instant. When this hazard is measured over the life of a system it tends to follow a bathtub curve (Ebeling, 2009) as shown in Figure 4 below:

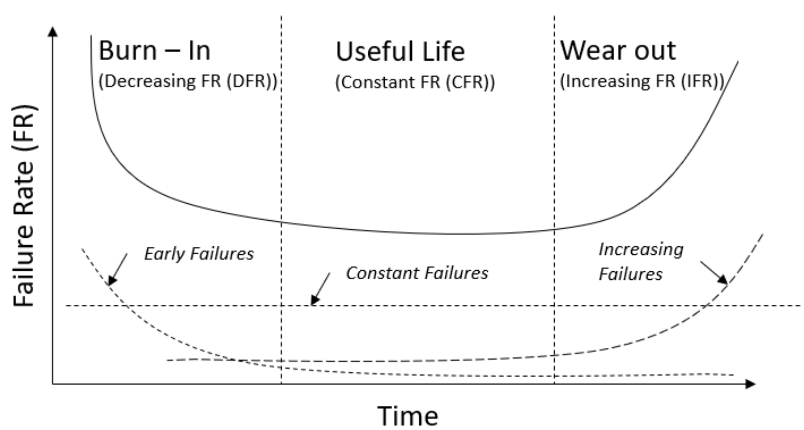

Figure 4: Reliability Curve (Ebeling, 2009)

This bathtub curve indicates that as time progresses failures will occur less often also known as a Decreasing Failure Rate (DFR), then failures will follow a Constant Failure Rate (CFR) during a components useful life, this is when the reliability of the system is at its best. Eventually, end items will enter a period of Increasing Failure Rate (IFR) as components age, corrode and wear out (Ebeling, 2009).

Learning Curve Theory

Learning curve theory was researched in an effort to understand the potential impacts of changing maintenance processes on the flight line. Learning Curve theory may offer some insight into the lead time needed to receive benefit to AA from TO. Course material from the Defense Acquisition University offers some insights into learning curve theory. Learning curve theory indicates that the repetition of the same task results in less time and effort expended on the task (Barber, 2011). The conditions that promote this are task familiarization and process improvements made from experience (Barber, 2011). These conditions lead to reduction in rework, repair time and scrap (Barber, 2011).

The literature is significant and valuable in this study as each of these findings will need to be represented in the model in order to control for their effects on AA. How this is done is discussed further in Methodology.

Literature Gap

Previous studies are robust in identifying the external challenges (i.e. age, weather) associated with sustaining the serviceable state of USAF fleets. However, a gap in the literature exists as no scholar has sufficiently researched ways senior leaders could control or reverse negative Aircraft Availability trends.

Focus

Reliability theory concepts discussed in the literature review are important as they offer possible explanation in the lead time needed to receive a return from DPEM and SE. To make this link between Reliability theory and DPEM a quick discussion on PDM which falls under DPEM is necessary. PDM involves extensive disassembly of aircraft, involving removal, checks and evaluations of the fuselage, landing gear, wings, flight control equipment, engines (Keating et al., 2008). After reassembly the aircraft goes through functional check flights and a repaint prior to pick up from the owning unit (Keating et al., 2008). Therefore, it is not unreasonable to view PDM as a remanufacturing process that resets an individual aircraft's position to an earlier point on the reliability curve. This position reset likely puts the aircraft in DFR and in order to reach a position of CFR, it must have a "break-in" period. Therefore, logical employment of the reliability curve supports the notion that aircraft may see a period of DFR upon returning from overhaul. Additionally, SE efforts are intended to fix supportability issues. At the component level, parts may experience IFR due to wear out, obsolescence etc. If SE is designed to close the gap in supportability issues, then it is plausible that SE will replace IFR components with components that are either DFR or CFR. It would appear that the four WSS processes are attempting to mitigate major AA issues with respect to these reliability theory related concepts. While, reliability theory offers some possible explanation as to how DPEM and SE effect AA. Learning Curve Theory also offers some possible explanations to how TOs effect AA.

Learning curve theory is important in this paper as it may offer some explanation to necessary lead times in seeing benefit related to TOs. Recalling the formulas for inherent and operational availability, Down Time and Repair Time also impact AA. Additionally, they likely effect AA in different ways (maintainability vs. reliability). In this case TOs likely effect maintainability. Closely following TOs is a strict expectation the USAF has for maintenance technicians (AFMC/A4FI, 2016). Therefore, the potential connection between learning curve theory and TOs is that as new and better information is provided it will take time for technicians to adjust. Once adjusted the processes in restoring aircraft will become more efficient. The constant updates and release of better technical data will not be learned and applied instantly by maintenance technicians. Therefore, Reliability Theory and Learning Curve Theory offer intriguing conceptual frameworks to understand how AA is impacted by WSS activities.

The literature proved to be a critical in deciding what level of focus is appropriate to study WSS impact on AA (all aircraft, specific airframes, base level etc.). As mentioned earlier, Jones et al. (2014) found that variability in sustainment to total life cycle cost proportions vary widely. Therefore, modelling more than one WS would introduce too much noise.

Under this context it is necessary to select a specific airframe for this research. Given the unique nature of fighter aircraft to the USAF over private sector a fighter platform was chosen to model WSS impacts to AA. F-15C/Ds were the best candidate to narrow the research. The F-16 has gone fleet consists of 139 different versions with over a thousand OEM upgrades provided since its inception (“F-16 Fighting Falcon Fast Facts”, 2020). Therefore, the F-16 is not a good candidate to study the effects of WSS on AA. Furthermore, F-15Es were not included due to the extensive use of the F-15E in combat operations since 2014 (Pawlyk, 2017).

III. Methodology

Previous studies have used Ordinary Least Squares (OLS) (Oliver, 2001; Fry, 2010) to build empirical models that explain AA or MC rates. Given the success use of OLS in previous research on the topic, OLS regression is sufficient in answering the outlined research questions.

Variables and Theoretical Model

The data used for the dependent variable; AA was pulled from LIMS-EV. While obtaining values for AA was simple, the independent variables were not as easily captured. To begin with, the activities and processes that fall under CLS, DPEM, SE and TO could be interpreted in a few different ways. Each WSS activity is physically categorized into one of the four categories. However, AFMC/A4F (2015) indicates that Program Managers (PM) divide WSS into different categories based on risk of meeting sustainment goals. Risk assessments are divided into various categories and documented into a system called Centralized Access for Data Exchange (CAFDEx) (AFMC/A4F, 2015). For example, heavy aircraft maintenance actions are categorized under DPEM if the maintenance was conducted organically under USAF owned and operated resources. If that same heavy maintenance were conducted by a contractor it would be categorized as CLS (AFMC/A4F, 2015). The risk categories were used to classify tasks into each of the four categories given that this study is interested in knowing the inherent benefit of each WSS activity. Therefore, aggregating like activities will reduce noise and provide a clearer understanding of the value of WSS. This is an optimal approach compared to using arbitrarily categories of WSS. Table (1) provides a concise breakdown of how each activity is aggregated into the four WSS processes.

Table 1 Classification of activities into WSS Processes

WSS Process	**Activities within each risk categories**
CLS	CLS Management; CLS Spares; Training
DPEM	A/B/M; Aircraft Depot/ Heavy Maintenance; Engines; OMEI; Software; Storage
SUST ENG	Sustainment Engineering
TO	Technical Orders

The literature found that age, weather, maintenance manning, the FHP, CSA, TRA and OPT also effected AA. Therefore, Unit Possessed Not Reported (UPNR), Flying Schedule Effectiveness (FSE), Depot Possession rates (Depot (%)) and age are included as variables to control for the effects of the variables identified in the literature. Using four control variables as opposed to eight (one for each previously identified effect) assists in greatly simplifying the model.

UPNR represents that portion of those resources by accounting for the times when depot teams are sent out to handle aircraft repairs in the field beyond the capabilities of available maintenance capabilities (LIMS-EV, 2020). Depot (%) accounts for the time aircraft spend possessed by the depot (LIMS-EV, 2020). UPNR and Depot (%) serve as proxies representing OPT. Flying units are limited to meet aircrew training requirements with only the resources in their possession. Accounting for UPNR and Depot Possession remove the resources normally available to the unit but unavailable due to technical issues and major maintenance actions.

FSE is the ratio measuring the number of adjustments in scheduled sorties compared to overall scheduled sorties (LIMS-EV, 2020). FSE was used as a quantitative proxy representing the qualitative effects of CSA, OPT and weather. Logically, FSE is chosen as units must decide when it is best to fly to meet training requirements without negatively effecting alert status aircraft and other requirements. FSE ultimately accounts for the month to month managerial decisions made between those are that are charged with meeting training requirements (flying units) and those charged with providing healthy aircraft (maintenance resources). This reasonably assumes that high monthly FSE is indicative of operations and maintenance units remaining conscious of upcoming deployments, redeployments, weather conditions conducive for flying, limitations and capabilities of available maintenance manpower, equipment and resources. With this understanding FSE controls for weather, TRA, CSA, FHP and OPT. Finally, age was simply the number of months since December 1979, to simulate an estimated age for the fleet. Since

Accounting for the control variable effects ensures the model is viable by removing covariance between the error term and the independent variables. Formula (6) and (7) outline the theoretical and additive model, given all the discussed variables.

$$\boldsymbol{Theoretical\ Model\ of\ AA = f(FHP, WSS, SE, CSA, TRA, OPT)} \tag{6}$$

$$\textbf{Additive } \boldsymbol{AA\ Model = \beta_0 + \beta_1 CLS + \beta_2 DPEM + \beta_3 SE + \beta_4 TO + \beta_5 UPNR + \beta_6 FSE + \beta_7\ Depot + \beta_8 Age} \tag{7}$$

Data

The dataset used to study WSS's impact to AA was developed from two separate sources, CAFDEx and LIMS-EV. The data from each source was narrowed to F-15C/D observations between January 2010 and September 2018. Historical AA, UPNR FSE and Depot (%) were all sourced from LIMS-EV for all months between January 2010 and December 2018. The WSS process data was sourced from the CAFDEx database and provided by the Air Force Resource Division (HQ AF/A4P) office. CAFDEx provides a wide range of financial planning, programming, budgeting and execution data (AFMC/A4F, 2015). The CAFDEx data consisted of 3,458 records documenting F-15 WSS obligations in Fiscal Years (FY) 2010 through 2018 (HQ AF/A4PY, 2019). The month of obligation is a key component in the study as an obligation is when the government is liable for payment of goods and services rendered (U.S. GAO, 2005). The monthly obligations are used as the point to represent when support functions were authorized and tasked to execute a sustainment activity.

Data Cleaning and Preparation

There were two inclusion criteria for data from the CAFDEX dataset. 1) recorded WSS activities must apply to F-15C/Ds or "common" F-15s and 2) recorded WSS activities must have a positive obligation funding amount. 442 records in the CAFDEx dataset documented activities that were performed by an F-15 program office but benefitted other airframes to include the A-10 and F-16 fleet. Several records in the data contained unexplained negative values, these values were adjusted to zero. All other tasks that directly impact the F-15C/D were preserved in the final dataset. The remaining data used in this study was pulled from LIMS-EV. All possible F-15C/D AA data available in LIMS-EV was pulled regardless of unit or assigned mission.

During the data cleaning, it was observed that the CAFDEx obligation amounts were recorded quarterly between 2010 to 2015 and the data. The monthly data was imputed by developing a sample distribution from the 2016 to 2018 monthly data. The sample distribution was made from the proportions that each month contributed to its respective quarter. This sample distribution was developed from a beta distribution using the minimum 2015 – 2016 proportion value, it's maximum value, and respective alpha and beta calculation. Monthly proportions were randomly drawn from this distribution as sets of three to represent one quarter. These sets of three only qualified as usable for the model if their sums were within .01 of 1. A histogram of the sampled proportions and the imputed values are provided in Figure (5). This method of imputation tethered monthly values to the actual quarterly data, adding increased rigor and validity to this study's findings.

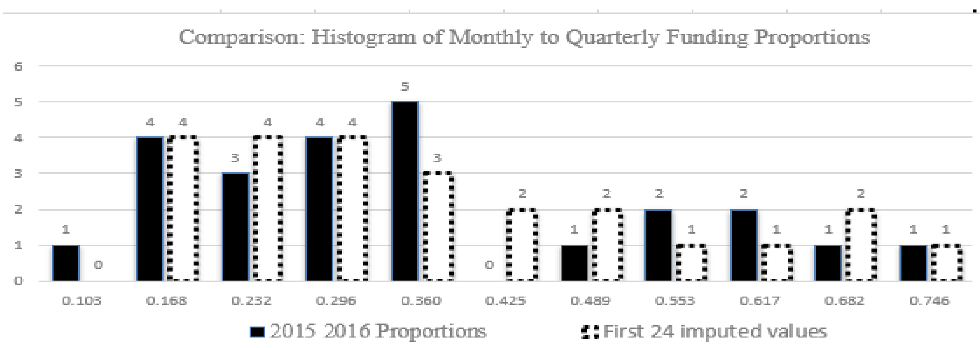

Figure 5: Histogram of Monthly to Quarterly Funding Proportions

Once the proportions were imputed the monthly observations were calculated by multiplying quarterly values to each month's imputed value. This allowed for imputed estimates to stay within the upper bounds of actual historical obligations.

After quarterly proportions were imputed the CAFDEx data needed to be adjusted to a single year's dollars in order to remove the effects of cost growth and inflation. According to the Department of the Air Force Cost and Economics Division (SAF/FMCE) (2018), USAF cost categories weighted indexes are required to be used to compare expenses over multiple years or to estimate future program costs. This normalization process puts all money in a single Base Year (BY) (SAF/FMCE, 2018). Obligations were normalized to BY 2019 dollars using the appropriate SAF/FMCE (2019) tables.

OLS Regression Assumptions

The statistical software *R* was used to develop OLS models. Since OLS regression was used to model WSS's relationship to AA; several requirements called "assumptions" must be met. All of these assumptions were statistically tested in R. The following outlines these assumptions and how they were tested and met:

1) Overall model will be statistically significant. Overall model significance will be evaluated at the .05 alpha using the F-test. If the F-Test P value is greater than .05, then the null hypothesis that the model does not adequately fits the dependent variable AA will be rejected.

2) The model must have independence from serial correlation. This will be achieved by correcting for any observed Auto Regressive (AR) correlations. Checks for auto correlation will be done through Auto Correlation Function (ACF) / Partial Auto Correlation Function (PACF) plots. These plots will check for a 95% confidence interval of autocorrelation. Those values must be within a range greater or less than $2/\sqrt{(n)}$.

Furthermore, the Durbin Watson (DW) test will be conducted to check for AR(1). A DW p value that is less than .05 indicates the presence of an AR(1) function.

3) Model residuals will be normally distributed and contain constant variance. To ensure the model has constant variance or homoscedasticity, the Breusch Pagan's (BP) test was used. The BP test was evaluated at the .05 alpha. If the P -value is above .05, then it is assumed the model has constant variance. Additionally, homoscedasticity is checked visually by inspecting the patterns in the standardized residual vs fitted values plot. Normality of the residuals were checked using the Shapiro Wilkes (SW) test, visual Q-Q plots and a histogram of the residuals. The SW test was assessed at the .05 alpha. If the p value stays above .05 it is assumed the residuals pass the SW test.

4) Variance Inflation Factors (VIF) will be less than 5 (unless polynomial or interaction terms are deemed necessary, in which case high VIF scores are to be expected between the base and power or interaction terms). A low VIF score ensures the effects of WSS variables can be assessed independently within the overall final model.

5) Covariance of the error term and the independent variables will be zero. It is difficult to truly know if zero covariance between the independent variables and the error term has been achieved. Therefore, it will be assumed this assumption is met so long as the model includes all variables previously identified in the literature review as having an empirical relationship with AA. However, if any of these variables become statistically insignificant, they will be removed from the final model.

6) All independent variables in the final model will have a p – value < .05.

7) Finally, unduly influential points will be visually checked using cooks distance plots from R's model summary output function. Influential points will have a cook's distance greater than .5.

OLS Regression Process

The first step of the modelling process was to record the correlation of the WSS variable lags as they correlate to AA. These lag correlations will be used to hone in on the likely lead times between AA and the WSS variables. Again, the premise of doing this is that DPEM and SE lead times are largely driven by Reliability Theory and a systems ability to reach the bottom of the bathtub or the CFR. The TO lags are informed by Learning Curve Theory. Highly correlated lags are indicative of the time it takes to procure, develop, distribute technical data and maintenance personnel to digest the technical data.

The second step is to develop an initial model containing the Independent Variables (IV) and Control Variables (CV) derived from the literature review. After an initial model is run the IV's representing WSS will be independently and iteratively lagged while holding all other variables constant (i.e. CLS lagged 1 while DPEM, SE and TO held constant, then CLS lagged 2 while DPEM, SE and TO held constant). Each model's beta coefficients, standardized beta coefficients, standard errors, t-values, P-Values, and the model's F-Test, R squared, Adjusted R squared assumption will be checked. Each variable will be lagged through 36 months and the best lag will be recorded. The process will be repeated for each variable until a sufficient model is discovered. Once a solid model is developed, the assumptions will be checked again proper corrections will be made to the model to ensure the model is BLUE.

During the modelling step the standardized beta coefficients will be calculated. These standardized beta coefficients will be used to determine how important each variable is within the model. This importance will be measured through a metric labelled "Model Contribution" and will be used as another method of evaluating variable importance in the model. This will be done through the following formula:

$$\boldsymbol{Model\ Contribution} = \frac{|\boldsymbol{\beta_{standardized}}|}{\sum_{1}^{n} |\boldsymbol{\beta_{standardized}}|} \tag{7}$$

IV. Analysis and Results

Estimating Lead Times

The lead time between historical AA and WSS are expected to be longer than the lead time between obligation and the physical completion of WSS tasks (i.e. aircraft returning to the unit post PDM). For example, F-15C/Ds going through PDM take roughly 6 months to complete (“F-15C/D PDM Flow Days”, 2020). AA should not expect to see a benefit from DPEM actions until after the 6-month period. This is predicated on Reliability Theory and the possible need for a break-in period to account for any DFR time. The correlation between historical AA and WSS from 1 – 36 month lagged time periods is provided in figure (6).

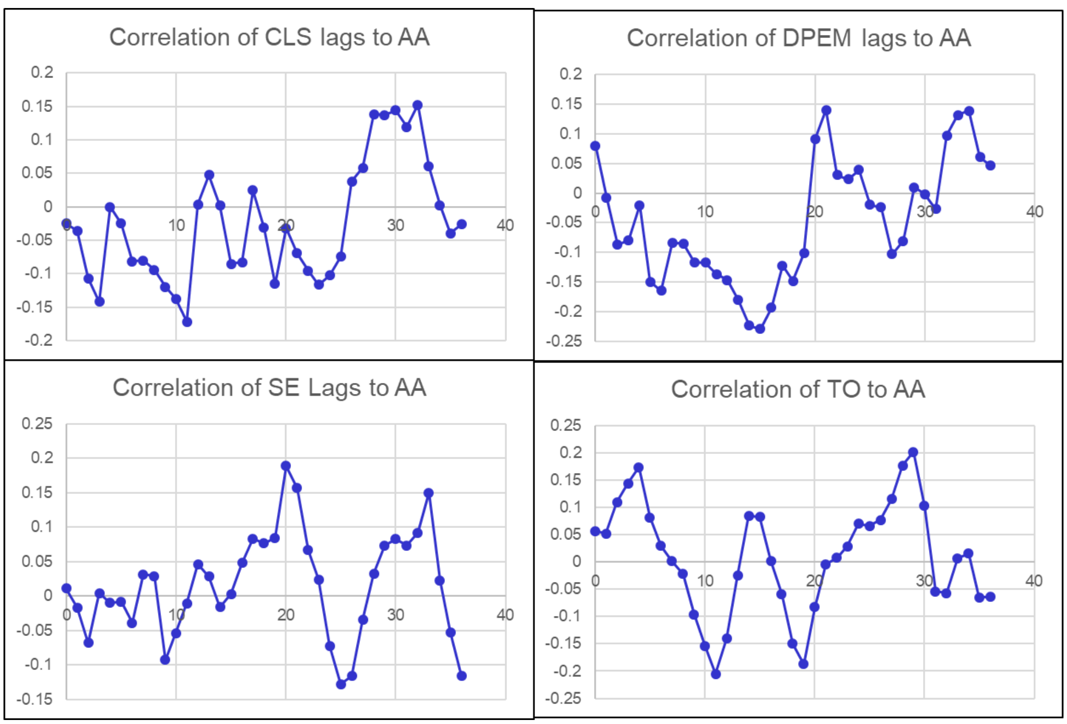

Figure 6: WSS Variable Lags to AA Correlation

Initial Model

The initial model was executed and the results were recorded in Table (2). None of the WSS variables at zero lag are statistically significant at the .05 alpha. Furthermore, all of the control variables are statistically significant. Also, the VIF scores were all well below five indicating that each independent variable can be adjusted while holding all others constant.

Table 2: Base OLS Model Outputs

Variable	Lag	Beta Coefficient	Standard Beta Coefficient	Model Contribution	Std. Error	t value	Pr(>|t|)	VIF
Intercept	N/A	56.403	N/A	N/A	4.3043	13.1038	< 2.2e-16	N/A
CLS	0	2.12E-08	0.03787586	2%	3.4902	0.6076	0.5448586	1.135451
DPEM	0	3.25E-09	0.0139913	1%	1.63E-08	0.1995	0.8422821	1.16812
SE	0	6.62E-03	0.09653	6%	6.68E-08	0.9912	0.3240042	1.126842
TO	0	-5.06E-07	-0.12591551	7%	4.35E-07	-1.1631	0.2475967	1.187525
Depot (%)	0	1.88E-02	-0.68112018	40%	1.24E-01	-9.2858	3.95E-15	1.36
Age	0	-1.06E+00	0.17912836	11%	8.78E-03	2.1364	0.0351132	1.490098
UPNR	0	1.71E+01	-0.27834376	16%	2.93E-01	-3.6284	0.0004533	1.08826
FSE	0	1.71E+00	0.28590756	17%	4.35E+00	3.9408	0.0001514	1.23182

In order to acknowledge the true value of the WSS variables, the base model violation of serial correlation must be corrected. All other assumptions were met as seen in Table (3) below.

Table 3: Base Model Tests and Model Measurements

Durbin Watson (DW)	p-value: 0
Breusch Pagan (BP)	p-value: 0.293
Shapiro Wilks (SW)	p-value: 0.6163
Overall Model Significance (F-Test)	p-value: 4.627e-12
R Squared	0.4979
Adjusted R Squared	0.4573

To further show the significance of the serial correlation the ACF/PACF plot is provided below in Figure (7).

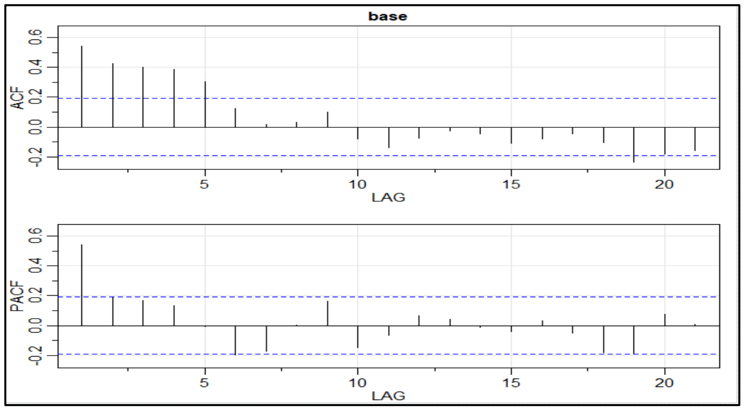

Figure 7: ACF/PACF plots of Base Model

The ACF plot indicates there is at least an AR process at the first lag (AR(1)). The PACF plot attempts to correct for AR(1). This indicates that there must be further existence of an AR process beyond AR(1) as there is still significant serial Correlation that must be addressed in the PACF.

The Q-Q Plot and Histogram of Residuals align with the findings of the SW Test, further reinforcing the error term to be normally distributed with a mean of zero. The Q-Q Plot and Histogram are provided below in Figure 8.

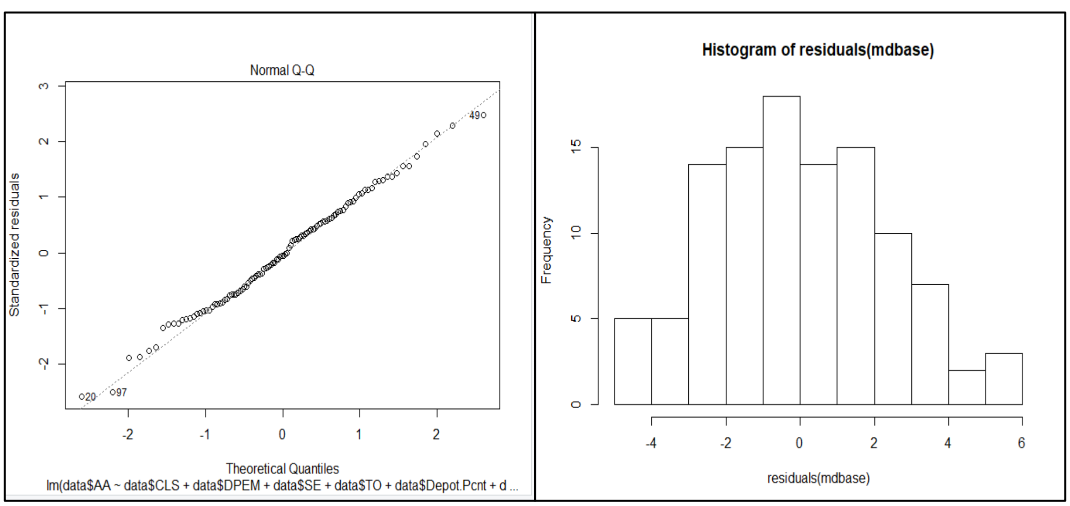

Figure 8: Base Model Q-Q Plot and Histogram of Residuals

Next, the Scale location graph shows a slight curvature in the error. This infers that there may be the existence of a polynomial or higher order term. Since this is the base model, there is no need to alter the base model to correct for misspecification of variables. Finally, the Residuals vs. Fitted plot indicates that there is some level of heteroscedasticity in spite of the model passing the BP Test. Again, since this is the base model, there is no need to address the heteroscedasticity at this time. The Scale Location and Residuals vs. Fitted plots are provided in figure (9).

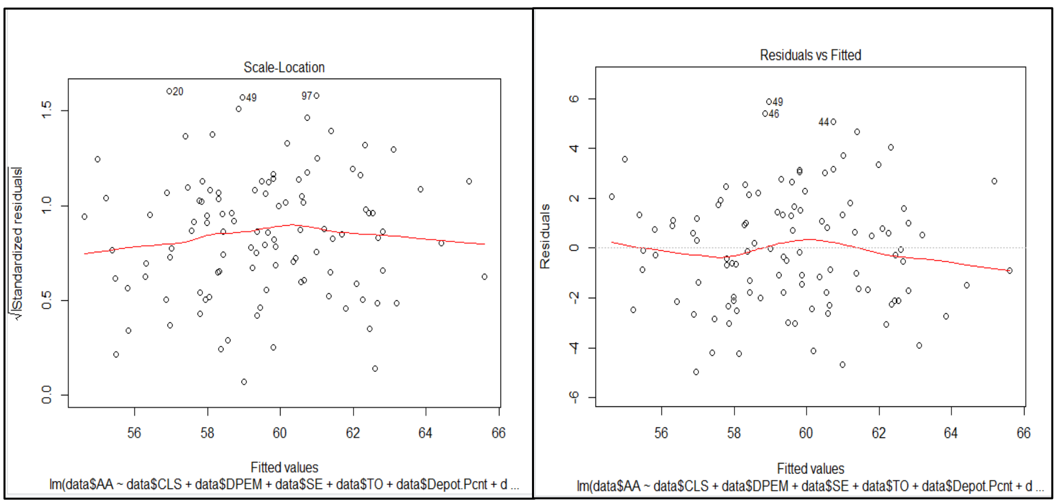

Figure 9: Base Model Scale Location and Residuals Vs Fitted Plot

Finally, the Cook's distance plot for the initial model indicates that there is minimal influence from outlier points. The Cook's Distance plot is provided in figure 10 below.

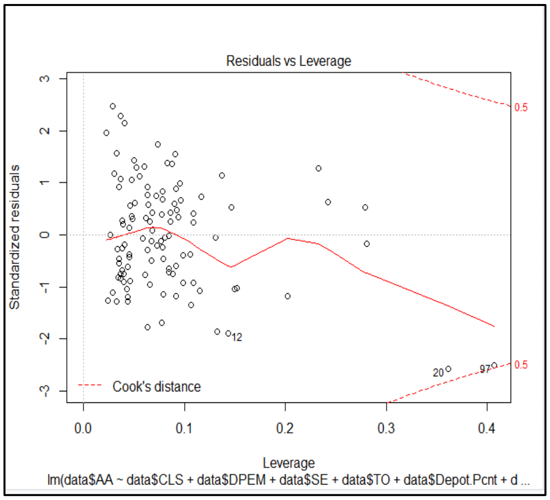

Figure 10: Base Model Residual Vs Leverage Plot (cook's distance)

In order to provide an acceptable base line. The initial model is rebuilt to correct for the serial correlation. The results found an AR Process of 1 (AR (1)) and 4 (AR (4)). The values for the standard error, beta coefficients and other variables are provided in table 4 below:

Table 4: Base Model Corrected for Serial Correlation OLS Model Outputs

Variable	Lag	Beta Coefficient	Standard Beta Coefficient	Model Contribution	Std. Error	t value	Pr(>|t|)	VIF
Intercept	N/A	20.509	N/A	N/A	5.171	3.966	1.43E-04	N/A
CLS	0	-2.97E-08	-0.05577916	3%	3.09E-08	-0.961	0.338833	1.16378
DPEM	0	-1.64E-08	-0.07021693	4%	1.34E-08	-1.227	0.222761	1.13148
SE	0	1.81E-08	0.02757805	2%	3.79E-08	0.477	0.63438	1.155
TO	0	-2.14E-07	-0.0531601	3%	2.37E-07	-0.902	0.369141	1.19967
Depot (%)	0	-5.81E-01	-0.3131486	18%	1.23E-01	-4.71	8.64E-06	1.5283
Age	0	1.60E-02	0.15201467	9%	6.74E-03	2.365	0.020103	1.42834
UPNR	0	-8.59E+00	-0.23330982	14%	2.09E-01	-4.121	8.18E-05	1.10813
FSE	0	1.65E+00	0.02826372	2%	3.83E+00	0.43	0.668275	1.49455
AA	1	5.62E-01	0.56203488	33%	7.26E-02	7.741	1.17E-11	1.82248
AA	4	1.35E-01	0.14093929	8%	6.27E-02	2.152	0.033965	1.4826

As with the original base model the WSS variables are not statistically significant and the control variables are statistically significant at the .05 alpha. Additionally, VIF scores still provide Ceteris Paribus. Looking at the initial model diagnostics adding the dependent variable lagged 1 and 4 appears to have corrected the serial correlation issues while all other assumptions are still met. This is seen in the DW test in table 5 below and the ACF plots in Figure 11:

Table 5: Corrected Base Model Tests and Model Measurements

DW	p-value: 0.356
BP	p-value: 0.2959
SW	p-value: 0.6311
F-Test	p-value: < 2.2e-16
R Squared	0.731
Adjusted R Squared	0.7021

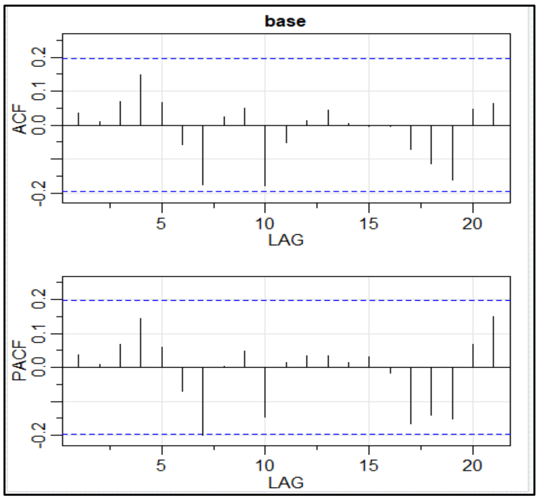

Figure 11: Base Model Adjusted ACF/PACF Plot

It is apparent that the corrections for serial correlation has greatly affected the R squared. This is likely due to the addition of the lagged dependent variables as they are 42% of the overall model contribution.

With the base model adequately in place. The next step is to iteratively lag each WSS variable to identify the lead time necessary to see the expected positive result in AA from each WSS. Again, these lags are conducted independently on each variable and recorded once the most statistically significant variable is found.

The final model found all four WSS variables to be significant. The final model did not find UPNR, Age, or FSE to be statistically significant at the .05 alpha. Those variables were removed to prevent undue influence on the beta coefficients and assumptions. The final modelling Beta Coefficients and P values are provided in Table (6).

Table 6: Final OLS Model

Variable	Lag	Beta Coefficient	Standard Beta Coefficient	Model Contribution	Std. Error	t value	Pr(>|t|)	VIF
Intercept	N/A	26.53	N/A	N/A	59.42	4.466	3.14E-05	N/A
AA	1	5.29E-01	0.53	33%	7.89E-02	6.697	5.26E-09	1.68316
Depot (%)	0	-6.26E-01	-0.36	23%	1.26E-01	-4.951	5.26E-06	1.45762
CLS	12	8.19E-08	0.16	10%	3.16E-08	2.589	1.18E-02	1.07529
DPEM	20	2.73E-08	0.14	9%	1.25E-08	2.192	3.18E-02	1.08792
TO	24	4.67E-07	0.15	9%	2.06E-07	2.27	2.64E-02	1.11698
AA	4	1.41E-01	0.14	9%	6.71E-02	2.105	3.91E-02	1.21139
SE	33	1.25E-07	0.13	8%	5.76E-08	2.178	3.29E-02	1.0176

The final model indicates that all four WSS are statistically significant at the .05 alpha. Depot (%) is the only remaining control variable that is statistically significant. The AA lagged 1 and 4 variables remained in the model as the serial correlation persisted throughout the modelling process. While the AA lagged variables model contribution remained about the same, the model contribution from the WSS variables greatly increased. The sum of the WSS variables model contribution from the original model was a mere 10%. The sum of the WSS variables model contribution in the final model was 36%. Depot Possession (%) model contribution also increased from 18% to 23%, this is likely due to the removal of the control variables that were not statistically significant at the .05 alpha in the final model. Additionally, the final model achieves Ceteris Paribus, VIF scores are all below 2, which means there should not be any issues with holding other variables constant to measure the effects of each variable independently. The results from the model test statistics and R Squared values are also favorable based on the standards set in methodology. Those values are included in the table (7) below:

Table 7: Final Model Tests and Model Measurements

DW	p-value: 0.496
BP	p-value: 0.777
SW	p-value 0.2823
F-Test	p-value: < 2.2e-16
R Squared	0.7552
Adjusted R Squared	0.7296

The DW test indicates that no first order serial correlation exists. The BP test strongly indicates that there the final model is homoscedastic. The SW test indicates that the model is normally distributed. Finally, there is only a minor improvement in R Squared and Adjusted R Squared from the initial model. This is likely due to the inclusion of AA lagged 1 and 4 months greatly contributing to the R Squared and continuing to be a strong contributor. The AA lagged variables are strong contributors to the model based off of their model contribution calculation (33% model contribution for lag 1 and 9% model contribution for lag 4).

The final model plots reinforce that the final model has met all of the required assumptions. Looking at the ACF/PACF plots indicate that the model is strongly independent of serial correlation. The ACF/PACF plot is provided in figure (12) below.

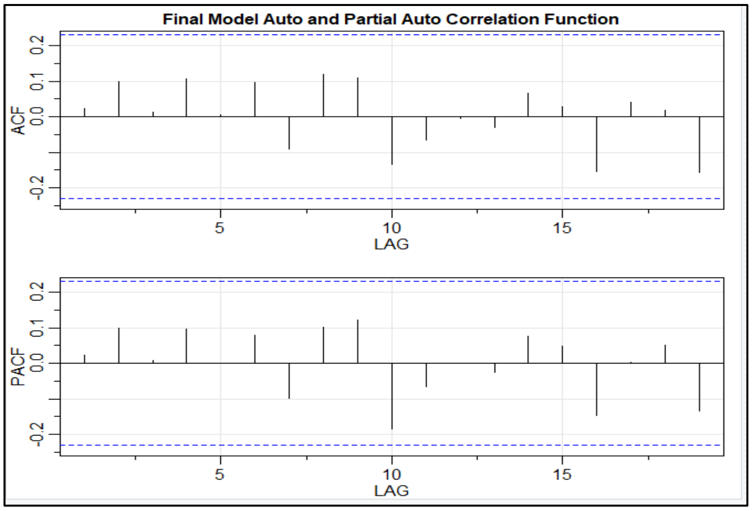

Figure 12: Corrected Base Model ACF/PACF Plots of Base Model

The plot of Residuals vs. Fitted and Scale-Location plots indicates that the model is correctly specified and reinforces the BP tests findings that the model is homoscedastic. The Residuals Vs Fitted and Scale Location plots are provided below in figure (13)

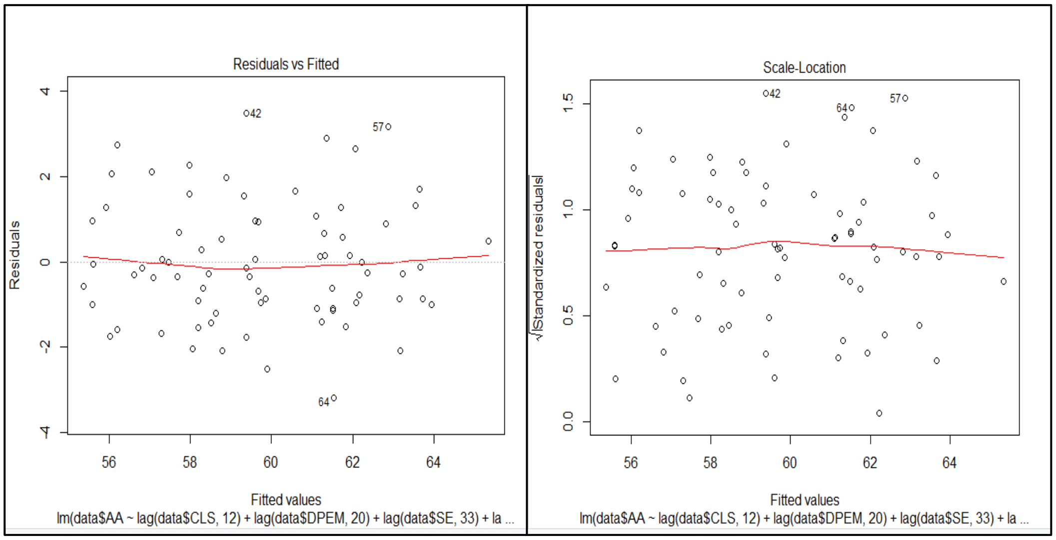

Figure 13: Final Model Residuals Vs Fitted and Scale Location Plots

Finally, the normality plots indicate that the residuals are normally distributed and the mean of the error term is approximately zero. Additionally, the shape of the histogram is slightly skewed right but the overall shape of the curve and the tails indicate that the distribution of the residuals is acceptable to infer statistical significance in the final model variables. The Q-Q plot also indicates the residuals are approximately normal. The Q-Q Plot and the Histogram of the Residuals can be found below in figure 14.

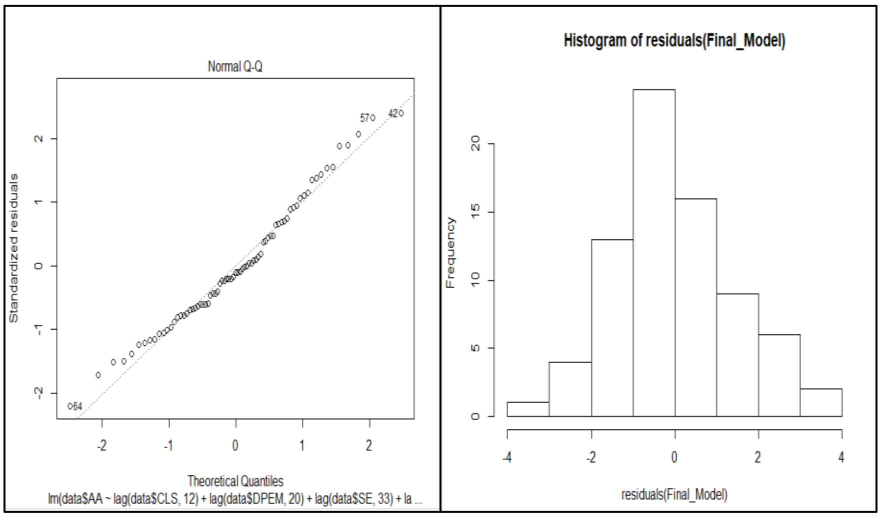

Figure 14: Final Model Q-Q Plot and Histogram of Residuals

The final model found statistical significance in all four major WSS categories while meeting all the necessary requirements to produce a BLUE model. Given this, the methodology has successfully produced results that are sufficient in answering the Research Questions outlined in the introduction.

Final Model Validation

While the statistical tests presented go a long way to validate the final model, these statistical tests are not designed to ensure the results adequately address the research questions and align with reality. The biggest area of subjectivity resides within the final lagged variables. In order to prove that the chosen lag periods are valuable a final sensitivity analysis was performed. In this sensitivity analysis, the final lags p values and Adjusted R squared values were independently assessed to ensure the found relationships are robust. This independent assessment matched five criteria:

1. The lags must align with reality. For example, lags earlier than six months on DPEM would not make sense. As it takes more than six months for an aircraft to go through PDM ("F-15C/D PDM Flow Days", 2020).
2. The beta coefficients cannot be negative. The research desires to know when we see a positive return from WSS to AA. While the study does not reject the notion that WSS may negatively affect AA at some point in time, it is also outside the scope of the research to find those areas in which AA is negatively affected by WSS. The research is firmly focused on finding real points in time when AA sees an improvement due to WSS efforts.
3. The P values of the beta coefficients must be below .05.
4. The Adjusted R squared must show an upward trend, either a plateau or peak then downward trend. This signifies that there is a range of months in which AA is positively affected by the variable. This range would be consistent with reality and reject the notion that the final values are simply spurious correlations.
5. The lag that best meets the above four requirements is chosen.

The results from this sensitivity analysis is provided below in figure (15):

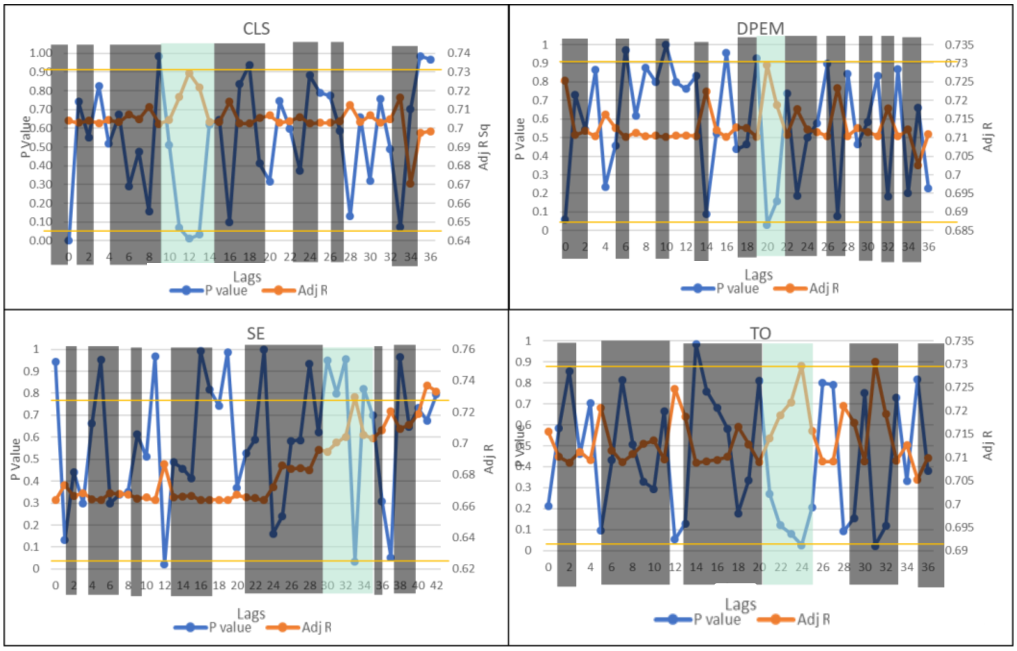

Figure 15: Final Model Sensitivity Analysis

The areas in grey represent the lags that resulted in a negative beta coefficient. The green shaded areas represent the areas in which a gradual increase, peak and decrease in Adjusted R Squared was observed. The two solid lines represent the .05 P value and the final model Adjusted R Squared point (.7296). The results from the sensitivity analysis indicate our lags for CLS and TO are robust. The SE patterns at lag 10 -12 could be debated as plausible solution space. Analysis is both an art and a science. The selection of the 33 month lag for SE leverages some of the "art" of analyzing data. The literature and the data cannot provide a hard date on when sustainment activities are typically completed. This is due to the wide array of supportability deficiencies that arise. It is assumed that most supportability deficiency re-engineering efforts would take longer than a year to complete, field and see an improvement in Availability. Therefore, the 33 month lagged time period is chosen as the most plausible indicator as to when AA would be positively affected.

V. Conclusions and Recommendations

In order to capture the value of this research within the conclusions and recommendations from this research is covered in the following order: 1) research questions 2) significance of the research 3) recommendations 4) future research.

Research Questions

RQ 1: How much variability in AA can be attributed to historical WSS funding?

The answer to this question is, it depends. If the measure of WSS's attribution to AA is looked at from the explanatory power of the entire model then 72.9% of the variability in AA is explainable with the inclusion of WSS in AA modelling. A better answer to this question would be through the use of comparing the model contribution metric from the initial model to the final model. Table (8) compares the model contribution from the initial model to the final model. Table 8 indicates that all variables gained influence in explaining AA with the lags, and WSS holistically contributes to 36% of movement within the model.

Table 8: Base Model / Final Model WSS Model Contribution Comparison

Variable	Initial Model Contribution	Final Model Contribution	Model Contribution Improvement
CLS	3%	10%	7%
DPEM	4%	9%	5%
SE	2%	8%	6%
TO	3%	9%	6%
Total	10%	36%	26%

RQ 2: What is the lead time in realizing AA benefits from each WSS business process?

The lead time in realizing benefit to AA from each WSS business process aligns fairly close with the initial estimates developed in the Results and Conclusions. To reiterate this time period is the time between when obligation occurred to the point at which AA responded. Table (9) below highlights those lead times.

Table 9: Lead Time in Months

Variable	Lead Time in Months
CLS	12
DPEM	20
TO	24
SE	33

Reliability Theory and Learning Curve Theory can provide some explanation as to why these lags are meaningful. First off, the F-15C/D models have spent approximately 180 days in PDM ("F-15C/D PDM Flow Days", 2020). PDM is a comprehensive process involving the removal wings, fuselages and engines (Keating et al., 2016). Given the extensive level of inspections and repair, it is believed that the position of where the aircraft sits on the reliability curve is reset. It is likely that the aircraft's reliability is reset back to a point in the DFR region and that it takes approximately 14 months (20 months minus the 6-month overhaul) to reach the CFR region where reliability is best.

Reliability theory likely explains the impact of SE to AA in a similar fashion. SE is intended to correct supportability deficiencies. The findings suggest that it takes approximately 33 months for an SE initiative to begin and for the field to implement identified corrections. These corrections could come in the form of changes in procedures in the depot. The F-15C/D fleet size is 284 (as of Jan 2020) (LIMS-EV, 2020), F-15C/Ds are expected to be overhauled on a constant 6-year cycle (Keating & Loredo, 2006). If it was assumed that F-15C/D depot production is steady, this would indicate that those infrastructure corrections would be applied to roughly 47 aircraft a year. Assuming those corrections improve reliability in some way, it is not unreasonable to see an improvement in AA in just the first year of SE improvements.

RQ 3: What impact does each WSS activity have on AA?

In order to answer this, the reciprocal of each WSS variable is taken. This is done to find the obligation value needed to improve AA by 1%. Those values are calculated and provided in Table (10) below.

Table 10: Obligations needed to gain 1% in AA by WSS variable

Variable	Point Estimate
TO	$2,141,327.62
SE	$8,000,000.00
CLS	$12,210,012.21
DPEM	$36,630,036.63

Significance of the Research

Finally, this model is different than any other research. No other research found used lags to determine the lead time needed for the USAF to realize statistically positive relationships to AA. Additionally, this research created a foundation for analyzing WSS effects on AA for other airframes. This improvement in WSS analysis could lead to better decision making in the $16 Billion dollar and growing WSS portfolio. Furthermore, it paves the way for future research to continue to find effective remedies to the negative AA trend. What is important to note, is that this is an explanatory model. It does not indicate that the found relationships are optimal. Because the data used is limited to the sampled data of monthly obligations to F-15C/D WSS activities it is difficult to surmise how AA would be impacted by values outside the sampled time period.

Recommendations

The process of cleaning and preparing the data to model the effect of WSS on AA was incredibly arduous. The USAF needs to continue to improve data collection intervals and the overall quality of the data. Furthermore, the USAF should consider the importance of consistency in budget execution, swings in budgetary actions make it difficult to isolate those factors that most impact AA.

Future Research

This model paves the way for several valuable future research outlets. First, how would this model change in the presence of active vs. guard aircraft. Secondly, The USAF is procuring more F-15s, how will new F-15s in the USAF inventory impact the way WSS influences F-15C/D AA? Furthermore, how does WSS effect different Weapon Systems? How does WSS effect different Weapon System Categories. Further research is needed in DPEM’s impact to reliability as well as SE’s impact to reliability. Finally, future research should consider how WSS specifically effects aircraft at the unit level by monitoring the reliability, availability and maintainability of aircraft at the unit level.

Appendix

Appendix A Table of Variables

Term /Abbreviation	Meaning
A/B/M	Area Base Manufacture
A	Number of Aircraft required for Alert Status
a	Attrition rate (expected rate of mission losses for a given year
A_0	Operational Availability
AA	Aircraft Availability
Aah	Historical Aircraft Availability
AA_{std}	Aircraft Availability Standard
ACF/PACF	Auto Correlation Function / Partial Auto Correlation Function
HQ AF/A3O	Air Force Division for Current Operations
AFMC/A4	Air Force Materiel Command Directorate for Logistics, Engineering and Force Protection
A_i	Inherent Availability
ALC	Air Logistics Complex
AR	Auto Regressive Function
BP	Bruesch-Pagan Test for Non Constant Variance
BY	Base Year
CAFDEx	Centralized Access for Data Exchange
CAM	Centralized Asset Management
CBO	Congressional Budget Office
CFR	Constant Failure Rate
CLS	Contractor Logistics Support
CSA	Critical Skills Availability
CV	Control Variable
CY	Calendar Year
Depot %	Depot Possession Rate (Hours aircraft possessed by Depot / Total Aircraft Inventory Hours)
DFR	Decreasing Failure Rate
DPEM	Depot Purchased Equipment Maintenance
DV	Dependent Variable
DW	Durbin-Watson Test for first order Auto Correlation
EEIC	Element of Expense Investment Code
F_{do}	Days available to fly during a given Fiscal Year
F_{dt}	Contingency and training flying days
FHP	Flying Hour Program
FSE	Flying Schedule Effectiveness

FY	Fiscal Year
FYDP	Future Year Defense Plan
G	number of required aircraft required for executing ground training
GAO	Government Accountability Office (formerly known as the Government Accounting Office)
HQ AF/A4LM	Air Force Division for Maintenance
HQ AF/A4P	Air Force Resource Division
IFR	Increasing Failure Rate
IV	Independent Variable
LIMS-EV	Logistics Information Management System – Enterprise View
MC	Mission Capable
MDT	Mean Down Time
MTBF	Mean Time Between Failure
MTBM	Mean Time Between Maintenance
MTTR	Mean Time To Repair
NMC	Non Mission Capable
NMC	Non Mission Capable
OLS	Ordinary Least Squares
OPT	Operational Tempo
OR	Operational Requirement
PDM	Programmed Depot Maintenance
PM	Program Management; Program Manager
R:	Number of Aircraft required to meet reserve/guard units flying requirements who fly active unit possessed aircraft
S:	Number of required Spare Aircraft
SE	Sustainment Engineering
S_o:	Sorties needed to complete all aircrew contingency training
S_t	Number of sorties required to complete training mission requirements
SW	Shapiro-Wilkes Test for Normality
TAI	Total Aircraft Inventory
TNMCM	Total Non-Mission Capable due to Maintenance
TO	Technical Orders
TRA	Training Resources Availability
T_u	Turn Rate (total sorties / flying period)
UPNR	Unit Possessed Not Reported
VIF	Variance Inflation Factor
WSS	Weapon System Sustainment

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14. ABSTRACT

This research focused on understanding the phenomena behind the cost growth of Weapon System Sustainment (WSS) and the simultaneous degradation in system availability for USAF aircraft. The primary modeling technique used was Ordinary Least Squares (OLS) while incorporating temporal effect. While other studies have looked at cost factors related to the Flying Hour Program and age. This study found empirical relationships between each of the four WSS business processes and the lead time in months it takes to realize improvements in system aircraft availability.

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