DISSERTATION

LEVERAGING OPERATIONAL USE DATA TO INFORM THE SYSTEMS ENGINEERING PROCESS OF FIELDED AEROSPACE DEFENSE SYSTEMS

Submitted by

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In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Summer 2023

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ABSTRACT

LEVERAGING OPERATIONAL USE DATA TO INFORM THE SYSTEMS ENGINEERING PROCESS OF FIELDED AEROSPACE DEFENSE SYSTEMS

Inefficiencies in Department of Defense (DoD) Acquisition processes have been pervasive nearly as long as the DoD has existed. Stakeholder communication issues, funding concerns, large and overly complex organizational structures all play a role in adding challenges to those tasked with fielding, operating, and sustaining a complex aerospace defense system. As legacy defense systems begin to age, logistics and other supportability element requirements may change over time. While research literature supports the evidence that many stakeholders and senior leaders are aware of the issues and the DoD faces the impact those issues cause to mission performance, most research and attempts to improve the performance issues have been focused on high level restructuring of organizations or policy, processes, and procedures. There has been little research dedicated to identifying ways for working level logisticians and systems engineers to improve performance by leveraging operational use data.

This study proposes a practical approach for working level logisticians and engineers to identify relationships between operational use data and supply performance data. This research focuses on linking negative aircraft events (discrepancies) to the supply events (requisitions) that result in downtime. This approach utilizes standard statistical methods to analyze operations, maintenance, and supply data collected during the Operations and Sustainment (O&S) phase of the life cycle.

Further, this research identifies methods consistent with industry systems engineering practices to create new feedback loops to better inform the systems engineering life cycle management process, update requirements, and iterate the design of the enterprise system as a holistic entity that includes the physical product and its supportability elements such as

logistics, maintenance, facilities, etc. The method identifies specific recommendations and actions for working level logisticians and systems engineers to prevent future downtime. The method is practical for the existing DoD organizational structure, and uses current DoD processes, all without increasing manpower or other resource needs.

ACKNOWLEDGEMENTS

I would like to thank Dr. Jeremy Daily and the rest of the dissertation committee, Dr. Gregory Marzolf, Dr. Erika Miller, and Dr. Daniel Wise for their support throughout this research project. I would also like to thank technical experts Mr. Russell Alford, Mr. Eric Jones, Mrs. Molly Statham, and Mr. William "Scott" Wrigley who provided the critical expertise on Air Force Life Cycle Management at the heart of this research. They are the best teachers, career guides, and mentors I have ever met. They have instilled in me the desire to improve upon the work we do as Air Force civilians and, more importantly, the world we live in. Finally, I'd like to thank my family for having patience throughout this process. I would not have had the energy, time, or resources to attempt this endeavor without the support of my husband Carl. And despite all our "stakeholder disconnects", he is my most critical "support element" in the "enterprise system" that is our life.

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Chapter 1 - Introduction

The United States (US) Department of Defense (DoD) is well known for keeping systems in service for considerable periods of time. For the US Air Force (USAF), fleets of aircraft models may be in service for decades, a considerable length of time for such highly complex systems faced with operating in challenging environments [1]. Methods for incorporating systems engineering processes into life cycle management strategies for aging systems like these are vital for continued system performance. This dissertation will analyze methods to improve the performance of fielded aerospace defense systems by utilizing data collected in the operational use phase of the life cycle to inform the continuous systems engineering processes responsible for maintaining system performance.

1.1 Background

Aerospace defense systems tend to be large, complex, and involve many different stakeholders throughout their life cycles. Changing battle environments, a large and often varied pool of stakeholders, inadequate sustainment strategies, and the often observed occurrence of long lead times spurred the DoD to focus on long term total life cycle management policies in its on-going battles to effectively acquire and operate defense systems [2]. The DoD continuously functions in an ever-changing battle environment with far-reaching operations spanning every continent around the globe. The disruptions to operations can be difficult to predict, and the USAF must determine ways to maintain its standards of performance across all its systems.

1.2 Problem Description

One of the most glaringly obvious defects in the current DoD life cycle management methodology is a lack of executable feedback loops in most of its systems engineering processes, particularly as they relate to monitoring the impacts on system performance from non-physical attributes of the system. Feedback loops help ensure communication for ongoing learning and decision making throughout a system's life cycle [3]. Since supportability elements such as logistics, training, facilities, and support equipment are managed, maintained, and operated by a variety of different stakeholders; connecting these critical elements to their impact on overall system performance can become challenging. While there are many laws, policy guides, and handbooks that target data collection and storage, USAF life cycle feedback loops are discussed as theoretical concepts at best, or inflexible data reporting at worst.

Actionable feedback in the form of recommendations or processes for monitoring, collecting, analyzing, and distributing operational use data with the intent to iterate and inform the systems engineering and life cycle management processes are almost non-existent. To maintain overall system performance, all supportability elements related to system operations must also maintain performance standards, particularly as it relates to supportability elements outside of the physical product. In particular, supply and logistics performance has a major impact on overall system performance, despite being external to the physical system design. According to a report from the Government Accountability Office (GAO), failure to meet performance goals can be attributed to logistical factors [4]. *If supportability elements fail due to changes in the system or environment, appropriate feedback data must be incorporated into the systems engineering life cycle process to adequately adjust overall system design to accommodate the changes impacting performance.*

Since systems and their environment change over time, the lack of feedback data that identifies issues with the current system is a significant issue that must be addressed for successful life cycle management and performance. Particularly for aging enterprise systems, feedback data loops that facilitate systems engineering processes and support total life cycle management should be clear and well defined. Given the large footprint of the enterprise system that is required to support USAF aircraft fleets, the lack of clearly defined feedback loops may impede the ability to successfully iterate enterprise system designs to allow successful sustainment throughout the life cycle of an enterprise system.

1.3 Need for a Solution

There are many documented issues with the current USAF approach to systems engineering life cycle management with primary drivers being poor performance of fielded systems and increasing cost concerns. The interest from leaders to resolve life cycle management issues generally stems from their desire to fund, develop, and field enterprise systems more quickly. Research indicates that this has been an on-going issue, spanning over the last several decades.

A 1985 report indicated that long lead times were due to failure to consider for human factors, manpower, personnel, and training in the weapon system acquisition process [5]. This issue has been attributed to various root causes over the last decade, with few published resolutions for identified problems, particularly as they relate to end-of-life performance issues for USAF fleets. Government Accountability Office (GA) reports, Congressional briefing transcripts, and the successive changes to military policy all indicate senior leaders in the government and military are aware of the problem facing life cycle management in the DoD and have been trying for years to fix it [6], [7], [8], [9], [10], [11]. Clearly, there is a problem with successful execution of life cycle management for DoD aerospace defense systems.

Issues with a lack of feedback loops or an inability to successfully execute life cycle management and systems engineering processes may not appear significant at first glance. But reports indicate that this issue causes impacts to mission due to increased costs and resource requirements and, more importantly, results in decreased performance. As of 2019, only three of forty-six aircraft met their annual mission capable goals at least 50% of the time [7], [12]. Given the continued increase in costs ([13], [14]) for Operation and Sustainment of legacy aircraft and the increasing lead times to procure and field new aircraft, a solution for better management of the late phases of the systems engineering life cycle are required.

1.3.1 Performance Impacts

One major theme in analysis of DoD acquisition issues is the suitability of appropriate process and policy to support life cycle management. By the early 1990's, senior Air Force officials were already recognizing that lack of focus on a long-term strategic goal could be a detriment to DoD priorities [15]. This lack of focus on strategic operations, combined with changing battlefield needs and developing technology, have contributed to a cycle of ever-changing process and policy guidance. As early as the 1960's, experts cautioned that much of public policy is not subject to any sort of quantitative analysis and that the systems approach may never be a purely rational, objective scientific aid to decision making [16]. The report went on to say that any recommendations for systems engineering processes must be possible to implement or they hold little value to the Department.

Despite this assertion, the continuous march of attempts to fix the policy guidance seems to have continued. A 1998 report contains implementation plans to streamline the acquisition workforce, organization, and infrastructure in addition to a re-engineering of the product support process [17]. As is the case with many large organizations, the USAF has challenges that result in separation of stakeholders which can impede communication of critical information that impacts overall system performance. The DoD is organizationally (chain of command), functionally (engineering, logistics, etc.), and geographically separated with operations that span the globe [11], [15], [18], [19].

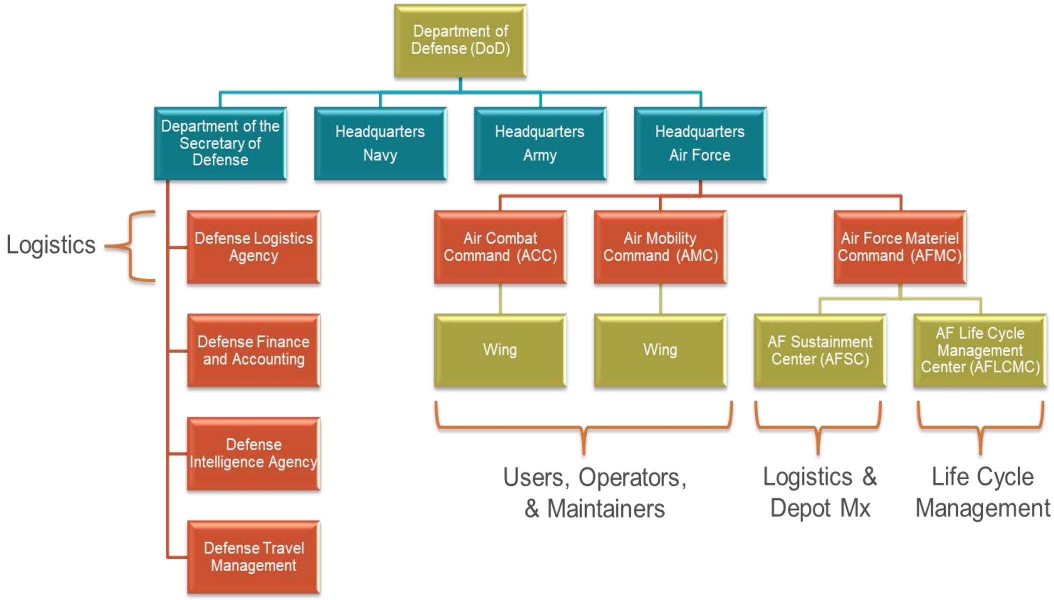


Figure 1: Notional DoD Organizational Structure Illustrating Organizational Separation

» 00 ALL PUBLICATIONS
» 01 Air Force Culture
» 10 Operations
» 11 Flying Operations
» 13 Nuclear, Space, Missile, Command and Con...
» 14 Intelligence
» 15 Weather
» 16 Operations Support
» 17 Cyberspace
» 20 Logistics
» 21 Maintenance
» 23 Materiel Management
» 24 Transportation
» 25 Logistics Staff
» 31 Security
» 32 Civil Engineering
» 33 Communications and Information
» 34 Services
» 35 Public Affairs
» 36 Personnel
» 38 Manpower And Organization
» 40 Medical Command
» 41 Health Services
» 44 Medical
» 46 Nursing
» 47 Dental
» 48 Aerospace Medicine
» 51 Law
» 52 Chaplain
» 60 Standardization
» 61 Scientific/Research And Development
» 62 Developmental Engineering
» 63 Acquisition
» 64 Contracting
» 65 Financial Management
» 71 Special Investigations
» 84 History
» 90 Special Management
» 91 Safety
» 99 Test And Evaluation

Figure 2: Screenshot of USAF Policy Guidance Illustrating Functional Separation [20]

In 2000, the Director of Defense Management Issues stated that various efforts for reengineering life cycle management and logistics management processes were incomplete and may not provide improved service and lower costs to the Department, and had taken steps towards reengineering its logistics processes but that the aspects of the plan were incomplete [6]. Problems with the plan included lack of controlled objectives making it difficult to link results to savings, lack of fully developed test plans, and lack of funding. In 2003 the GAO stated that the DoD needed a clear and defined process for setting Aircraft Availability (AA) goals, and that performance issues were "caused by a complex combination of logistical and operational factors" [4]. And in 2005, the DoD established a Parts Management Reengineering Working Group which found that poor logistics planning and standardization in the early phases of life cycle management led to poor operational reliability and availability after fielding [21].

By the mid-2010's, a focus on total life cycle management was beginning to form. In 2014, a study was accomplished on the previous 10-years of Defense acquisition history. This study asserted that post-September 11, 2001 DoD leadership acknowledged that the defense community was not where it needed to be, and "product support planning too often failed to occur in a timely manner, long-term sustainment execution skills were deemed inadequate and, although long espoused, a true focus on total life-cycle systems management was lacking" [2]. The impact that logistics and supply have on the performance of weapon systems was becoming clear.

The consensus of DoD, GAO, and Congressional reports during this timeframe confirmed that the life cycle management process for DoD enterprise systems did not achieve the primary goal of reducing costs, reducing time to fielding, or providing other benefits to the DoD and that much of this poor performance could be related to supply or logistics issues. Clearly, the need to have an efficient, standardized process had been identified, but the Department struggled with defining a new process and putting it into practice. When combined and considered as a complete history, these reports illustrate that senior DoD officials have been trying to resolve the life cycle management issue for decades. Yet costs continue to increase, and performance remains short of Department goals.

1.4 Goals, Research Questions, and Contributions

The broad goal of this research is to determine whether systems engineers can leverage existing operational use data from fielded aerospace defense systems as data for feedback loops to inform the iterative life cycle management process in the operational and sustainment phase of currently fielded USAF aircraft fleets. Given the large research area this goal covers, this research is further scoped to focus on those factors related to supply and logistics performance impacts on the weapon system. Furthermore, the research will be scoped to identify actionable strategies that systems engineers at the working level can individually implement given the current policy and guidance.

1.4.1 Statement of Research Questions

To accomplish the goals outlined in the previous section, research questions were identified. The specific research questions for this report are as follows:

- What existing ***operational data*** can be leveraged as feedback to assess or improve performance of fielded systems?
- What is a ***process framework*** for identifying applications of operational and logistics data for performance improvements?
- What ***performance improvements*** to fielded systems can be realized by utilizing the operational data and process framework?

It is hypothesized that a link exists between USAF operational and maintenance data and logistics performance data; and that proper analysis and review of this data can be leveraged to positively influence system performance. The expectation is that this research will contribute a set of specific recommendations or methods that working level systems engineers and logisticians in the USAF can use to improve system performance. Research will determine what factors, if any, have impact on supply performance rates and what actions systems engineers can take to provide feedback to logistics stakeholders to positively influence enterprise system performance.

1.4.2 Contributions

The research contained herein will provide several contributions to the body of knowledge of systems engineering to improve upon existing processes related to life cycle management of complex aerospace defense systems. This research provides a useful model for aircraft systems engineering processes tailored to the operations and sustainment phase of life cycle management. The model connects the traditional systems engineering Vee-model with a continuous improvement loop to illustrate the criticality feedback loops amongst stakeholders. The research also provides a new link between operational data and aircraft downtime, linking USAF operational data to logistics performance measures. An innovative method to prioritize which subsystems to analyze now that a new data link has been established. This method allows systems engineers to work within the existing constraints of manpower, time, and other resources. Finally, this research demonstrates a novel ability to update logistics requirements by utilizing the newly identified data link between operational and logistics metrics. This method connects stakeholders to each other and to the data, resulting in actions that will update requirements.

1.4.3 Assumptions / Limitations

This research will be accomplished utilizing the existing USAF regulations and operating instructions that dictate how operational, maintenance, and logistics data is collected, stored, and used. The data pulled from official repositories is assumed to be correct and complete. This research will not attempt to prove or disprove that the metrics collected or analyzed as required by regulation are the correct or best data to collect and analyze. Additionally, while the links and correlations between field data and logistics performance will be investigated, it is not the intent of this research to create a model to predict performance or to recommend changes to existing policy. The goal of this research is to work within the existing DoD and USAF organizational policy and process framework by leveraging existing data collection systems, manpower, funding, and other resources to create actionable recommendations for feedback data to positively influence overall enterprise system performance by resolving specific parts issues at the lowest working level.

1.4.4 Definition of Terms

There is no single agreed upon definition of a system. The Institute of Electrical and Electronics Engineers (IEEE) defines a system as "a combination of interacting elements organized to achieve one or more stated purposes" [22]. The International Council on Systems Engineering (INCOSE) defines a system as "a system is a purposeful whole that consists of interacting parts" [3]. Blanchard and Fabrycky define a system as "an assemblage or combination of functionally related elements or parts forming a unitary whole", and that not every combination of parts, methods, or procedures is considered a system. These authors further state that systems are made of components (the parts of a system), attributes (properties such as characteristics, configuration, qualities, power, constraints, and state, and relationships (which link components to other components) [23].

For the purposes of this paper, when discussing an aerospace defense system, the term "enterprise system" will be used. An enterprise system is defined herein as a collection of resources comprising the manufacturing, operations, maintenance, and logistics capabilities that participate in the systems engineering life cycle to include the people, products, and processes that support the system. The term "enterprise" was chosen, in lieu of the standard "system" or "system of systems", to highlight the complexity of all the various capabilities and resources required when continuing to operate and sustain aging legacy aerospace defense systems. The term “enterprise” is used to focus the reader on the concept that a system is more than just its physical software or hardware component parts, but instead includes all the people and capabilities necessary to sustain that system for the entirety of its lifecycle. It is important to note that these capabilities may also be considered systems in their own right. The term “supportability elements” will be used to describe all of the factors, systems, knowledge, and other resources that play a role in the performance of the aircraft system but aren’t part of the actual hardware or software of the configured end-item.

Chapter 2 - Literature Review and Existing Methods

To identify a methodical approach to resolution of the issue identified in Chapter 1, an investigation of relevant U.S. law, DoD and USAF policy documentation, and independent research regarding DoD system performance was accomplished.

2.1 USAF System Enterprise Metrics

Since the purpose of this research is to ultimately identify feedback loops that help exploit early warning signs of issues to prevent negative performance impacts, it is prudent to first review how the USAF measures performance. The primary means of measuring aerospace defense enterprise systems for aircraft are two metrics: Aircraft Availability (AA) and Mission Capability (MC). The AA and MC rates for an aircraft are the primary measure used by the DoD to determine an aircraft's long-term performance and are the preferred statistic used to determine the operational readiness in the USAF fleet [24][25]. The Air Force reports on its standard targets for both AA and MC, which vary by aircraft type called a mission design series (MDS) [26]. But AA and MC metrics have been declining over the past decade, and the operational performance of MDS's with them [12].

$$Aircraft\ Availability\ (AA)\ Rate\ = \frac{Mission\ Capable\ Hours}{Total\ Aircraft\ Inventory\ Hours} \times\ 100\ \%$$

Equation 1: Aircraft Availability

$$Mission\ Capable\ (MC)\ Rate = \frac{(Fully\ Mission\ Capable\ \ + Partially\ Mission\ Capable\ Hours)}{Posessed\ Hours} \times 100\%$$

Equation 2: Mission Capability

At the basic level, AA rates are a percentage of the time aircraft are available to accomplish the mission, compared to the total number of hours available to all aircraft in the fleet in a year. AA rates are a measure of how many aircraft are ready to fly, regardless of the reason they may be down, be it scheduled or unscheduled maintenance. Similarly, MC rates are the percentage of time aircraft are available at the unit level compared to the total number of hours in possession of the operational unit. Unlike AA, MC rates exclude aircraft scheduled to be down for heavy depot maintenance activities and only include aircraft inventory hours of the aircraft possessed by operational units.

MC rates are a good indicator of operational readiness at the unit level. Aircraft in possession of operational units are expected to fly missions, whether they are scheduled months or mere minutes in advance. Meanwhile, AA rates are an indicator of the health of the fleet, and a fleet's holistic operational readiness. The issue is that neither AA or MC provides insight into factors that prevent aircraft from being mission ready [27]. To truly understand these metrics, it is vital that the various components that make-up the metrics are understood.

There are two types of metrics related to aircraft maintenance and operational performance: lagging and leading. Lagging indicators show firmly established trends, and typically do not correlate to a specific event such as an aborted mission or backordered part. Rather, lagging indicators are used to help senior leaders accomplish an "apples to apples" comparison amongst different aircraft model types and performance standards. Leading indicators typically show problems with aircraft performance immediately, with no time lag between the negative event, such as an aborted mission or backordered part, and serve as early warnings to problems that may escalate over time. Leading indicators are a direct reflection of the operational unit's ability to execute its mission [28].

According to Rainey, "Leading indicators are those that directly impact maintenance's capability to provide resources to execute the mission. Lagging indicators show firmly established trends" [25]. Leading indicators generally are the first indicator of a problem or issue, and lagging indicators show the trends over time. Since the cornerstones of aircraft maintenance are Aircraft Availability (AA) and Mission Capable (MC) rates, metrics related to those areas are prime candidates to include as the performance indicator variable serving as the dependent variable.

Leading indicators include metrics such as failures, break rates, ground aborts, air aborts, flying schedule effectiveness, mission deviations, and other similar metrics. It should be noted that many texts and research regarding statistical methods related to prediction models and regression techniques warn against data mining, or selecting variables because they are "easy" to analyze. Therefore, the metrics will be reviewed prior to formal statistical analyses to determine which can be reasonably identified as a determining factor in the output variable.

2.2 Evolution of Systems Engineering in the DoD

Complex systems have existed almost since the beginning of recorded history. The Great Pyramid of Giza, Hanging Gardens of Babylon, Roman aqueducts, and other ancient wonders were either created by complex construction systems or are considered complex systems themselves. Schlager writes that "the first need for systems engineering was felt when it was discovered that satisfactory components do not necessarily combine to produce a satisfactory system" [29]. As systems become more complex, the need for systems engineering is more easily recognized.

This is particularly true for the aerospace defense industry. According to INCOSE, one of the key milestones for the modern origin of systems engineering dates back to the mid-1930's with the analysis of a British air defense system [3]. The complexity of aerospace defense systems and the modern need for documented systems engineering processes have developed together over the last several decades. Many systems engineering methods and processes were created in direct response to the need to manage complexity and change [3].

In the DoD, systems engineering policy guidance has similarly evolved over the past several decades. This evolution began as a concentrated effort by the DoD in the mid-1980's when it established the DoD Under Secretary for Acquisition with a focus on developing better life cycle management strategies [30]. The US had seen a significant increase in the time, effort, and cost to deploy new enterprise systems than in previous decades, and the slowdowns were occurring at a time when technological development was changing rapidly [31].

Systems engineering as a function, or even a career field, came as the result of the Defense Acquisition Workforce Improvement Act (DAWIA) of 1990. Soon after incorporation of DAWIA into law, Defense Acquisition University (DAU) was established and competency-based training was required for what the DoD termed "acquisition professionals [30]. Systems engineering was a key topic of training and education for senior technical personnel. Early versions of DoD training identified systems engineering as "consisting of two distinct disciplines: the technical knowledge domain in which the systems engineer operates, and systems engineering management" [32].

Regardless of commercial industry or aerospace defense sector, most scholars agree that systems engineering is required to successfully translate a user's needs into a definition of a system to build the final product. While the exact execution strategy may depend on company or industry, and has certainly evolved over time, a successful systems engineering strategy is required to ensure complex systems and products are successful.

Most commercial industries agree that life cycle management was first developed to reduce the total cost ownership of complex systems. Additionally, studies have shown that "a significant part of the system is characterized by a high intensity of changes based on the changing functional requirements of the customer's stakeholders" [33]. In other words, systems change as they progress along their natural life cycle and our systems engineering processes need to accommodate those changes to ensure successful life cycle management throughout the entirety of the system's existence. If designers can ever hope to manage life cycle costs, systems engineers must actively manage the requirements of the system. The study of this topic has produced several different methods and models to assist with successful execution of systems engineering processes during the life cycle of a product or enterprise system.

2.2.1 Waterfall Model

The Waterfall model was originally used for software development and was developed by Royce in the 1970's [3]. It gets its name from its sequential development process in which a project "flows" through a series of steps, phases, or stages. The Waterfall model is a very linear process, with each life cycle stage sequentially following the previous stage.

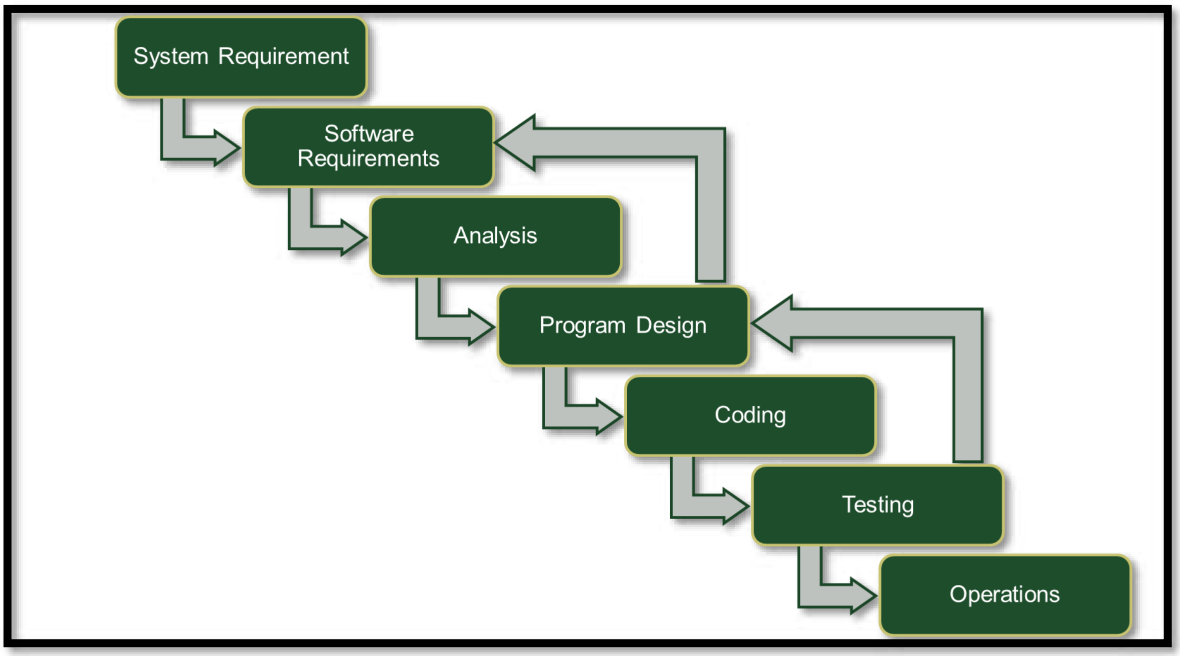


Figure 3: Waterfall Model for Software Development

Depending on the industry or author, the model usually contains between five to eight steps in a series of phased activities [23]. Since the process is very linear, functionally there is minimal focus on iterating the process to refine the final product. Feedback and feedback loops are discussed as a concept, but very little in either the graphical models or the text discussion provides actionable steps to assist with collecting feedback and incorporating it into the process. The Waterfall method in particular, based on its graphical representation, significantly contributes to the misconception that systems engineering is a single pass through the life cycle management model or, at best, a method that's iterations cease once the system reaches its operational phase.

There is priceless information, data, and system insight that should be exchanged between life cycle stages in order to ensure adequate system and requirements definition across the enterprise system [3]. One of the top ten assumptions of systems engineering is that traditional systems engineering is a sequential approach [34]. But the purpose of feedback is to help facilitate the flow of data between the sequential stages of the process. Clearly, this indicates the process is not unidirectional, as most sequential models illustrate.

The DoD adopted the waterfall method soon after it was developed. However, it was quickly apparent that the waterfall process model could easily fall victim to the pitfalls of complex organizational structures and complex technology. The DoD was particularly hindered by a culture and acquisition policy that favored "large programs, high-level oversight, and a very deliberate, serial approach" [35]. This inhibited the DoD's ability to quickly develop and field systems, particularly as they related to complex products. The waterfall method's lack of iteration, to provide feedback from later stages throughout the life cycle of the system offers a significant deficiency in DoD life cycle management and was soon dropped as the preferred method of DoD acquisition.

2.2.2 Spiral Model

The Spiral system process model was developed in the mid-1980's by Boehm to introduce a risk-driven approach into the project development process [23]. The DoD implementation came about in the early 2000's, as a way to attempt to manage the ever increasing costs of weapon system management [36]. The spiral model has similar phases to the more linear waterfall method but incorporates the use of feedback with iterative loops. The draw to the spiral model was that the incremental requirements allowed project managers to mitigate uncertainties in long-range requirements, mitigate uncertainties in funding, and incorporate evolutionary technology (which is always developing) at later stages of the program [37]. Customers could refine their requirements iteratively through product development, and features could be released in phases.

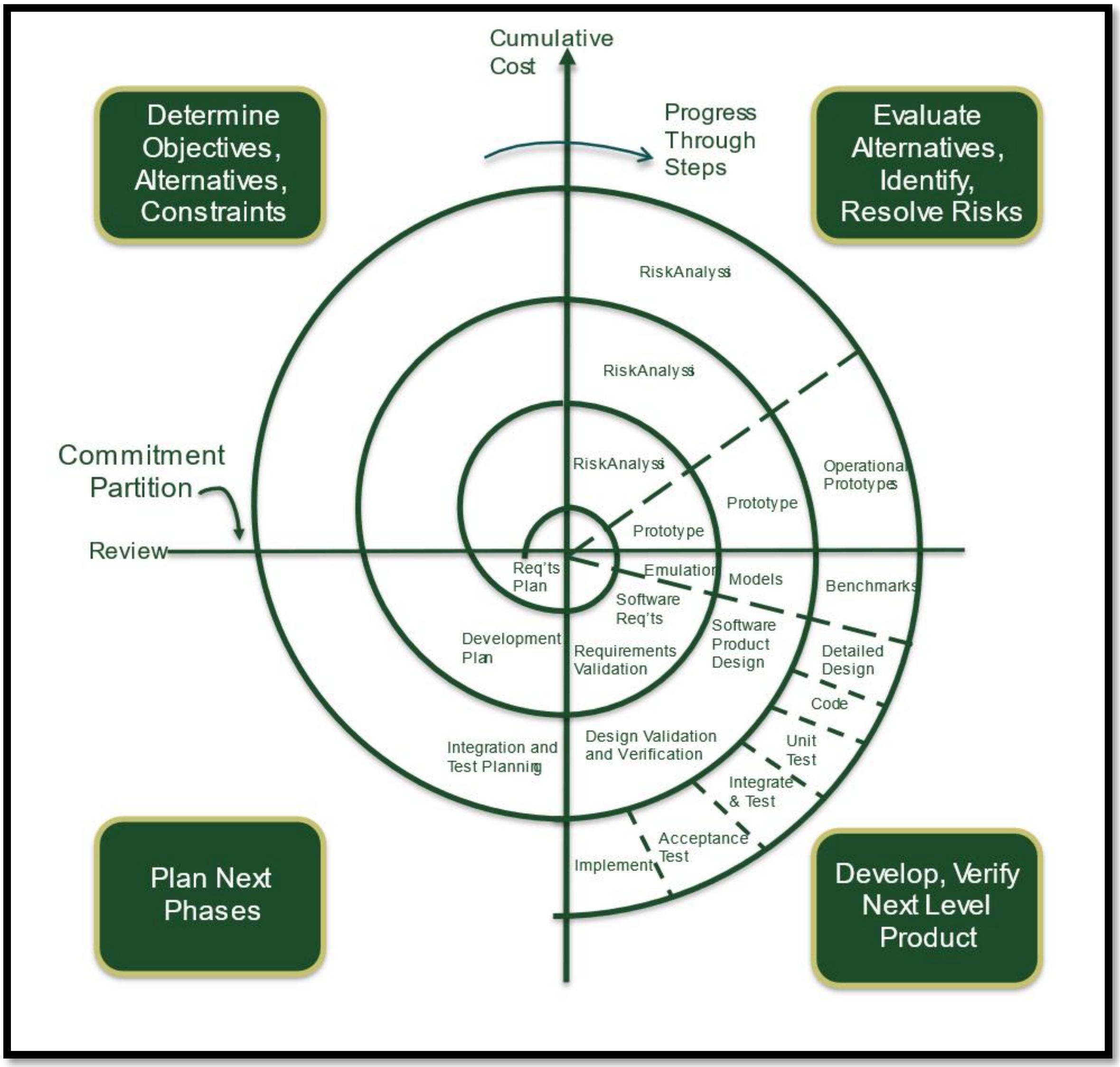


Figure 4: Spiral Model

However, users of this model quickly realized that there were serious pitfalls in its execution, and the spiral method was not necessarily useful for all types of projects. Communication and feedback must be continuous, the logistics community must buy into having multiple configurations in the field, and the user must be able to accept fielding a less capable solution in the beginning of the project [38]. The DoD, with its large logistics community and rigid policies and processes regarding procurement of spare parts, modified technology, and other resources struggled to successfully implement the spiral methodology. Ultimately, the DoD moved away from spiral acquisition and termed it the “death spiral” of acquisition methods [8], [36], [38].

2.2.3 Vee Model

The Vee process model was developed by Forsberg and Mooz and has similar sequences and phases as the waterfall method.

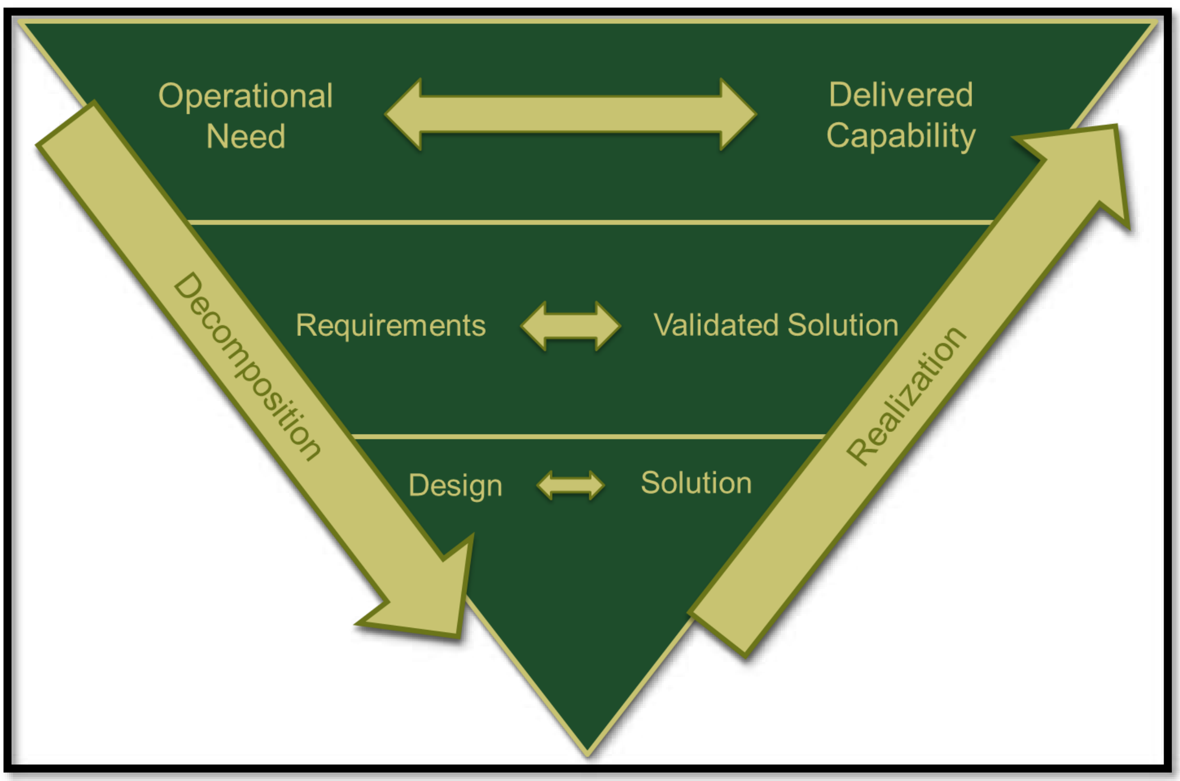


Figure 5: DoD Vee Model

The difference is that the phases are broken out into two sides of a Vee: Decomposition and Definition along the left hand side, and Integration and Verification along the right hand side

[39]. The Vee model is the most common form of systems engineering life cycle management and is widely used today. Variations on the Vee model have also been developed.

For example, the German Association of Engineers developed a Vee-model with an additional phase in the middle. The three phases are decomposition on the left of the Vee, domain-specific design processes in the middle of the Vee, and verification/validation on the right hand side of the vee [40]. Subsequent changes and updates have occurred over the years [41], but the Vee-model has remained true to its core purpose, which was to define the interactions between the early and later stages of the life cycle model. The Vee model does a much better job of illustrating the connections between the various life cycle management phases. But it still fails to fully integrate the concept of feedback loops as actionable steps in the process.

2.3 DoD Life Cycle Management Related Performance Issues

Life Cycle Management (LCM) is the active engagement of all stakeholders of a system between the time it begins to operate until it is decommissioned and removed from use [42]. The idea of life cycle management, or product life cycle management, is not a new concept for the DoD. Incorporating logistics considerations into the design process with the intent of reducing cost over the life of an entire system has been around in some form of official policy since 1964 [43]. More recently, life cycle management has been the focus of many DoD initiatives since the late 1990's. As policy evolved, the DoD attempted to define life cycle management with the goal of focusing on the total cost ownership to provide and support high quality goods and services required by the warfighter [17]. The approach to successful life cycle management in the DoD has changed over time, and the DoD and its sub-organizations have accumulated a multitude of policy, regulation, and guidance information for assist systems engineers with life cycle management tasks.

The DoD has created its own unique process to fit the needs of defense acquisitions. Life cycle management and product support are Congressionally mandated and required by law. This method utilizes a milestone based life cycle management process, specific to the DoD, complete with training provided by Defense Acquisition University (DAU) which was created for the sole purpose of educating the DoD acquisition and life cycle management workforce [44].

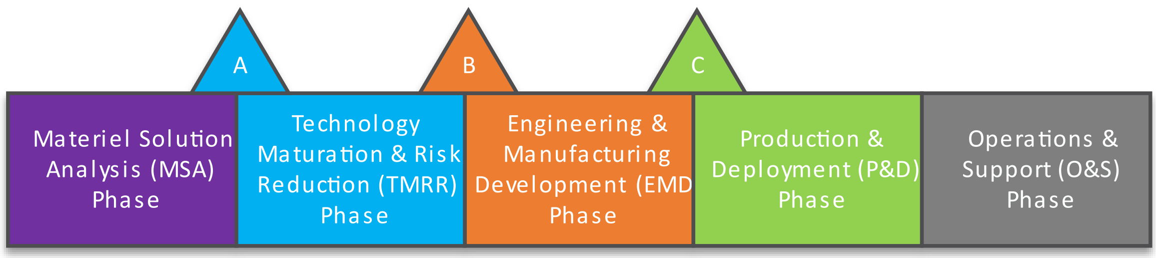


Figure 6: DoD Lifecycle Milestone Chart

The DoD defines the life cycle of a system using the term “cradle to grave” terms which includes the development, procurement, operation, support, and disposal phases of life cycle management [6]. DAU defines the term life cycle as “All phases of the system's life including research, development, test, and evaluation (RDT&E), production, deployment (inventory), operations and support (O&S), and disposal” [45]. Clearly, there is an understanding that a product’s life cycle is more than just its development and production. But issues arise during the O&S phase when changes to supportability elements and operating environment begin to impact system performance. While there is no physical change to the aircraft system, the enterprise system which facilitates operations of the physical product may experience changes that impact overall system performance.

A better life cycle management model has been refined in recent years that provides a systems engineering approach cyclical approach combined with traditional serial life cycle model phases utilizing the introduction of feedback from each phase or stage to the previous phase or stage. Blanchard and Fabrycky [23] have created an model diagram that best illustrates this concept.

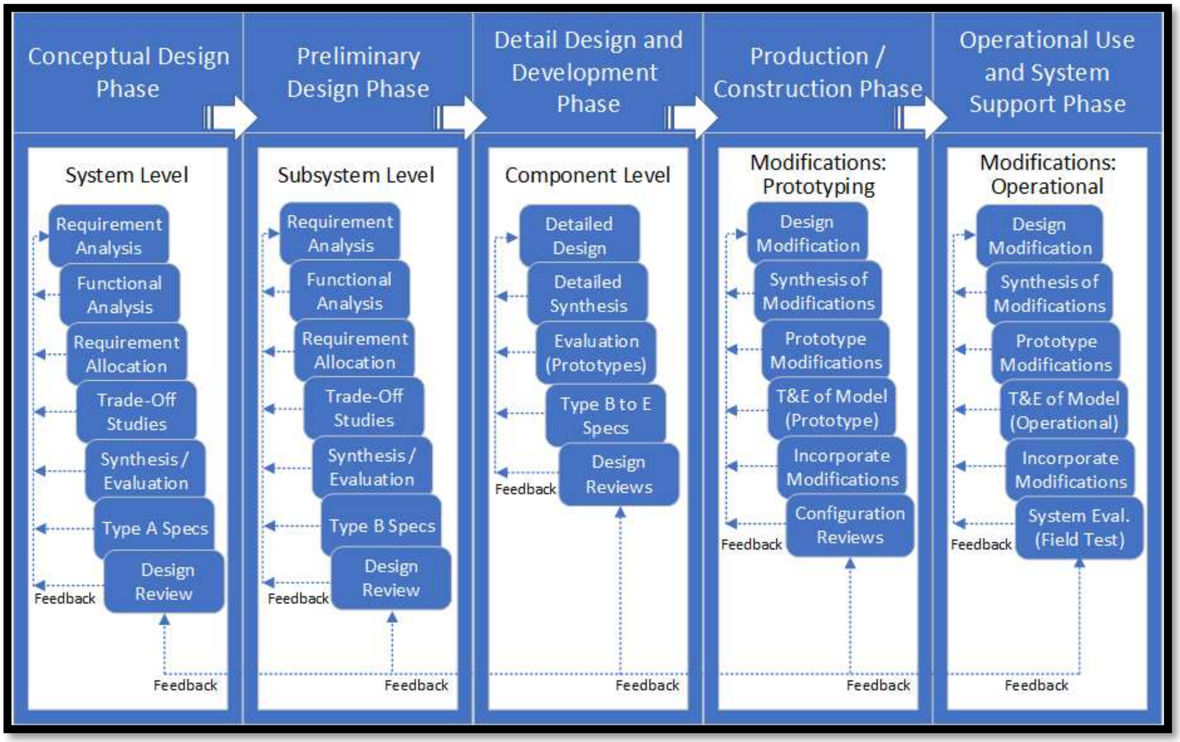


Figure 7: Life Cycle Model with Feedback Loops **[23]**

The USAF's inability to deviate from the DoD prescribed life cycle model, serial in nature, has contributed to the performance issues many complex or enterprise systems face in the later stages of their lifetime. Research regarding DoD and USAF systems engineering and life cycle management policies and processes and the impacts or causes that prevent those policies and processes from being successful are explored in the following sections.

2.3.1   Funding Processes Influence Enterprise System Design

One contributing factor to the neglection of robust feedback loops is the influence of the DoD's funding process on enterprise systems. The DoD's long-standing tradition of focusing on the Material Solution Analysis (MSA) phase and the Engineering & Manufacturing Development (EMD) phases of the life cycle for cost savings measures versus the Operations and

Sustainment (O&S) phase can cause issues in the later phases of the life cycle, primarily due to the way in which major enterprise systems are funded. The term “an act of Congress” literally describes why the focus on development and production gets such high-level media attention: Congress must approve and pass a budget for each specific development of a new enterprise system [46]. Congress achieves this by allocating funds by appropriation category, which dictates what type of work the funds may pay for.

Congress then provides budget authority to the Department of Defense, usually through the annual Defense Appropriations Act, which specifies each appropriation that may be used [47]. New programs in the Research, Development, Testing & Evaluation (RDT&E) phase of the DoD life cycle milestone process get a significant level of scrutiny [48]. DoD programs are funded directly by Congress and appear as line items in their budget [46], [49], [50]. This process for funding programs leads to an uneven level of attention on the procurement and development phases and tends to neglect workload in the O&S phases of the enterprise system life cycle. For example, appropriation category Operations and Maintenance (O&M) 3400 funding is used to pay for civilian salaries, travel, training, maintenance, the procurement of parts and components (aircraft parts and office supplies), and facility operations [49]. When senior military leaders must inform the U.S. Congress on costs, status, and schedules, for new development acquisitions, the life cycle management focus can be disproportionately applied to the early phases of a program. This leads to increased costs and inefficient sustainment methods [51].

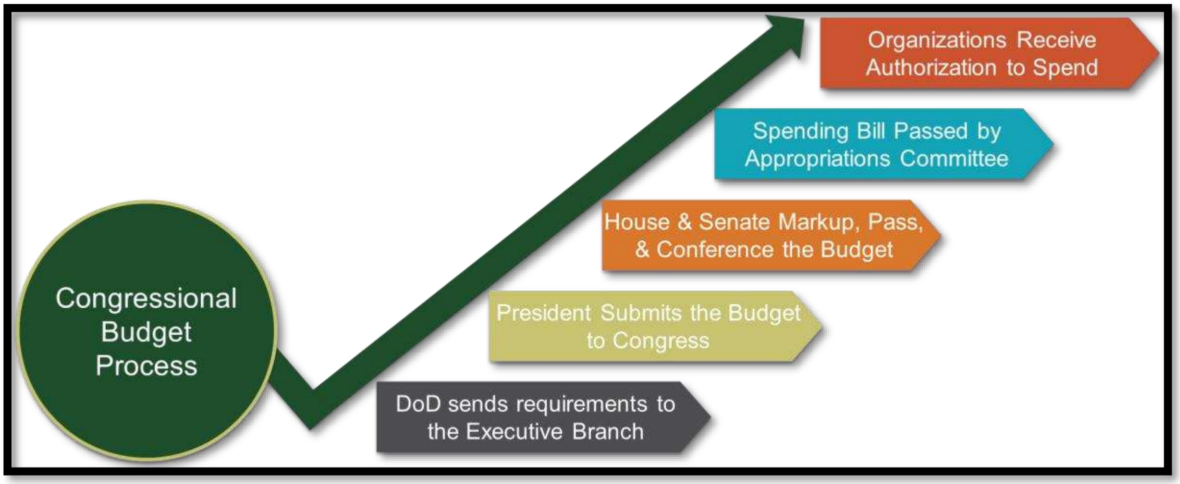


Figure 8: Congressional Budget Process, High Level Overview

Sustainment costs are separate from new procurement and tend to be segmented into several sub-categories and usually appear on reports and budgets as a single line item [46]. There is something of an intangible prestige within the program management and logistics community to be able to point to the Congressional budget's line item of their development program and say, "that's my program". This is simply not attainable for personnel who work on programs in the sustainment phase, due to the nature of the funding protocols. Instead, legacy systems that are already fielded and in use are in the Operations and Maintenance (O&M) category. This category includes costs such as civilian salaries, travel funds, construction projects, training and education, recruiting, depot maintenance, spare parts, and base operations support. [47]. While there are reliability, availability, and maintainability projects included in the O&M funding, they are buried into other categories and do not appear as their own budget line items at a higher level. For example, the budget may be broken out by O&M costs for a specific fighter jet, and even further broken out for sustaining engineering costs, but each specific reliability improvement project will not be listed [46].

By their very nature and lack of glamor, O&M funded projects, which includes the programs in the O&S phase of life cycle management, generally do not get the level of scrutiny and attention that an investment program would receive. In 2010, an article published by the Institute of Electrical and Electronics Engineers (IEEE) Annual Reliability and Maintainability Symposium stated that “one of the major unintended consequences of Acquisition Reform efforts during the 1990s was a reduction in rigor of sustainment planning and effectiveness throughout materiel development programs” [52]. Additionally, a GAO report warned that acquisition professionals should focus on total ownership cost, particularly operating and support costs, as a performance objective for major weapon systems [53]. Similarly, a Defense Science Board task force identified that the single most important step necessary to system performance is a viable systems engineering strategy to include Reliability, Availability, and Maintainability (RAM) programs in the O&S phase [19]. But none of these reports or articles identified specific ways to plan for change in the form of feedback data for critical stakeholders. And while they do highlight why planning for non-physical aspects of the system is critical in the O&S phase, they stop short of recommending a shift of Congressional budgetary focus, and thus the problem persists to this day.

2.3.2 Cost Reduction Strategy Impacts to Performance

The Congressional funding process isn’t the only factor that contributes to the DoD’s focus on the procurement phase of the life cycle. Since the budget process appears to be here to stay, the DoD next turned to making the existing acquisition process more efficient. The nature of the military’s procurement focus started shifting in the early 1990’s with the collapse of the Soviet Union and the end of the Cold War. As a result of the collapse, the DoD identified a need to modernize the armed forces to meet new and modern threats. Given the length of time it takes to successfully fund, design, build, and field an enterprise system, the DoD had to evolve quickly to respond to the new threats of the modern era [54]. One of the ways it accomplished that was to focus the procurement of new systems, particularly the upfront cost and speed at which they could be procured [55], [56]. It certainly makes sense to focus on fielding new systems as quickly as possible, particularly given today's battle environment that includes cyberspace and the challenges of staying relevant in a quickly changing world [57], [35].

But the focus on investment cost as a separate discussion from total life cycle ownership costs proved to be a poor strategy. A GAO report indicated that fully 72% of enterprise system costs are associated with operation, maintenance, and disposal [53]. Additionally, focusing on the early stages of life cycle management once again yielded poor performance in the latter stages of the system lifespan. This is evidenced by, shortages of spare parts and equipment, and is illustrated by the growing O&S costs due to poor planning at such a significant amount that it has impeded the DoD's buying power [58].

A report by Rand Corporation examined methods to compare O&S costs of various aircraft [59]. This metric is commonly known as Cost Per Flying Hour (CPFH). According to Rand, "CPFH is widely used by the military services….to budget resources to achieve aircrew proficiency" [59]. The calculation of this metric can be quite controversial. The Rand report includes the DoD debates on whether CPFH should be a O&S straight cost per total flying hours vs. some type of normalized metric whereby other considerations are included. These considerations could be things such as aircraft in scheduled maintenance being removed from the calculation, or whether weapon system costs not strictly in the O&S budget should be included (such as major modifications). But this report focuses solely on providing the optimum method to compare different aircraft fleets and neglects to account for the additional costs of modernization, which are included in the budgeting that occurs for new developments and not O&S costs. Once again, the rift between development and sustainment costs, caused by the Congressional budget process, has impacted the DoD's understanding of total ownership cost. The report fails to address total ownership costs to include modernization costs (i.e., development costs) that arise due to unavoidable requirements changes that occur naturally throughout an enterprise systems lifetime (be it from supply, support equipment, training, or physical product modernization).

The focus on reducing early costs also has a negative impact on lifetime performance. One study identified that organizations tend to focus on identifying major cost drivers and instituting various changes to reduce ownership cost of those high drivers, but by doing so risk increased costs later in the life cycle [60]. The DoD also fallen into this trap, by reducing costs in the “procurement” phases which focus on material development, technology maturation, and manufacturing, as way to drive down total ownership costs. When viewed from a fiscal data context, it makes sense. If the current year’s budget biggest line item is weapon system procurement, cutting that line item makes the current year budget much less. Due to the way the DoD creates its budget, the high dollar value acquisition costs of new development projects are an easy target to focus on for cost reduction. One GAO report asserted the issue with this approach is it results in insufficient data on operations and maintenance strategies and costs, which drive up total life cycle costs and impact the system’s ability to perform once it is fielded [53].

This is a particularly concerning state of affairs, given that systems change over the lifetime and adequate O&S phase funding (and planning) is required for the enterprise system’s continued performance. According to INCOSE, requirements change over time, and change is inevitable [3]. Therefore, it is unrealistic to assume that a system’s needs, particularly something as complex as an enterprise system, needs will remain static over decades of use. But continuously changing requirements can effect cost, scheduled, and performance of a project or system [61]. Given the DoD’s lengthy modification process, aerospace defense enterprise systems are likely to experience informal requirements changes. An informal requirements change is defined as any change in requirements initiated by any stakeholder that bypass most of the policies or controls imposed by a formal change management process [62].

Even a simple technical order change can seem incredibly long. Many aircraft fleets in the Air Force inventory were fielded when technical orders (T.O.s) were paper-based instruction manuals. As early as 1997, the Air Force made attempts to convert its paper based T.O. system to a digital version in order to speed up the change process [63]. But according to the most current guidance for Air Force Technical Change Management processes, routine changes may take up to 365 days to incorporate into technical orders [64].

Logistics workarounds to supply difficulties, such as repair or cannibalization, can have significant impacts on the performance of the aircraft or the logistics requirements for the life cycle management process. One study found that “even if the quality of components is sufficient for reuse, it is difficult to put them into production without scheduled collection” [65]. Additionally, several studies have been conducted on specific aircraft types (i.e. C-5A, C-21A, KC-135, etc.) to analyze the complex problem of optimum time to retire a fleet, in part based on the severity of logistics problems [66] [8]. None address the root cause issues that prevent the life cycle management process from anticipating and adapting to the changing requirements of complex enterprise systems.

2.3.3 Aging Aircraft Impact on Logistics Performance

While the increase in O&S costs can partially be attributed to a focus on procurement leading to fewer resources for sustainment planning, a significant additional factor in rising cost is the age of the DoD fleet. It is no secret that U.S. military fleets are aging faster than they are being replaced. A GAO report indicated that the average age of aircraft in the U.S. military fleet was 29.1 years and rising, with 21 unique aircraft fleet averaging 40 years or older [1][7]. Given the complexity of funding, contracts to award replacement capabilities, and the significant lack of strategic planning in past years, it is no wonder the USAF fleet continues to age.

The commercial airline industry faces the same challenges for aircraft aging but seems to approach the issue in a much more quantitative approach. A 2013 Boeing study indicated that most commercial aircraft fleets have a strategically planned withdrawal from service [67]. While data indicates that commercial aircraft, on average, are slightly younger than their DoD counterparts, commercial aircraft are, on average, approximately 27 years of age [67]. This is a very similar age to the Air Force's average 29.1 years. The key difference is that with commercial fleets "various industry entities, including airlines, airplane financiers, leasing at airplane leasing companies, airplane manufacturers, and aviation suppliers, all use specialized definitions of the strategic plan to retire based on multiple parameters of interest specific to the entity (e.g., business model, fleet planning, geographical operation factors, local economic conditions, acquisition timing, etc.)" [67]. In other words, the industry identifies what is most profitable for aircraft retirement, and then accepts that strategy. By contrast, the DoD's bottom line is not easily equated to profit and is instead defined in terms of "Air Superiority" or "Mission Success". These goals are much harder to quantify, and the decision to retire aircraft or aircraft fleets becomes much more subjective. Various lobbyists influence our public policy and which in turn influences fleet funding. As a result, retirement decisions can become a less than objective decision with politicians advocating for projects that benefit their own constituents [54].

One major issue with aging aircraft is the cost of their sustainment. A DoD study indicated that, historically, planners have relied on the retirement of older aircraft to free up funds for maintenance and operations of newer aircraft [10]. Due to the way in which the U.S. government forecasts planned expenditures, shortfalls in budgets can only be resolved by moving funds from other initiatives. Alternatively, planners can simply accept the lack of resources and accept a decrease in aircraft availability which appears to be the strategy for older fleets [10]. This strategy works around the funding shortfalls at the expense of system performance, and there is no recommended strategy to do both.

Another issue for aging aircraft is difficulty with continued sustainment over decades of life. In the last few decades, the world has seen technology grow by leaps and bounds. A legacy system needs older technology for its continued use and operation. Maintenance and operations require both human capital and materials which must be acquired, trained, and deployed in order to support legacy aircraft [10].

As an enterprise system ages, it becomes increasingly difficult to find the human capital and materials to acquire for continued operation. This is the core issue under investigation and the driver that prompted this research. Experts that designed, developed, maintained, and operated the system for decades begin to age out of the workforce. A GAO study indicated that effective management processes and tools are needed to ensure that new technologies can be transitioned successfully to operators [68]. Integration with legacy fielded systems can be complex, and the study did not provide specifics on how to integrate new technologies given the constraints of the existing funding and management framework.

Use of a system over several decades also highlights issues when processes and planning don't account for the natural end of life of component parts, business software, support equipment, and other supportability elements. Most engineers would probably agree that any system lasting 40, 50, or even 60 years is likely a well-designed and reliable system. There are many systems that last 4 or 5 years and are considered successful and inherently reliable. For example, Nokia made a famously indestructible phone that has popular culture marveling at its longevity. This was accomplished in an industry were systems are frequently place every few years or even annually [69]! If a complex system such as an aircraft lasts 40, 50, or 60 years, logic would assert that it is an inherently reliable physical design. But this is not generally the case for USAF systems. The Air Force measures success in terms of Aircraft Availability (AA) and Mission Capable (MC) rates. Many of the Air Force's aging fleets no longer meet their AA and MC goals [1], [7]. Reports on this topic often imply poor AA is due to bad design [14], [7].

However, this assertion assumes that all causes of aircraft downtime are related to the physical product. It is critical, at this point, to distinguish between the reliability in the technical design of a physical product, and the reliability of the enterprise system and its supportability elements. If a physical design is inherently reliable, the proof of which is supported by its long performance history, engineers should be take extra care to truly identify the root cause of the grounding issue for the aircraft. If the technical design of the system has been proven to work for decades, it may be the enterprise system, not the physical components, that has become the limiting factor in enterprise system performance as opposed to the physical design.

People may conclude that if a part breaks it is unreliable. But for complex aircraft systems with a proven use history, this is typically not the case. What performance evaluators actually observe is the natural end of life of component parts and subsystems [70]. This is easily recognizable if engineers plot failure rates over time. For most physical mechanical systems, the resulting graphical diagram will resemble a bathtub with the largest quantity of failures occurring at the beginning of the life cycle (i.e., infant mortality), or at the end of the life cycle. Most mass-produced items will follow this basic curve [71], [72], [73], [74].

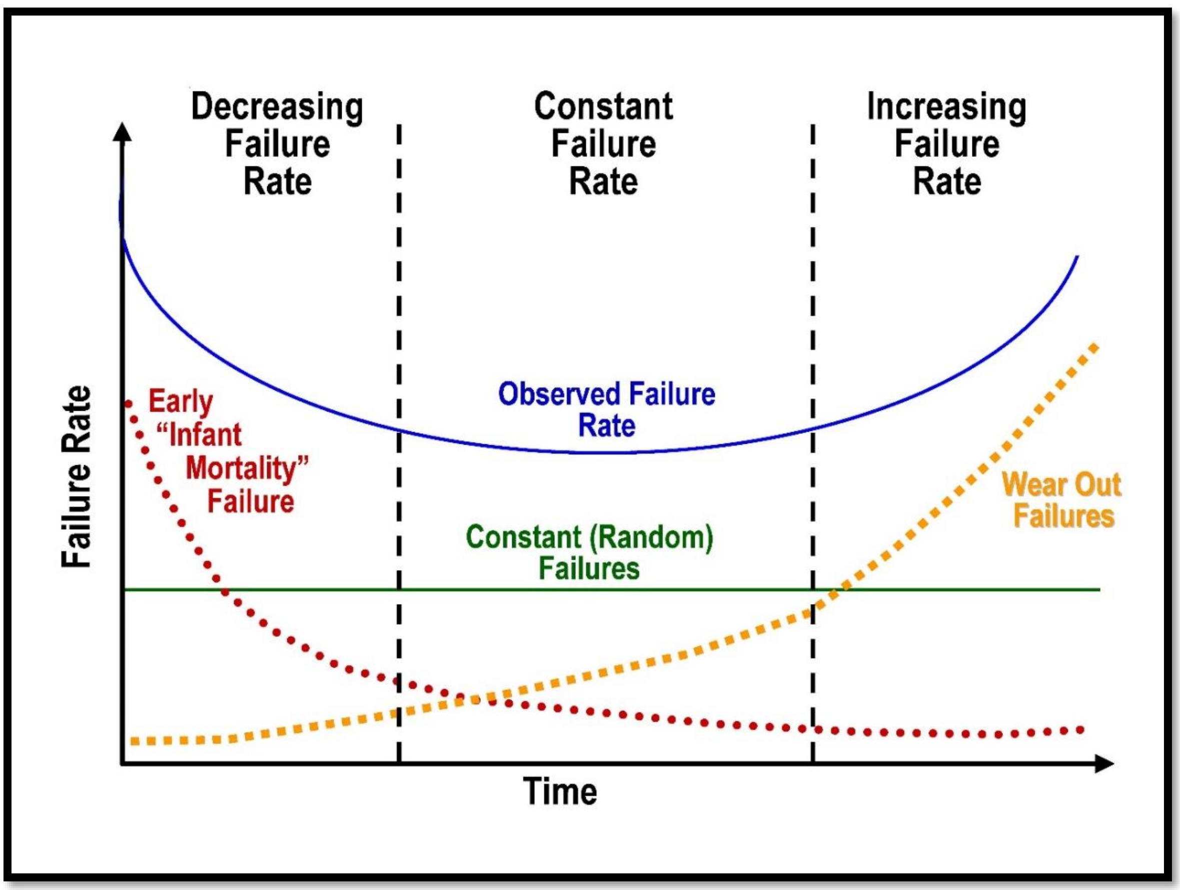


Figure 9: Bathtub Curve Diagram **[74]**

Unfortunately, USAF acquisition professionals may believe that when an aircraft system experiences an increased quantity of failures it can only be due to an inherent design flaw within the component part or sub-system and recommend a redesign. But the true issue may reside somewhere else within the enterprise system. Parts failing as a natural part of their life cycle should be expected and adequately planned for; and the logistics community should be providing replacement parts as part of normal life cycle sustainment activities. If there are reasons the logistics community cannot provide parts, those reasons should be identified and adjudicated prior to making the decision to redesign or replace the entire enterprise system (or even its component parts) with something new. After all, if the root cause issue is not addressed the community runs the risk of fielding a new item that is also unsupportable. A recent analysis of alternatives to reverse engineering as a solution to lack of component parts supports the assertion that systems engineers should address the root cause issue and not focus on the physical product redesign as a stand-alone solution [75]. However, the analysis stopped short of recommending specific actions to prevent degradation of system performance due to issues with enterprise systems due to age.

2.3.4 Procurement Decisions Impact on Logistics Performance

Component parts and subsystems also play a role in determining the sustainment needs of complex enterprise systems in the aerospace defense industry. One initiative to reduce O&S costs was the push for the aerospace defense industry to utilize Commercial-Off-the-Shelf (COTS) products. The problem with COTS is the significant differences in the product life-cycle estimates. There is a discrepancy between industry, which expects a 4-7 year product life cycle in commercial electronics systems, and the military, which expects a 25-30 lifecycle for its enterprise systems [76]. This significant difference in lifecycle requirements can be felt for all the sub-systems, component parts, and processes and external systems that help sustain an aircraft fleet: support equipment, training, facilities, test equipment, logistics systems, inventory, etc. Modifications to an enterprise system can take decades to implement, which makes it difficult to accommodate commercial industry life expectancies [46].

The DoD Diminishing Manufacturing Sources and Material Shortages (DMSMS) guidebook states that “COTS items pose a significant problem to weapon systems” because of the likelihood that the product line will be discontinued prior to the retirement of the enterprise system [77]. The guidebook highlights that one of the side-effects of procuring COTS items is that users typically do not get a technical data package when the item is purchased. If the OEM ever decides to cancel a product line because it is not profitable, users are left scrambling to find replacement systems and/or parts. This issue can be prevalent with DoD enterprise systems because of the differences in product life cycle expectations mentioned previously.

For example, very often COTS parts are chosen at the time of design due to a generally low cost compared to custom parts in the development phase. However, if industry use decreases over time and the Original Equipment Manufacturer (OEM) chooses to stop production, the DoD becomes the sole user of an item, and the COTS component has now become a liability towards long term sustainment needs. This poses a significant risk for the government, and the subsystem or component part has now become Government unique which can cause both airworthiness issue and forced modifications [78].

The COTS issue also impacts management of aircraft fleets in other areas, such as airworthiness. The Federal Aviation Administration (FAA) defines the airworthiness certification process as encompassing a review of any proposed designs and methods used to show that the designs comply with standards, ground and test flights to demonstrate the aircraft meets standards, and evaluations to determine the required maintenance and operational suitability for aircraft inducted into service [79]. For military aircraft, which in many cases are not FAA certified, the Airworthiness process is the responsibility of the airworthiness authority for the enterprise system, or aircraft fleet. By regulation, the airworthiness authority has to be of a separate organization of the acquisition program and operational units in order to present an objective assessment of airworthiness, safety of flight risk, and to provide overall engineering oversight for the airworthiness process [80].

The problem of airworthiness stems from changes to system design that occur when COTS products go obsolete. Changes made by an OEM force recertification of aircraft for airworthiness, which can include both ground and flight testing in addition to analyses, off-aircraft tests, and reviews [78]. This can be a very costly and time-consuming endeavor. Similarly, changes to the enterprise system to encompass new designs when products go obsolete also necessitate recertification. A simple change in a component part can have huge ramifications for the sustainment costs and timeline of a military aircraft fleet.

Smaller fleet sizes compound the issues of obsolescence and the use of COTS items. Commercial airlines have relatively large aircraft fleets compared to the military. American Airlines has two hundred sixty-six Boeing 737's, and over two hundred Airbus A321's [81]. Additionally, while total quantity of other fleet models may be smaller (dozens instead of hundreds), these commercial aircraft share component parts and fleet size worldwide including other airlines raises the numbers significantly. For example, American Airlines has less than fifty Boeing 787's, but worldwide Boeing has produced over 800 of this aircraft model flying 1900 routes in 150 countries [82]. A commercial aircraft typically has multiple customers, which helps reduce the risk of product line obsolescence. The more customers, and the more likely an OEM will provide support and component parts during its life cycle to ensure its customer base remains satisfied with customer support.

But the DoD has shown a trend over the last several years of buying fewer, but more specialized aircraft fleets [83]. The DoD's Fiscal Year 2021 (FY21) budget estimates included data of total force size dating back as far as 1940. A review of this data indicates that the Air Force has been reducing its total manpower over the last few decades as well [48]. The changes to both fleet inventory and manpower have been reduced over the last several decades. Additionally, the Air Force is not buying enough new aircraft to keep its fleet inventory at a steady-state [84]. There is a correlation between fleet size and operating cost that helps inform procurement decisions in the Air Force. The CPFH metric referenced previously, while useful in comparing model to model aircraft costs, does not capture the Air Force inventory's fixed costs, which are not linear [85]. Fixed costs are those costs that the Air Force incurs simply for owning and operating each model of aircraft, regardless of the size of the model fleet (e.g., 1 aircraft or 100 aircraft). But fixed costs are an important part of overall life cycle costs. And as fleet sizes shrink, the fixed costs per aircraft or per flying hour will also increase. A 2018 study by MITRE corporation indicates that "per aircraft O&S costs rise dramatically when fleets are smaller than approximately 150 aircraft" [85].

But the structure of the Air Force fleet has changed over the past several decades. Gone is the WWII era framework, when specific aircraft types were produced by the hundreds or even thousands. During the post September 11th build-up, the Air Force did not grow its manpower and equipment, as did some of the other DoD agencies. Instead, the Air Force had fewer new acquisitions compared to its programmed retirements, resulting in a reduction in aircraft inventory, [86].

2.3.5 Operational Need Impact on Logistics Performance

Logistics deficiencies also play a major role in issues with the current DoD life cycle management processes. A common principle in the logistics management community is to focus on costs themselves or the reduction of the logistics footprint to reduce costs. Regulation and policy support this concept, with overarching regulatory guidance requiring that managers adopt practices that "reduce cycle time and cost" of subsystems and component parts [87]. The directive to reduce costs can sometimes be at odds with long term sustainment needs given the DoD's unique requirements. For example, commercial airlines are used in a consistent predictable pattern. Their routes are predetermined, and the quantity of passengers is scheduled ahead of flights. Additionally, if the commercial airline industry suddenly saw a surge in the demand for flights, they are under no obligation to meet that demand. If an increase in passenger flight demand is not profitable or attainable, airline companies will simply choose not to schedule additional flights (and perhaps even raise ticket prices to capitalize on the increased demand).

But the aerospace defense industry does not have that luxury. DoD policy directs that materiel management should be conducted in response to warfighter needs in both peacetime and war requirements, and should balance the trade-offs for risk to mission success and total cost [88]. The quantity of flights may rise or lower depending on the current operational environment need. And while forecasting, strategic outlooks, and planning certainly occurs, it would be impossible to know the exact quantity, time, and type of support of all required missions in the future.

Given the unpredictable nature of warfare, and the complexity of enterprise systems, one can see the scope of the supportability and logistics problem that the DoD faces. Logistics and supply chain elements must support all aspects of the enterprise system, not just the aircraft or end-item, and accomplish that supportability with unknown timeframes and quantity requirements. Additionally, all procurement is accomplished while adhering to restrictive policy and laws that are aimed to prevent fraud, waste, or abuse of federal tax dollars [49], [50]. Even with intense planning, the scope of unknowns is significant.

2.4 Research on DoD System Performance Improvements

While research on life cycle management processes, requirements management, and other policy and procedure type topics is critical to successful performance of an enterprise system, adjusting strategies once the system is fielded is also a relevant topic. Given the age of many of the USAF's enterprise systems, it is prudent to review research focused on improving performance of legacy fielded systems. The following sections detail the academic and industry research found on this topic.

2.4.1 Improving System Performance by Better Planning

Cohen researched the question of publishing public strategic-planning documents in an era where overhead and administrative costs are under public pressure to be cut completely [9]. The planning for product support that is required to ensure adequate feedback loops are present in an enterprise system could be considered an administrative overhead cost. So perhaps the public pressure to reduce this cost could be a cause of DoD's approach to life cycle management strategy. But while the report identifies long term planning strategies and some of the costs associated with those strategies as a panacea to this issue, it does not identify how parts obsolescence strategies, reverse engineering efforts, or other policies and approaches to address long term life cycle management impact long term planning decisions.

A 2011 report indicated that the total cost of sustainment activities for the Air Force exceeds the operating costs of commercial aviation companies such as American Airlines and Delta Airlines [11]. The report goes on to assert that about $100 billion of the DoD budget is procurement of new development systems, but that 70% of an enterprise system's costs occur in the O&S phase of the life cycle. This means that the $100 billion quoted above is only 30% of the cost of the new weapon systems under development! While this report does an excellent job of highlighting the importance of adequate planning for the cost of the O&S phase, it is too broad to focus on specific strategies, and it does not address the issues caused by changes to enterprise system supportability elements unrelated to the physical product end-item.

2.4.2 Reverse Engineering Methods to Resolve Logistics Performance Issues

When early phase life cycle costs are reduced by shortchanging O&S phase planning, the impacts to supportability elements are almost inevitable. When parts are no longer procurable, reverse engineering emerges as a favored method to resolve logistics problems. Parts obsolescence and reverse engineering efforts have been an on-going issue for some time, as illustrated in a 1989 report by Bakhshi and Worthington [89]. This report asserts that the costs for reverse engineering are significant and can continue to grow as a weapon system ages. The report recommends focusing on high priority reverse engineering efforts to get the most return on investment for the Army and the purpose of the report was primarily to validate the reported savings due to reverse engineering efforts. In that regard, the report falls short of identifying how to leverage field and use data to inform efforts or force cost savings from a data informed designed.

Thompson, Owen, and Germain provided a report that focuses specifically on reverse engineering of mechanical parts as a work around to supply shortages [90]. The research provides insight to extraction of information about each part from 3-Dimensional (3D) scanned/sensed data, and the complications of producing highly accurate models using this data. But the report does not address utilizing field use and maintenance data to help inform the reverse engineering process, nor does it identify costs or return on investment associated with reverse engineering.

Chang and Siddique reported on “Reengineering and Fast Manufacturing for Impact-Induced Fatigue and Fracture Problems in Aging Aircrafts” [91]. Aircraft skin panels and secondary structure are notoriously hard to reverse engineer, since older aircraft were manufactured using mylar or point cloud data instead of modern computer aided design (CAD). While the scope of research is focused on structural fatigue/fracture components, the methods used to feed the reverse engineering process potentially apply to other types of components in aerospace defense systems. However, the research is limited to physical parts, parametric solid models, and optimal design characteristics using available manufacturing machines. There was no consideration of using field and use data to inform the reverse engineering effort.

2.4.3 Using Data Analytics to Improve System Performance

Given the nature of the issues facing today’s aerospace defense operators and maintainers, it would seem prudent to utilize legacy field data to inform the life cycle management process. But that does not appear to be taking place in the current framework of DoD life cycle management. Anton, McKernan, Munson et al. provided a deeper dive into the Department of Defense's use of data analytics in acquisition processes [92]. They found that the DoD spends an estimated $15 billion per year on analytic work and about $3B per year on information systems directly related to acquisition. The report asserts that the DoD is exploring how to assess program performance at the mission level to further inform the acquisition process. The report did an excellent job of identifying the current information gaps within the DoD as they relate to using field data to inform repair vs. replace decisions but stopped short of identifying how to utilize the existing data analytics to inform those decisions, prevent issues from occurring, or even use the data to solve real-time problems.

An article by Armstrong analyzes system integration and the use of data to drive this process [93]. This research addressed the impacts of integration on system characteristics that typically get overlooked, such as reliability or maintainability. It identifies that often stakeholders are primarily concerned about the function of the system as it relates to the stated requirements, but the impacts of secondary conditions can often significantly impact a system's success once fielded. While the article does a good job of identifying the issues with overlooking secondary characteristics early in the life cycle, it stops short of determining how to use a system's existing field service data to inform the integration efforts of the future.

The article "Big Data in the Aerospace Industry by Badea, Zamfiroiu, et. al addresses the need for large volume data analysis in the aerospace industry [94]. Many of the issues identified in the article (such as migrating data from old databases, lack of appropriate database management tools, and lack of appropriate processing capability) are common in the DoD. The crux of the issue is the sheer volume of data generated in today's world. The article uses the example that the average Boeing 737 generates 20 terabytes of information per hour. Today's aerospace industry struggles to capture, store, process, and make meaningful decisions from that data. The article provides information about current data systems, and opportunities to use data in the future, but fails to describe how to take field service data to make decisions (and what type of decisions) in the aerospace industry.

Opare provided research on “System Verification through Reliability, Availability, Maintainability (RAM) Analysis & Technology Readiness Levels (TRLs)” [95]. The paper outlines the use of a RAM roadmap to ensure system milestones in development and maturation are adequate to meet system goals. The research indicates that best results can be found when the analytical/simulation tool used to track availability is tailored based on the maturation level of the system. This paper focuses on the nuclear energy industry and doesn’t apply directly to the aerospace industry although the RAM concepts should be similar. But the article stops short of addressing RAM needs or data in sustainment, when parts obsolescence will increasingly become problematic and costly.

The New Department of Defense (DoD) Guide for Achieving and Assessing RAM by Jackson, Tabbagh, et al. identifies an area of primary concern that US Defense systems have often been found to have insufficient RAM performance during OT&E [96]. The research states that in the operations and support phase (i.e., sustainment phase), the most important use of RAM data is to facilitate the retention of RAM capability and enable improvements in the design. Unfortunately, the report assumes that systems will utilize the “design spiral” type of systems engineering. While the research identifies the importance of RAM in the sustainment phase, it stops short of defining how to use RAM data specifically to inform reverse engineering or repair vs. replace decisions.

2.5 Research on Predicting USAF Fleet Performance

There are numerous examples of mathematical analyses, academic studies, and other statistical research techniques related to forecasting multiple regression data sets for almost every imaginable application. Several of these examples are related to USAF metrics and supply concerns, in addition to many more related to total aircraft performance with Aircraft

Availability being the primary focus. Most of these methods focus on creating multiple prediction models, then testing the models, ranking their performance, and choosing a result based on the comparison. Predictive analytics as it relates to aircraft performance and the studies involved in those areas generally take a similar approach.

2.5.1 Studies Correlating USAF Metrics to Performance

Many analyses, research, and reports focused on optimizing aircraft schedules, maintenance schedules, policy, and other factors to predict or accommodate AA rates. The focus of most research is from a prediction viewpoint. Authors try to discover what influences the final AA metric, and how to predict it or recommendations involve improving AA by exploiting known influencing metrics to prevent degradation of AA, MC rates, or any other performance metric. But there is little research that recommends identifying the root cause of drivers early in the failure process to prevent the negative factor from occurring in the first place.

Inman et al studied the timing of the introduction of new technology to legacy fielded weapon systems related to fighter aircraft in the USAF fleet. Using multivariate methods, collected data compared Mach number, mean time between failure (MTBF), and several other factors to create a predictive model to determine the first flight of fighter aircraft. Predicting an aircraft's first flight may be a useful tool for predicting a product's date of release which allows the USAF to adjust schedules and plan mission accordingly. The study compared the use of Technology Forecasting using Data Envelopment Analysis (TFDEA) combined with classical regression-based modeling methods. This is another example of utilizing forecasting methods and multivariate data sets in applications related to USAF fleets to create real world applications [97]. While the study shows how the data collected by the USAF can be used in predictive models successfully, it does not cover the topic area of logistics performance as it relates to aircraft performance.

Hobbs and Williamson studied factors related to aircraft performance from a safety perspective. This research reviewed over 600 safety occurrences involving aircraft maintenance, compiled the types of errors, and identified the contributing factors leading to poor performance. Links were identified specifically related to human factors such as rule violations, memory lapse, and fatigue. This research serves to illustrate that it is more than simply reliability or poor optimization of system resources that may lead to poor aircraft performance [98].

Carrol and Malins analyzed the justification of converting to a model-based systems engineering (MBSE) approach from legacy document-based systems engineering (DBSE) approaches [99]. The report focuses on defense, space, and complex systems and concludes that utilizing MBSE early in a life cycle has profound benefits. While the report does take cost into consideration it does not address the cost or return on investment of converting DBSE to MBSE, nor does it address how to leverage O&S data to inform the SE model of either type.

Jordan et. al provided thorough study of the KC-135R Stratotanker aircraft availability performance over a period of 7 years [100]. The research utilized more than 2700 unique data points with 72 different supply, logistics, operational, and maintenance metrics. The analyses asserted that small fleets with high tasking rates would see higher trends than other units of similar characteristics but fewer mission taskings. The research concluded that the results of the analysis cannot replace human judgement based on the environment or conditions at the time a decision is required. The research did not review other aircraft in the USAF fleet, nor did it attempt to identify causal relationships, or actionable methods by which to improve AA. While knowing which factors directly relate to AA are important, it is more important that systems engineers can use the information to take action to improve performance across the fleet. The research recommended that the USAF utilize the results to tailor fleet scheduling based on future AA predictions. In other words, instead of trying to improve AA, schedule around it! While this indeed may help optimize mission and maintenance schedules, the criticality of USAF assets and equipment, particularly during emergency or global political events, means that there are times when we cannot subjugate the mission to the aircraft schedule.

Fry accomplished a study utilizing the AA formula to determine where to spend Operations and Maintenance (O&M) funding [101]. This funding is a specific acquisition category with code 3400. This category is the primary source of funding weapon systems in the O&S phase of the life cycle. The study shows that some aircraft fleets have AA drivers that are influenced by O&M funding levels more than others and concludes that decision makers should focus funds on metrics that both drive AA and are influenced by funding levels. While this study does show that metrics can be data mined for multiple regression purposes, it does not create actionable recommendations for personnel on how to improve performance, rather it recommends focusing funds on areas that influence performance the most.

D'Amato also accomplished a study related to funding [102]. The author investigated the relationship between funding levels and readiness levels specifically as it relates to depot level funding and downtime hours associated with depot maintenance. The analysis ultimately did not find any conclusive relationship between downtime hours and funding. The author recommended that adjusting for autocorrelation in the model was very difficult due to the complexity of the relationships between variables.

2.5.2 Studies on USAF Logistics Performance

Multiple studies have reviewed factors that influence aircraft availability, supply performance, not mission capable rates and other metrics surrounding performance related to the logistics impact on USAF fleets. Most of these studies use multivariate methods, regression techniques, structural equation modeling, and other advanced mathematical analyses to draw conclusions about the driving factors regarding fleet performance. In fact, there have been many studies that show some of these relationships.

Harper utilized agent based modeling and simulation (ABMS) to develop a framework for the risk management of supply chain performance [103]. The author utilized supply performance drivers specifically for consumable (not repairable) items of supply. The study focused on integrating software agents to perform the data mining required to generate simulations that highlight risks to the supply chain. But this study did not address the impacts to overall enterprise system performance or create recommendations for logisticians to take action based on the model's predictions.

Chapa performed a high level analysis of what variables influence Aircraft Availability (AA) and utilized multiple regression analysis to determining influencing factors for the KC-135R [104]. The author included dependent variables using metrics related to personnel and staffing, environment, reliability and maintainability, operations and maintenance, and logistics operations. The study identified 10 variables that are correlated to KC-135 performance. The author also proved that operational funding levels for the aircraft did not appear to correlate to its AA performance. But the author did not address what actions personnel should take to prevent negative performance or improve the existing performance.

Gehret explored improving readiness levels by improving the supply chain for management of low-demand component parts [105]. The study proposed two frameworks to improve the supply chain's stock management policy, which is part of the overarching life cycle management strategy. The analysis then focused on test cases in the A-10C and B-1 fleets. The author created a mathematical model that would generate risk and reliability scores as they relate to supply chain demand, which will allow the stock manager to make better decisions in supply forecasting. But the analysis stopped short of tying supply directly to AA, nor did it address tying supply forecasting to actual aircraft events.

Weber researched the impact of fulfillment errors on military operations [106]. The research investigated correlations between supply discrepancy reports on readiness metrics such as cannibalizations, not mission capable rates, AA, and other supply drivers. The results showed improvement in some metrics if supply discrepancy reduction strategies were implemented. The research did not address how to prevent downtime or discrepancies.

Femano studied supply chain resiliency and strategies to improve it [107]. The author utilizes a theory of constraints framework to categorize resiliency strategies and examined the links between those strategies and supply performance. The study focused on F-15 aircraft historical mission capable rates as the dependent variable of a multivariate analysis. The paper concluded that utilizing non-lateral suppliers and slower surface shipping modes for MICAP parts decreased supply resilience and validated recommended strategies such as decreased recovery response time that can improve supply performance. Femano fell short because the research did not connect supply performance to AA or mission capable rates.

Pendley researched the factors that influence C-17 aircraft mission capability rates [108]. The author utilized structural equation modeling to evaluate relationships between mission capable rates and other variables. While the author did identify some new correlations previously ignored, the research did not attempt to identify causal relationships or strategies for preventing downtime.

Haynes researched logistics forecasting models to predict Mission Capability (MC) rates [109]. Results provided insight into why tracking AA vs. (MC) rates may provide better forecasting for mission needs. The author accomplished a linear regression to determine correlations between the independent variables and MC and AA rates, and compared those findings to surveys done by personnel who work USAF logistics. The research showed discrepancies between what local commanders measured for performance vs. true correlation of metrics. The study did not indicate what actions should be taken to prevent downtime drivers altogether.

2.6 Literature Review Summary

The literature review shows a significant amount of research that asserts the need for robust DoD life cycle management processes with feedback loops. Both industry and government policy guides assert the need for effective systems engineering processes that connect stakeholders. There is also a large amount of research regarding the correlation of metrics or data to system performance, but none recommend specific ways to accomplish this feat, except in rare instances that aren't directly related to aircraft availability or mission capability.

Most of the research reviewed in this section focuses on predicting one of the various performance measures used in the O&S phase of major weapon systems. The assertions behind most of the existing research is that the DoD schedules missions, maintenance, and operations based on the predicted performance regardless of the original performance goals, operational need, or inherent reliability of the physical system. If the goal is increased performance, these approaches don't meet the need. The next chapter will lay out a proposed method and approach to identify early predictors of downtime in order to leverage systems engineering life cycle management process to establish the necessary feedback loops that will prevent downtime drivers.

Chapter 3 - Research Method

This chapter discusses the framework for analysis conducted in this research effort. The purpose of this research is to identify indicators, or early warning flags, to help maintainers and systems engineers ultimately prevent aircraft downtime. Therefore, the precise relationship between metrics or performance measures does not need to be specifically determined. Rather, the mathematical model will be used to determine whether certain events or metrics are good indicators for potential downtime drivers, allowing systems engineers to further investigate failures and execute feedback to the logistics personnel who can take action to prevent downtime related to supply issues. Therefore, the methods used in the study are a combination of quantitative mathematical modeling, along with a review of the processes surrounding life cycle management in the USAF.

Aircraft performance data has frequently served as the source for research questions regarding MC rates, AA rates, and other aircraft performance evaluators [10],[129],[130]. These research techniques use linear regression, multiple regression, and non-linear regression techniques to analyze possible causal or non-causal models of the relationships among the proposed variables. The methodology for this document's research attempts a similar approach to achieve a different outcome: the use of statistical modeling at an aggregated Air Force level to drive changes to systems engineering processes to impact overall performance. The intent is to identify metrics that can be reviewed real-time to scope the workload of systems engineers to analyze aircraft failures real time.

Instead of modeling the data to predict future performance, this research attempts to determine which metrics, if any, are related via causal relationship to specific negative performance events in a way that USAF personnel can take action to intervene prior to aircraft grounding events. In this way, the research hopes to improve aircraft performance even when all factors impacting that performance are not fully understood. The proposed methodology to gain insight into the stated research questions is as follows:

- Create a model framework to facilitate systems engineering activities in Operations & Sustainment (O&S) phase.
    - Identify failure modes in existing guidance and processes; develop process model to address gaps is methodology.
- Accomplish statistical analyses to link operational data to negative aircraft performance.
    - Identify data sources and aggregate data; identify relationships between operational data and supply performance.
- Develop method to prioritize system analysis based on the new data links.
    - Review DoD analysis guidelines; identify constraints in analysis processes; develop prioritization procedures.
- Develop method to inform stakeholders to update supply demand requirements.
    - Review DoD supply demand forecasting and new requirement documentation policies; identify processes to exploit.
- Validate findings and results with case studies from aircraft performance data.
    - Implement the process model using the new data link to prioritize case studies; analyze data to determine validity.

3.1 Feedback Processes During Operational Use

In commercial and academic circles, the purpose of the systems engineering life cycle management process can be simplified as starting with a user need and ending with a user validated enterprise system. According to INCOSE, "Verification ensures you built the system right, Validation ensures you built the right system" [3]. In the DoD, user validation occurs during Operational Test and Evaluation (OT&E). The Vee Model illustrates this objective visually. Verification and validation activities start at the lowest level, component parts, and progress to the subsystem, system, and finally enterprise system level. At each step going up the right-hand side of the Vee Model, there is a corresponding feedback stream to check performance against the original requirements.

One issue that many DoD life cycle managers assume is that operational verification or testing occurs at a single point in time, or at least within a defined timeframe. Even the DoD's life cycle milestone chart identifies Operational Test and Evaluation (OT&E) as a single task that has a beginning and an end within a phase of the life cycle [44]. For simple products, with an identified service life expectation and static operating environment, this approach makes sense. Any variety of household goods or everyday products are expected to serve out their useful life and be discarded upon consumption. Mechanical pencils, shoes, household appliances, even modern technology such as laptops or cell phones are expected to have a life limit which eventually necessitates the replacement of the product. In fact, the Defense Acquisition University's (DAU) glossary describes "Major System" as a combination of the elements INCOSE includes, but excluding construction or other improvements and cites both a federal law and DoD Instruction regulation as the source of this information [110]

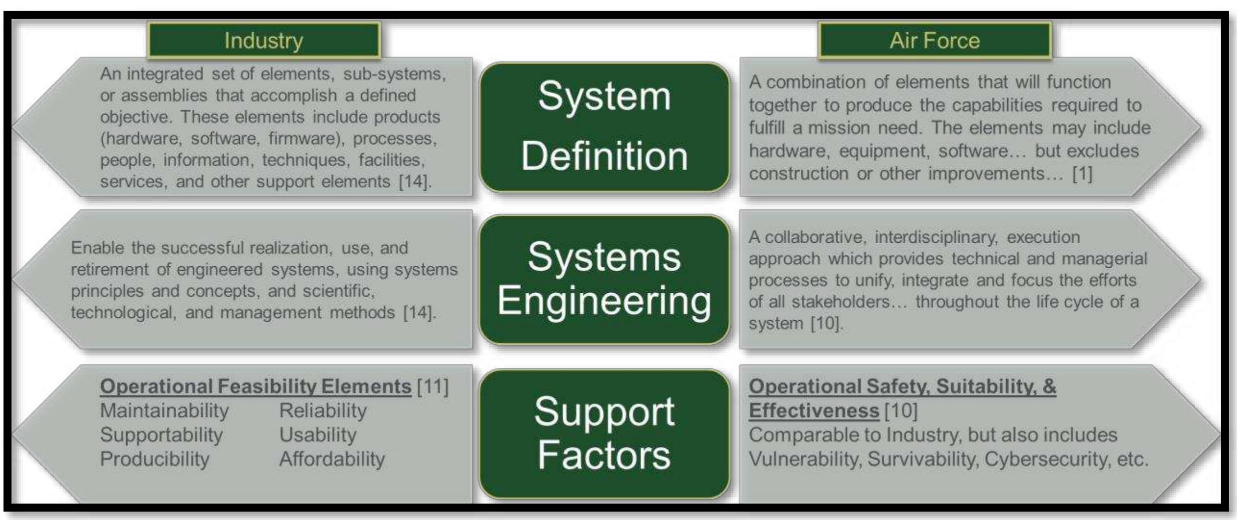


Figure 10: Comparison of Industry vs. USAF Systems Engineering Concepts

But complex products, such as aerospace defense enterprise systems, operate in dynamic environments. Life limit expectations aren't always static and as discussed in the literature review there are external influences that may cause the original life expectancy or even operational goals to change over time. A company like Delta Airlines may easily plan for replacement of its fleets, but the decision to retire an aircraft literally takes an Act of Congress, with all the political maneuverings associated with such a high level attention topic [49] [111]. The ability to discard an aerospace defense enterprise system is much more complicated than even comparable commercial systems that serve similar functions, simply due to the way in which DoD systems are funded, procured, and used. Therefore, a tailored approach to systems engineering and feedback processes is required.

3.1.1 Proposed Systems Engineering Method

To successfully operate, an enterprise system must be operationally feasible. Accomplishing operational feasibility in the early stages of system design is required to field an initial operating capability. But as an enterprise system ages, its operational environment or customer needs may also change. These changes are likely to affect elements of the enterprise system that are critical to its operation, but often overlooked because they are not part of the hardware or software that directly supports the user's need. Although system designers tend to focus on electrical, mechanical, structural, software, and related engineering areas as embodying the primary purpose of the system, these areas and components are not sufficient on their own to successfully operate an enterprise system.

According to Blanchard and Fabrycky, operational behaviors are dependent on the non-traditional engineering parameters that surround supportability elements, which they call operational feasibility elements. They assert that "consideration of these parameters during the design of a system is essential if the desired operational behaviors are to be realized" [4]. As shown in the previous figure, industry and academic systems engineers identify operational feasibility elements or categories as: Reliability, Maintainability, Usability, Supportability, Producibility, and Affordability. As previously stated, DoD in acquisition guidance does not recognize these elements are part of the "system". But the USAF engineering guidance regarding Operational Safety, Suitability, and Effectiveness (OSS&E) does acknowledge that these factors are critical to the successful operation of a major weapon system, and essential to achieving mission goals [112]. A high-level overview of OSS&E systems engineering duties and responsibilities is shown in the figure below.

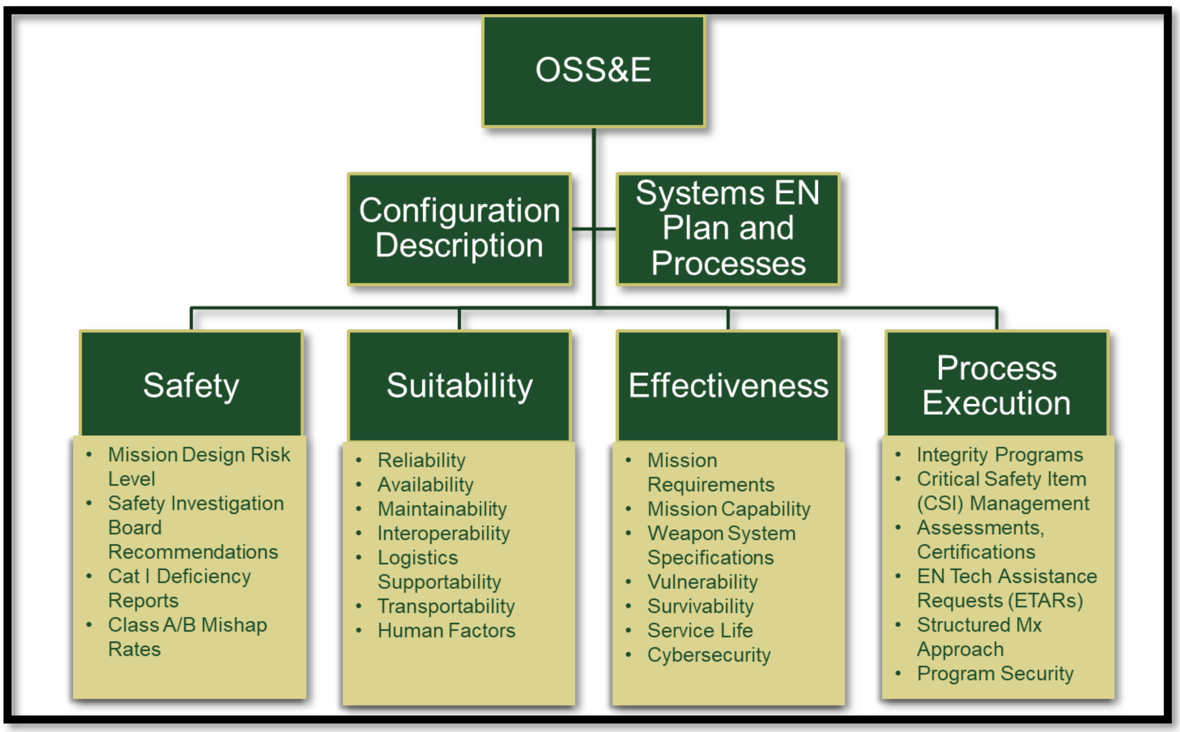


Figure 11: Operational Safety, Suitability, and Effectiveness (OSS&E) Responsibilities

These regulations give systems engineering in the USAF the responsibility to account for supportability impacts to system performance, but not the authority for the processes, manpower, and other resources involved in successful implementation of that responsibility. Processes related to adequately forecasting and supplying sub-systems and components parts to operational units is one of these non-traditional engineering parameters. The processes and feedback loops regarding supply are critical to adequate parts planning, which is critical to adequate supply inventory and stocking, which is critical to meeting aircraft component part demand during the O&S phase.

One example of the impact that support elements have on system performance is an example related to training, requirements management, and stakeholder disconnects. Many older aircraft are manufactured using bonded aluminum honeycomb structural panels as the aircraft skin. This type of material is very strong compared to its weight. It is similar in structure to carboard; a honeycomb core is bonded to two skin panels. This was considered cutting edge technology in the 1960's and there are many USAF inventory aircraft that are still in use today that were designed using this concept. But modern aircraft utilize fiberglass or composite skin panels. And, indeed, there is significant manpower savings associated with composite skin repairs vs. the original methods used on bonded aluminum honeycomb panels. There are even methods and procedures to utilize fiberglass repairs on old aluminum structure. One such repair was attempted for a corroded skin panel on an aging aircraft in the USAF fleet inventory. Maintenance requested permission to utilize a fiberglass repair on one such corroded skin panel. The structural engineer responsible for authorizing repairs reviewed the drawings, technical reports, and other aircraft information to review the request. In this case, the aircraft was approaching 60 years of age, and many of the original engineering reports were handwritten. In addition to understanding the technical aspect of structural repairs, engineers had to understand how to search and find information in the mass repository of data that existed without the digital and automated links we expect in today's modern work. In this case, the engineer determined a fiberglass repair was a structurally sound approach in this case. Unfortunately, unbeknownst to the structural engineer, the skin panel served as a grounding surface for an antenna that mounts onto the skin panel after assembly. Since the structural engineer and the electrical engineer were organizationally separated, and the requirements were not linked in any way, the repair was authorized despite the fact that it would cause the radar system to fail during functional test. Similarly, the technicians who installed the skin panel are not radar technicians and were unaware of the issue with the type of skin panel repaired that was used. It took many manhours of troubleshooting to identify the root cause issue due to significant stove piping of functional expertise. This issue is shown in the figures below.

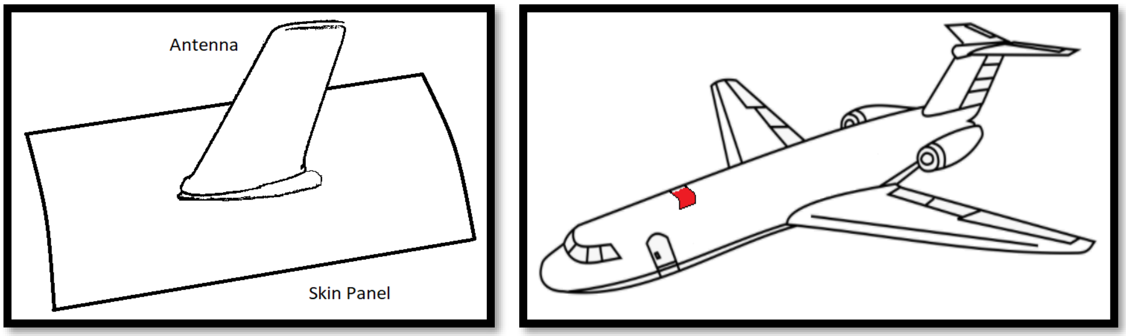


Figure 12: Sketch of Aircraft Skin and Antenna

Figure 13: Piece of Aluminum Honeycomb Skin Panel, Photo by Amy Eddy

Eddy and Daily [75] provide an example of the criticality of operational feasibility elements related to manufacturability. In decades past, casting was a cost-effective way to manufacture large quantities of parts. As aircraft age, eventually those parts will need to be replaced, either due to end of life failures or from external damage, loss, etc. In this example, a manufacturer refused to bid on a valve that was still in use on an older aircraft. Supply personnel originally requested that engineering qualify a new manufacturer since the old one refused to bid. Qualification of new sources can be extremely complex (due to airworthiness concerns) and time consuming. Instead, engineering requested the vendor provide more information on why it could not supply parts. The vendor asserted that it could still provide parts, but that it was not cost effective to meet the original design requirement of casting the valve housings. Modern manufacturers use Computer Numerical Control (CNC) machining and have largely automated manufacturing of these type of parts. The engineer, logistician, and vendor were able to work together to identify a manufacturing change that would still meet the functional need of the aircraft, but made the process cost effective for the vendor. This is illustrated in the figure below:

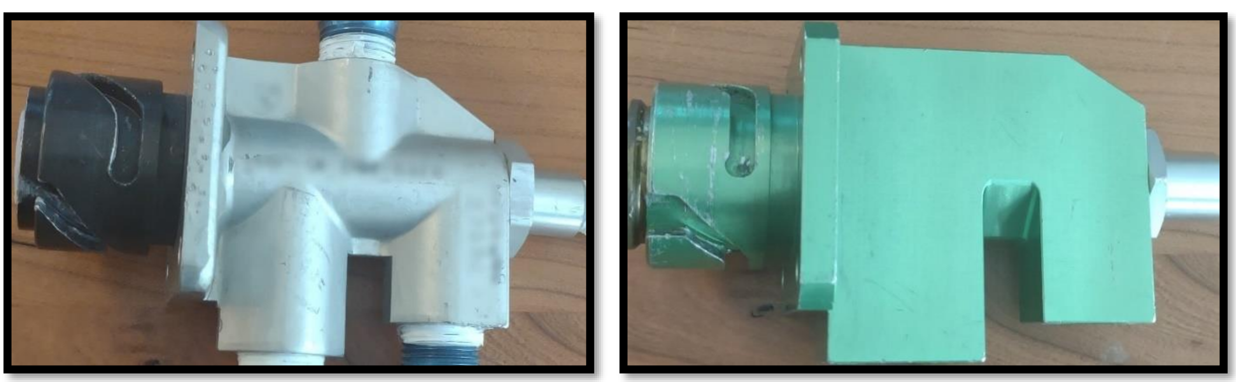


Figure 14: Old Cast Valve and New Machined Valve (Photo by Amy Eddy)

A final example is the impact of maintainability on system performance. Aircraft in the USAF fleet are used past their original life limits or retirement dates. This is accomplished by undergoing a Service Life Assessment Program (SLAP) and a Service Life Extension Program (SLEP) and is documented in Air Force Instruction (AFI) 63-140, Aircraft Structural Integrity Programs. The focus of the program is to "reset" the service life and activities include analyzing critical components and safety of flight systems to ensure that the right maintenance and logistics footprints exist to safely extend the life of the aircraft. However, rarely does a SLAP/SLEP initiative look at ALL components and parts of an aircraft. For time, cost, and resource concerns, the focus is typically on impacts to airworthiness or to address the ***current*** capability or reliability problems. This can cause unintended consequences since the entire enterprise system must remain functional for the extended life of the system.

In the example shown below, the original legacy duct was installed in an inconvenient location on the aircraft [75]. During the original service life, this was not much of an issue since these ducts rarely failed. But as the system aged, more replacements were required and the custom sized rubber boot in the center was frequently out of stock due to low demand. Systems engineers evaluated the root cause issue and consulted with logisticians who advised that due to such sporadic demand the rubber boot would be difficult to keep stocked. Given this constraint of the USAF supply system, engineers identified a new technology perfectly suited for on-demand manufacturing: 3D printing. There have been several research studies identifying the positive benefits of additive manufacturing both in the aircraft industry and others [113], [114], [115], [116], [117], [118]. The original duct and final solution are shown below:

Figure 15: Top, 3D Printed Duct; Bottom, Original Duct with Rubber Boot

Enterprise systems identify and attempt to mitigate uncertainty and risk during the development phase of the life cycle [119]. It is at this stage that plans and strategies are developed with the intent to last the enterprise system throughout its life cycle. But it is unreasonable to expect that users, customers, systems engineers, logisticians, program managers, and other experts could possibly anticipate every possible outcome that may occur during a system's life cycle, adequately plan for the potential realization of risks, and successfully execute mitigation strategies should those risks occur. This is particularly true for aerospace defense systems, which are already incredibly complex and may last five to six decades before retirement and operate in a dynamic battlefield environment.

This research proposes that the true validation of an enterprise system is proven by its performance throughout the operational phase of its life cycle. The answer to INCOSE's question "Did we build the right system?" is demonstrated in the system's continued ability to perform its mission throughout its life cycle. In other words, the verification activity at the operational enterprise system level should never fully end. As the system is used, maintained, and sustained, systems engineers should continually monitor the data gathered from the operational phase (the right-hand side of the Vee Model) and evaluate that data against the originating specifications and requirements documents (the left-hand side of the Vee Model).

With acceptance of this assertion, it becomes clear that the monitoring that occurs in the O&S phase is a validation process, and there should exist feedback loops and processes such that stakeholders using and operating the system can communicate its performance to the appropriate stakeholders that can take action to change and update the enterprise system. The enterprise system is continuously evaluated to ensure it still meets user needs. Since the environment in which aerospace defense systems operate is constantly changing, systems engineers should continuously validate that the system remains, using the words of INCOSE, "the right system" for the user need.

Eddy and Daily illustrated how a continuous validation loop effectively turns the O&S phase of an enterprise system into an on-going, continuously monitored, validation effort [120]. The traditional DoD Vee-model gets an update that reflects the ongoing validation tasks:

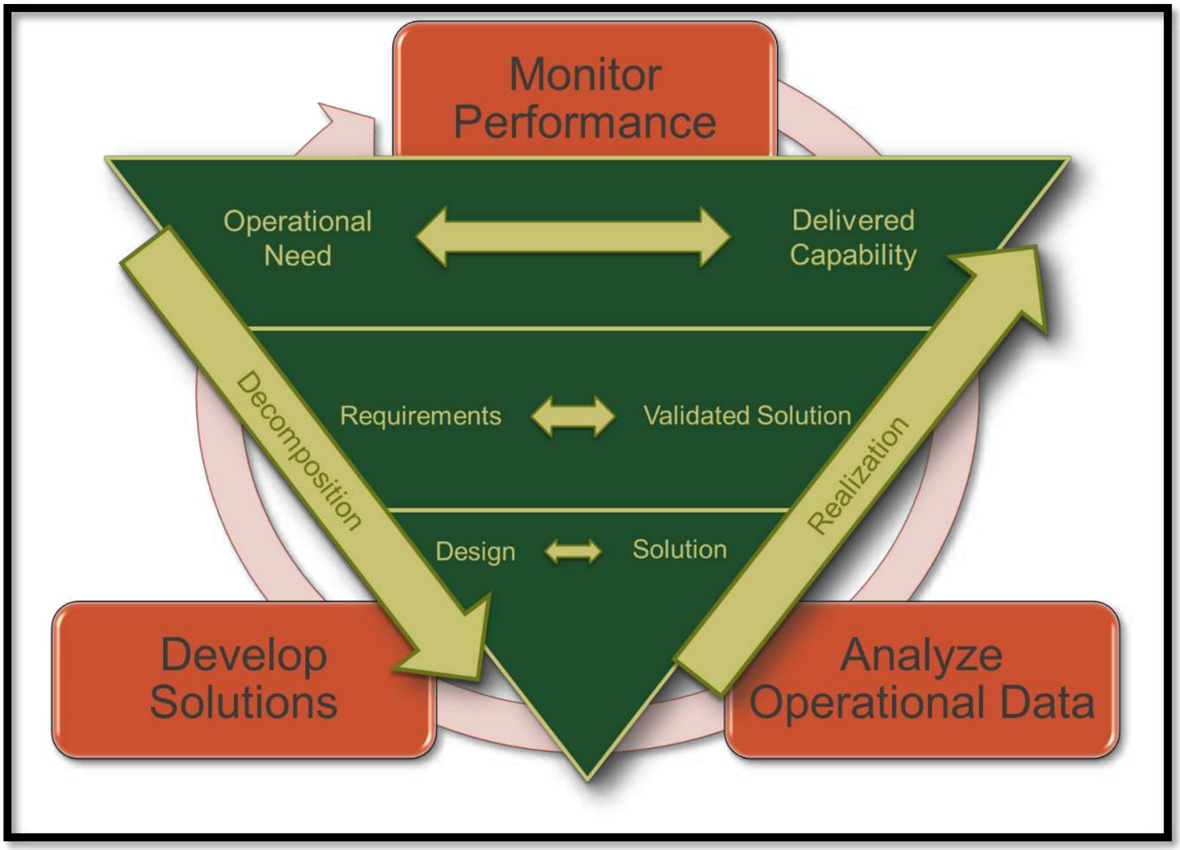


Figure 16: Proposed Feedback Model Diagram

For example, the proposed addition to the systems engineering process Vee model is to add continuous tasks to 1) Monitor Performance, 2) Analyze Operational Data, and 3) Develop Solutions to any issues that are preventing aircraft performance. The operational data in question are the collected metrics on performance or operations, maintenance, and supply actions. Since the goal of this research is to prevent downtime events due to lack of parts or logistics issues, it is prudent to choose a performance metric related to logistics and supply that is also tied to aircraft downtime. Documentation in the form of forms, database entries, and aircraft records occur at each step in the process, all of which can be found in a variety of USAF regulations [121], [45], [122].

For DoD logistics, the most logical place to find data to implement the proposed method is to leverage the data being collected at the tactical level that documents supply workarounds. Cannibalization rates, procurement data, local manufacturing information and other logistics data should be used to inform logisticians that support the enterprise system that a failure of the support system has occurred. Systems engineers can utilize early warning indicators to do a thorough review of system component parts, failure modes, and end of life calculations. This information can then be fed back into the already established processes for documenting change to supply demand. Logisticians can then adjust their procurement forecasts with the data and work to provide items of supply. This research will focus on capturing information from workarounds to supply issues as well as early indicators from logistics, maintenance, and operations leading indicators. These metrics may indicate that a larger supply issue may be realized in the future.

3.1.1 Existing Feedback Processes

The organization responsible for managing an enterprise system often has little or no official budgetary authority over all the elements that combine to make up the system. The many organizations that manage, maintain, or operate the various elements required to keep an enterprise system operational have competing priorities, budgets, schedules, and leadership chains of command which can complicate any enterprise system decision [87]. As a result, when issues occur in operational feasibility parameters the user that experiences the failure may not have a clear line of communication to supporters that can help resolve the issue.

This lack of communication illustrates the missing feedback loops in from the operational user to the systems engineers tasked with providing an operational enterprise system. Exacerbating the issue is the sheer size of the DoD organization. As noted in the literature review, the DoD's cumbersome organizational structure frequently stovepipe's different career functional areas (such as maintenance and supply) making informal feedback almost non-existent [123], [11], [53]. There is also a variety of research asserting the need for stakeholders to establish robust systems engineering and life cycle management processes specifically to avoid organizational inefficiencies [124], [125]. To develop strategies for improving issues related to these challenges, we must first consider what the existing process looks like.

3.1.1.1 Issues with Standard Supply Forecasting

Given no other inputs, logisticians are required to forecast parts based on the previous two-year history of demand. This requirement is established in the Federal Acquisition Regulation (FAR), DoD policy guidance, and USAF policy guidance [126], [88], [50]. This type of forecasting strategy works well for high demand, frequently used components parts with established manufacturers. This method does not work well for items with sporadic demand, or ones that have not been procured since initial fielding.

There are, however, existing feedback loops established that would allow logisticians to utilize other sources of data for procurement. One such process is identified in the Air Force's AFI63-143, Centralized Asset Management (CAM) regulation. This regulation provides a process and forum for engineering to identify issues affecting the maintenance of AF weapon systems that may adversely affect airworthiness. It directs personnel to validate maintenance requirements, and stipulates that existing requirements may be updated based on changes to the enterprise system [127]. There are many sub-processes in this guidance document, but this research focuses on processes related to support of existing maintenance and use requirements, called the Logistics Requirements Development Process (LRDP). This process dictates that stakeholders identify all the logistics requirements for maintenance activities. It is through this process that engineers could assist logisticians with better data for forecasting parts. A comparison of these two processes is in the figure below.

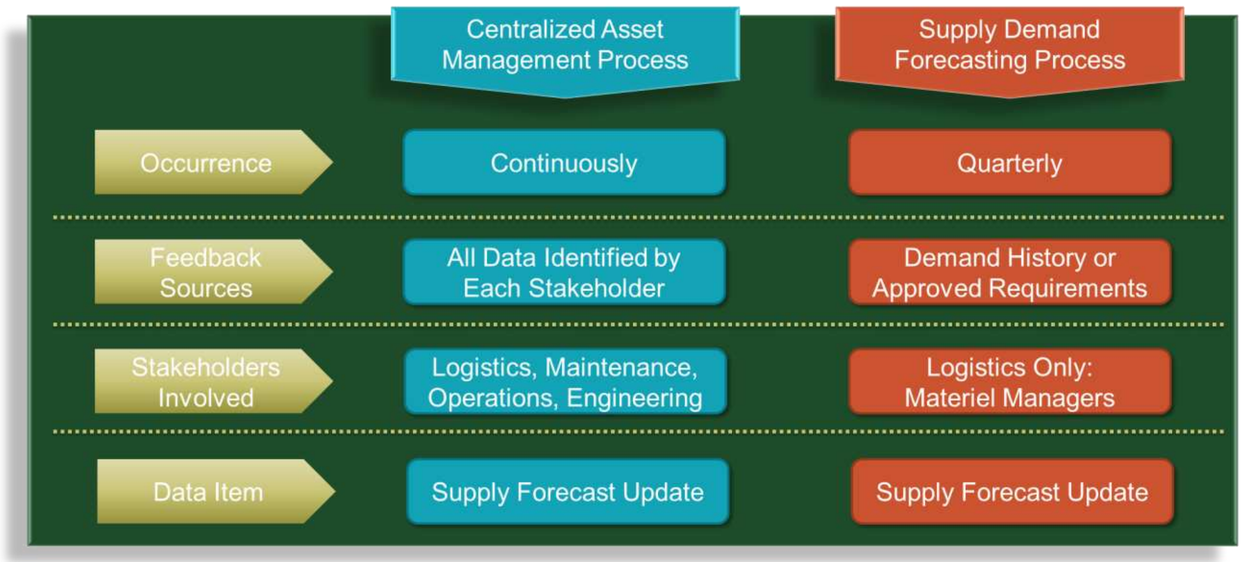


Figure 17: Comparison of Differences in Logistics Forecasting Processes

One issue that impacts logistics is the potential in older fleets to experience part demand aligned with the natural end-of-life of component parts as defined by traditional bathtub curves. The potential impact on logistics performance from this issue is staggering. But senior leaders are well aware of this problem, which is reflected in the advent of the Diminishing Manufacturing Sources and Material Shortages (DMSMS) programs and policy guidance within the DoD [128]. The purpose of these programs is to ensure that older parts have adequate replacement strategies to provide assets to the weapon systems they support [129]. This is another type of feedback loop available when component parts are identified as having supportability issues. Engineers can make recommendations through DMSMS programming to get parts reverse engineered as needed.

3.1.1.2 Forecasting Data Bottlenecks

Given that feedback loops to provide additional data for logisticians exist, and feedback loops to help engineers prioritize pending DMSMS issues also exist, why then do weapon systems experience parts shortages? This issue essentially boils down to the availability of manpower to generate the necessary data to support logistics procurement actions. Policy guidance dictates that supporting data must be provided in order to violate the supply policy of forecasting based on the most recent two-year history [88], [127]. In order to provide this level of documentation, reliability analyses showing the impending predicted failures must be provided by engineering to logistics personnel.

The LRDP guidance was largely built upon the idea that Reliability Centered Maintenance (RCM) was the preferred failure analysis and forecasting strategy for logistics and maintenance programs. Historically, aircraft were designed to fly-to-failure for most component parts, with the exception of Critical Safety Items (CSI) which were generally time-changed to specifically avoid unexpected failure. Unfortunately, this strategy leads to the realization of unscheduled maintenance quite frequently. Over the past several decades, the Air Force has attempted to mirror commercial aviation's Condition Based Maintenance Plus (CBM+) and Maintenance Steering Group Three (MSG3) type maintenance strategies. CBM+ attempts to use Automated Intelligence (AI) to identify potential early warning flags that parts are about to fail. CBM+ is usually executed in conjunction with an existing RCM program to add condition-based inspections during scheduled maintenance [125].

CBM+ works best when data specifically related to system performance (i.e. from sensors or on-board diagnostics) is available and aging aircraft fleets do not always have this type of data available [130]. Given the long lead times of Air Force supply, predicted failures would have to be identified years in advance to adequately plan for parts. MSG3 works slightly better for older aircraft fleets since its approach is to identify the systems required for flight and the failure modes most likely to impact flight operations (i.e., cancelled flights). The maintenance strategy is designed to remove and replace parts before they fail, which prevents unscheduled downtime [131]. This is a better approach for older aircraft in terms of the ability to plan for supply concerns, however it does lead to an abundance of scheduled downtime at the cost of aircraft availability.

RCM policy dictates that parts be reviewed from the component level and build upward to determine reliability [132]. This guidance requires that systems engineers review RCM data every two years, to ensure requirements are adequately captured. In an ideal world, this strategy would work well. Systems engineers would review cycle data, original design specifications, usage data, life limit data in addition to all of the metrics generated by operations, maintenance, and supply to do a thorough review of the expected life expectancies of component parts in order to provide supply forecasting data.

Unfortunately, this is not possible given the current staffing of systems engineers. Systems engineers largely reside in the Air Force Life Cycle Management Center (AFLCMC) in the System Program Office (SPO) assigned to weapon systems. This author has resided in three different SPO's in the last 20 years, and none were ever staffed above 45 engineers. Even if engineers could produce RCM analysis a day working 7 days a week, they could only produce a little over 32,000 analyses per year. Given that the typical aircraft has hundreds of thousands of parts, it is not realistic to expect systems engineers to accomplish RCM analysis to the detailed level necessary for parts forecasting. The fact that these engineers are also responsible for the day-to-day fault isolation, emergency field requests, procurement technical data package reviews, deficiency reporting, technical order and manual creation and updating, and modification programs, makes the issue even worse. Engineering has become a bottleneck for providing the required data to support logistics procurement actions. Additionally, even if the engineering manpower to accomplish this massive effort magically appeared today, the bottleneck would simply move to logistics personnel for being understaffed to execute all the new procurement requirements.

3.1.2 Proposed Additional Feedback Processes

Since staffing and manpower is not something working level logisticians or systems engineers can control, the next best step would be to prioritize the maintenance and demand data analyses that do get accomplished. If systems engineers employ a continuous monitoring of fielded operational systems for validation of the user's need, there is the potential to exploit field data to help prioritize the analyses sent to logisticians to update demand forecasts.

Similar to the theories behind Condition Based Maintenance Plus (CBM+), systems engineers and logisticians could employ a conditions-based logistics approach. Utilize the existing operational use data to determine if there exist early warning flags that identify when parts are about to become high downtime drivers before the downtime is realized in the field. These indicators could then be used to prioritize which systems or component parts get formally analyzed to justify alternative logistics actions and artificially add demand requirements to historical records as required by logistics policy.

Using the proposed modified vee-model with continuous validation loops, the specifics on what types of data and information need to be identified are illustrated in the figure below.

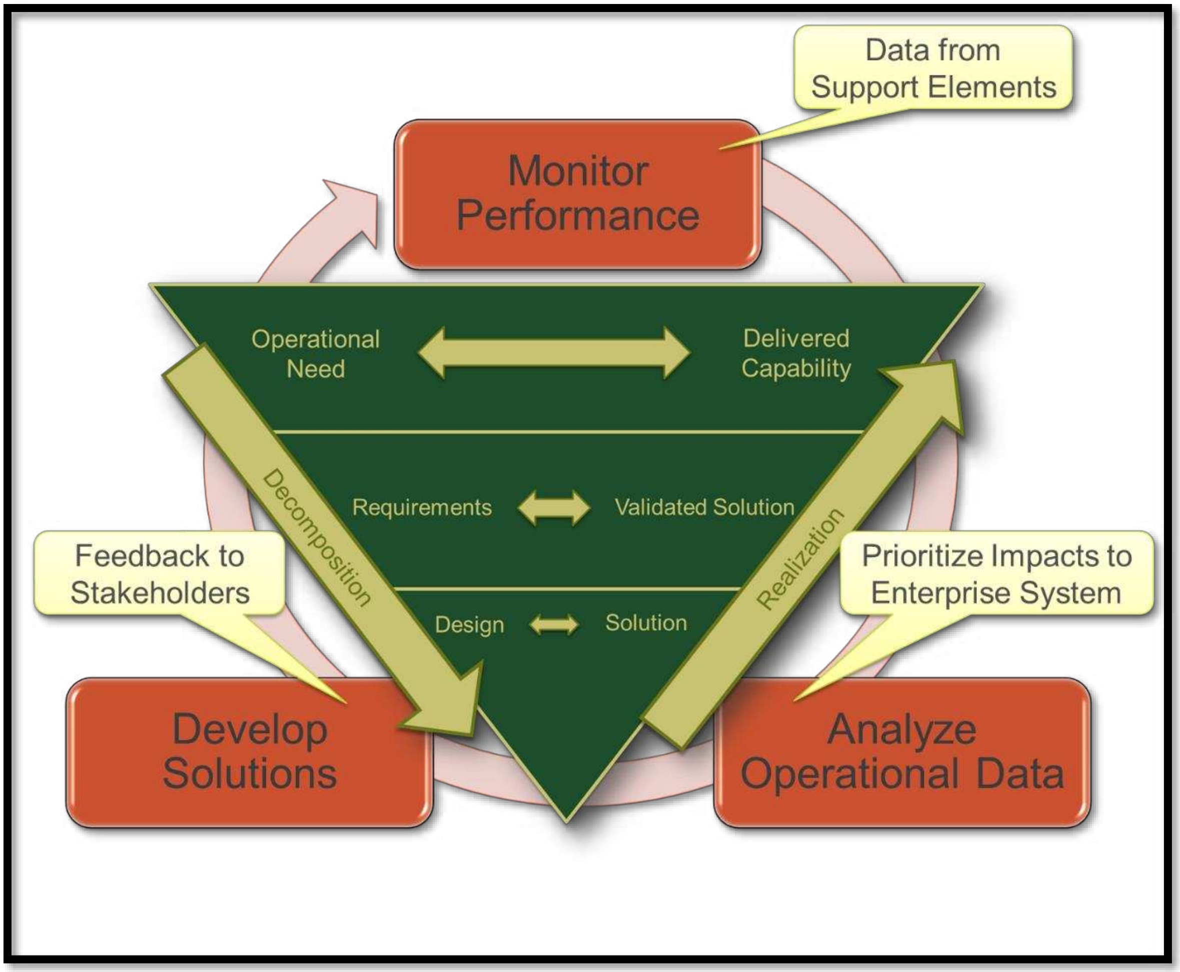


Figure 18: Inputs to Proposed Continuous Monitoring Systems Engineering Process

In an ideal world, the data and processes required to successfully monitor an operational system to identify issues before they impede operations would be identified early in the design process. Most legacy fielded systems in the DoD operate in an enterprise system that has rigid data collection and reporting processes which are generally standardized across each military department [88],[59]. Users at the working level tasked with operating the system, and systems engineers tasked with supporting the user's mission are unlikely to affect much change on policy that is created at a much higher organizational level. The proposed method above acknowledges the limitations on personnel who support systems that are already fielded. With this method, systems engineers can identify critical data from support element stakeholders, prioritize the issues that are impacting system performance and achievement of mission goals, and provide specific analysis or data directly to the stakeholders that can take action to change a requirement. Therefore, this dissertation will focus on data already identified and collected by the DoD for its enterprise systems that can be leveraged to assist with system engineering decision making.

3.2 Data Identification

The DoD has identified itself as a data-centric organization and that data is a strategic asset that should be leveraged for both strategic and tactical advantage [133]. The DoD uses its data to make informed business decisions, to gain advantage on the battlefield, and most importantly to improve DoD management [133]. If the DoD hopes to make improvements to life cycle management of aging aerospace defense systems, leveraging this data to inform the systems engineering processes that help execute life cycle management is critical to its success.

3.2.1 Metrics

As identified in this document's literature review, there are many regulations, policy, and guidance documents that dictate maintainers, operators, logistic managers, program managers, and various other career fields collect data. Research via the literature review of factors influencing aircraft availability, mission capable rates, schedule optimization, and performance prediction models was accomplished to help identify data pertaining to the research topic. The proposed approach for this research is to determine what data is an early indicator of poor logistics performance, and then identify methods to provide feedback to the logisticians to take action to prevent parts shortages.

For the purposes of this research, metrics are defined at the simplest level as characteristics of a system that indicate the system's status, configuration, or performance either at a certain point in time or as a historical trend. Some metrics are measurable, with units of measure such as quantity, inches, or hours. Some metrics indicate a status, such as an aircraft being Mission Capable (MC) or Not Mission Capable (NMC) and are not measured from the aircraft but are counted and usually displayed as sum, count, or average. An actionable metric is defined specifically for this research as a metric resulting from an observable event, directly related to enterprise system performance, for which root cause can be determined, and resulting in downtime hours being accumulated. For example, an aircraft grounding is a specific event that results in downtime hours. The aircraft records can be reviewed to determine the root cause of each grounding event such as a sub-system failure (e.g. engine flameout) or external environment incident (bird strike).

The impacts from the events that cause downtime may be permanent or temporary, and some may even be considered routine (e.g. events like scheduled maintenance). Metrics such as total hours or rates are not as useful to this research as those related to incidents or occurrences. This is because historical trends, averages, and totals generally cannot be broken down into specific root causes. If root causes cannot be determined, determining the fix or performance improvement initiative becomes much more difficult. For this reason, the research will focus on instances or occurrences of metric related data. Leading indicators are likely good candidates for inclusion in the mathematical model. Lagging metrics show trends in aircraft performance over time, but do not indicate a specific issue traceable to a specific aircraft or event that caused downtime [24].

3.2.2 Data Sources

The previous sections of this chapter identify the mathematical and statistical methods to evaluate a set of data and build representative mathematical models. The data source for this analysis is the Logistic Installations and Mission Support – Enterprise View (LIMS-EV) data repository. This system is used by the Air Force to report and review data metrics related to many different functional areas. Data under review for the purpose of the analyses contained herein was collected via LIMS-EV. Aircraft performance data was retrieved from the LIMS-EV repository for the entirety of the USAF fleet (all tail numbers, all models).

The LIMS-EV system uses a database framework created using software SAP SE corporation called Web Intelligence (Webi). Data sources from all over the DoD and USAF are collected and compiled in LIMS-EV. These metrics are available via the LIMS-EV Weapon System View, Office of the Secretary of Defense (OSD), and Logistics View module. Subsets of this data are displayed on the Weapon System Dashboard module which is utilized to create overview charts on system performance. These metrics are listed in the appendix and designated as leading, lagging, or neither as identified by USAF policy documents.

The data surrounding logistics and maintenance records are hand entered by logisticians or maintainers [26], [121]. While more modern sensor data and performance data may be automated straight from aircraft data storage into systems for the analyst to review, much of the day-to-day activities surrounding logistics and maintenance activities still depend on a human operator entering information into a system. For the purposes of this research, the analyst assumes the data collected and entered in the LIMS-EV repository accurately reflects the observed information in the field.

Maintenance metrics are tracked daily for all aircraft (by tail number, location, etc.). Units are responsible for recording the data into the system of record. Since there are multiple systems utilized for capturing maintenance, operational, and supply data, LIMS-EV consolidates the information into one data repository but segregates the data into different collections called universes. Definitions and formulas for these metrics are not available in the repository or through queries, but are available through a variety of published USAF policy and guidance [121], [134], [45], [24]. The prudent analyst should research the metrics required prior to building queries in LIMS-EV to avoid metric confusion.

It should be noted that LIMS-EV has some significant limitations with respect to collecting operational data. The databases that feed into LIMS-EV are typically established by career field (e.g., logistics or maintainers) and data is limited to the inputs of chosen by those experts. Supply and logistics data is inherently collected by date, by requisition number, or by National Stock Number (NSN), with logistics performance metrics center around timeliness for filling open requisitions. The goal for logisticians is to provide parts quickly, so this makes sense from a performance review standpoint. Maintainers and operators, on the other hand, focus on aircraft and specific events that cause downtime. Their data is generally collected by aircraft tail number, fleet type, operating location, or operational status and is typically organized by Work Unit Code (WUC) an identifier that categorizes the event by the sub-system or component part on the aircraft. While both approaches make sense given the performance measures for individuals in each career field, it makes correlating aircraft events to supply events quite difficult.

This causes issues when pulling data across multiple repositories that have been consolidated into LIMS-EV. Filters that are inherent in operational data may be missing from supply or logistics data and vice versa. It is difficult to pull supply metrics and correlate to specific aircraft, yet exceedingly easy to pull such metrics over a specific timeframe. Essentially, the supply and logistics data cannot be organized by aircraft type or serial number only by date; the weapon system data can be organized by aircraft type, serial number, or date. The common organizer is date; therefore, the dataset herein will be limited to timeseries organization rather than by aircraft model series and type.

3.2.3 Operational, Maintenance, and Supply Data Relationships

When an incident or event causes an aircraft to become not mission capable, other processes are implemented to restore that aircraft to service and metrics recorded at each step of the process. LIMS-EV returned approximately 200 available metrics that measure weapon systems in some way. This data includes leading indicators, lagging indicators, maintenance metrics, supply metrics, and operational metrics. Including all these potential metrics into statistical software for modeling would be an imprudent approach with results that would be difficult to interpret. Not because statistical software is unable to handle large data sets, but because the causal relationships become harder to identify when multiple related variables are used in the model. Additionally, utilizing all available data sets simply because they are available is data mining without context, and is considered poor statistical technique [135].

To determine the most likely metrics that influence downtime related to supply, we must first understand some basic principles of aircraft and mission operation to identify potential data to exploit for the purposes of this research. Aircraft are operated and undergo scheduled maintenance as part of routine procedures. Systems engineers track and monitor fleets to identify any issues that may impede operational use or maintenance. When issues are identified, a root cause analysis is accomplished to identify factors that may be impacting performance. Stakeholders prioritize the deficiencies and apply resources to those with the biggest return on investment for aircraft performance. The resolution for the deficiency is implemented, and the aircraft is restored to operational use and maintenance.

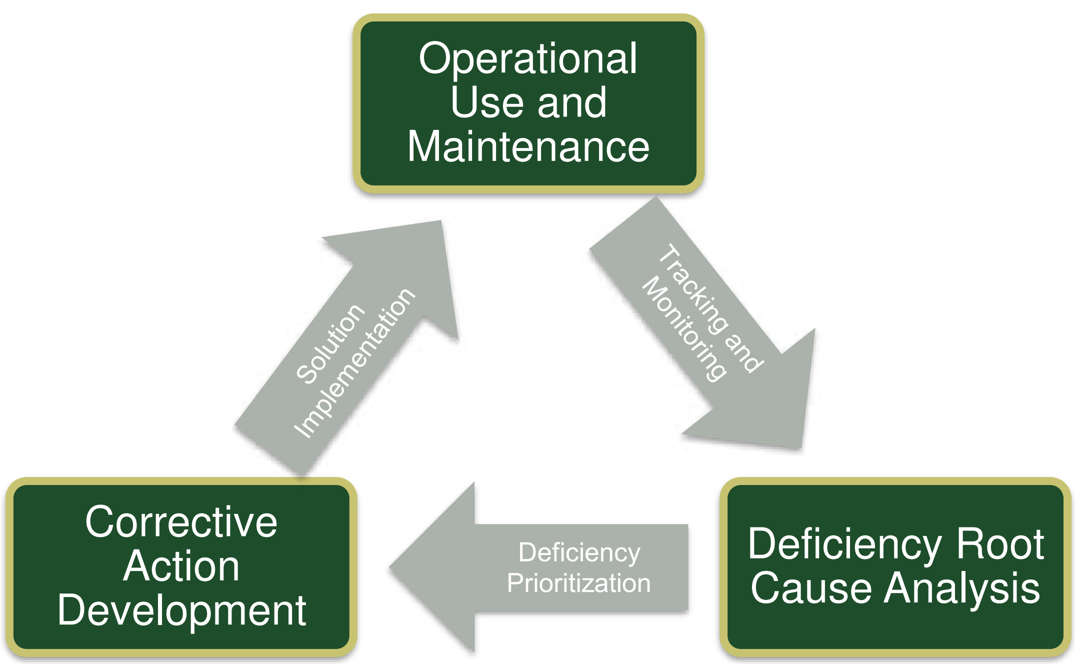


Figure 19: Operational Use Cycle

The nature of operations is such that there are always deficiencies that need attention, but some have more impact on performance than others. For example, a faulty coffee cup holder on transport vehicle will not impact performance in the same way that aircraft engine malfunction would. The basic use cycle flows as follows:

1) Aircraft are operated, used, and maintained.
2) Stakeholders monitor their area of responsibility for performance metrics against pre-specified standards.
3) When events occur that prevent operational use and maintenance, stakeholders accomplish research, data mining, inspections, and other avenues to determine the root cause of the issue preventing or impeding the performance of operational use.
4) Deficiencies are prioritized based on their impact on mission need, and funding resources applied accordingly.
5) Corrective actions and solutions are developed.
6) The aircraft is restored to operational use.

The process above is generic and can be applied to any industry or product. It boils to using a system, monitoring its performance, and resolving issues that impede performance. This process can be tailored to specific areas or stakeholders. For example, let's consider the logistics functional area as it relates to performance of aircraft systems.

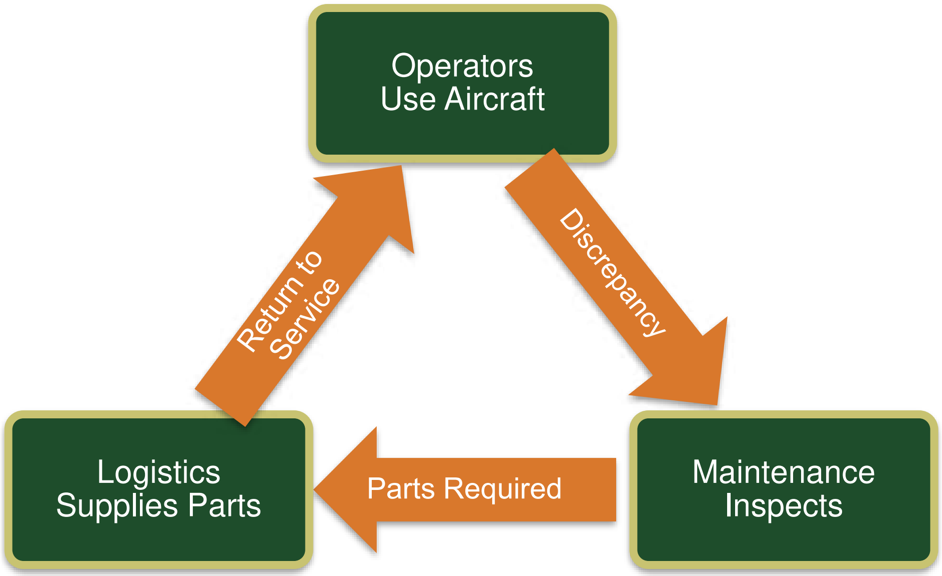


Figure 20: Aircraft Operations, Maintenance, and Logistics Relationship Cycle

This is very similar to the previous figure, but it has been tailored specifically to identify the relationships between the different stakeholders (operators, maintainers, and logisticians) that are all critical to the performance of the enterprise system that support aircraft. This figure illustrates the following process.

1) Aircraft are operated and used.
2) A discrepancy occurs which causes negative performance to the aircraft.
3) Maintenance inspects to determine the cause of the poor performance.
4) Parts are ordered as required.
5) The aircraft is returned to service
6) Aircraft are once again operated.

But what happens when there is an issue that impedes performance? For example, what if supply does not have the parts that are required? The cycle would be broken, and aircraft would become unusable. This is a significant issue that plagues many stakeholders and enterprise systems. If we apply the proposed feedback method from the previous section, we should identify ways to monitor operations, analyze operational data, and develop solutions to any performance impacts. To successfully implement this process, systems engineers should identify what operational data may indicate future performance issues, analyze that data to identify useful information, and submit that data to the critical stakeholders that can take action to update requirements.

A key takeaway from this process description is to realize that impacts to performance are expected, and processes to identify and resolve those deficiencies are built into nearly every organization, career field, and functional area across the board. This is illustrated in the various policies that stipulate the appropriate procedures to follow when impacts to performance are realized by the Warfighter [136], [137], [138], [88], [126]. To summarize, the proposed new feedback process entails systems engineers utilizing existing operational use and maintenance data to identify trends associated with future downtime related to logistics issues. This data can then be used to prioritize analyses related required to provide logistics with justification to procure additional parts. Data could be incorporated into the existing Logistics Requirements Development Process (LRDP) and Reliability Centered Maintenance (RCM) process.

Given the large amounts of available metrics surrounding USAF operations, logistics, and maintenance, it is appropriate to determine the best approach for factor reduction to avoid data mining. Factor reduction involves reducing large amounts of potential independent variables into a smaller, focused group that is statistically relevant. There are hundreds, if not thousands, of various metrics available for research and review residing in the LIMS-EV repository. But identifying a mathematical expression that can predict the dependent variable is not the goal of the research. Rather, once an explanatory variable is identified, this research strives to determine ways to exploit the relationship and take action to prevent mission performance degradation. This purpose influences the approach to factor reduction.

With that in mind, it is critical to identify factors that, once identified, allow systems engineers to act in order to improve, not predict, performance. If causal relationships are identified but no action can be taken to prevent their negative impact on performance, the research becomes less useful for operators and maintainers. To facilitate this goal, the first step for factor reduction will be to review the type of metrics available for analysis. As discussed in the previous section, lagging vs. leading indicators are already identified in Air Force literature for maintenance, primarily in the Maintenance Metrics Handbook [21]. This guide also briefly touches on available leading indicators for logistics.

Instead, before modeling any relationships mathematical, a review of how metrics are related to the process of operating aircraft should be accomplished. A very high-level categorization of some of the types of metrics collected during operational use is shown below:

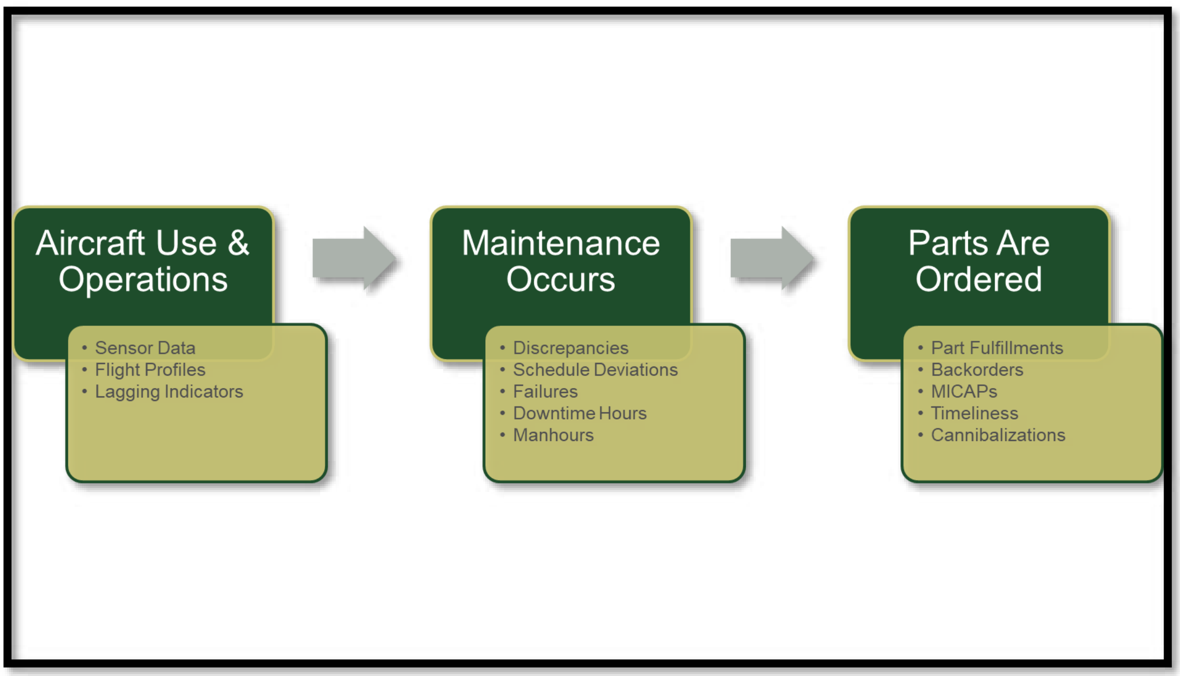


Figure 21: Examples of USAF Metrics Collected in O&S Phase

Additionally, many metrics are reported in hours, rates (either per sortie, fleet size, or total aircraft inventory hours), number, quantity, occurrence, or incident. While these metrics do create additional data sets and indeed may provide different insights to performance based on how they are analyzed, ultimately this research focuses on actionable data that personnel can use to prevent negative downtime drivers.

3.2.4 Metrics from Operations

Aircraft Use & Operations is generally captured by monitoring leading indicators from aircraft sensor data and flight profiles, or lagging indicators that measure broader performance trends. Aircraft sensor data is varied across fleets, and there is no standardization in the types, quality, or even location of the data collected. This is due to the wide and varied types and ages of aircraft fleets across the USAF. Aircraft that are approaching 60 years old simply do not have the sensor technology of newer fleets. Since the intent of this study is to utilize existing data, sensor and flight profile data will be excluded since it is not standardized across the USAF.

Lagging indicators, on the other hand, are standardized across USAF fleets. These metrics are calculated as directed by policy guidance. There are many studies from a variety of sources including Government Accountability Office (GAO) reports, academic studies, and third-party contractor studies surrounding the DoD and its logistics community. A high-level overview of Not Mission Capable lagging indicators is shown below:

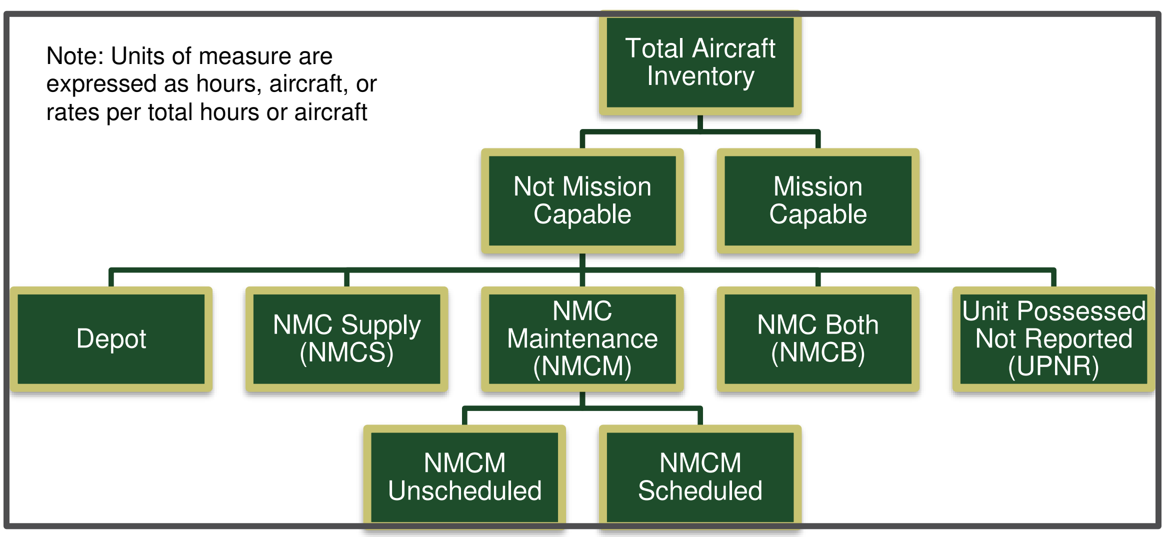


Figure 22: Taxonomy of Common USAF Lagging Indicators

The formulas used to calculate these lagging indicators are based on the aircraft status. When an aircraft is experiencing downtime, it is required to have a status code assigned that tracks why the aircraft is down. While the taxonomy above illustrates the basic relationship and breakdown of the lagging indicators, many of the relationships are too difficult to explain graphically. Most lagging metrics are calculated by using the hours related to NMC downtime for various categories. A sample of common supply and logistics lagging indicator formulas are shown below, calculated in accordance with the guidance in a variety of policy manuals [45].

$$TNMCS\ Rate\ = \frac{NMCS + NMCB}{Possessed} \times\ 100\%$$

Equation 3: Not Mission Capable Supply Calculation

$$NMCS(NA)\ \mathrm{Rate} = \frac{NMCS(NA)}{Total\ Aircraft\ Inventory}\ \times\ 100\%$$

Equation 4: Total Not Mission Capable Supply (NA) Calculation

$$NMCS\ Rate = \frac{NMCS}{Total\ Aircraft\ Inventory}\ \times\ 100\%$$

Equation 5: Not Mission Capable Supply Calculation

Hours reported with the “NA” designator are the sum of hours for aircraft in combat status, test support, airlift, operational support, special missions, etc. Hours reported without the “NA” designator include all hours assigned to that category regardless of aircraft status. This means aircraft awaiting maintenance, in heavy depot maintenance, being transferred from one location or owning unit to another, those awaiting maintenance determination, and those awaiting retirement consideration are all included in the non-NA hour summation [24]. Possessed hours only include aircraft that are in the possession of the owning unit. Total

Aircraft Inventory Hours are essentially all hours accumulated by an aircraft fleet, with limited exception for those in disposal or other similar statuses.

3.2.5 Maintenance Metrics

Aircraft maintenance typically occurs in one of two ways: 1) it is scheduled as part of routine operations, or 2) it is unscheduled (e.g., broke unexpectedly). Whether scheduled or unscheduled, aircraft maintenance drives certain metrics such as downtime hours (NMC hours) and maintenance man-hours. Additionally, records of aircraft discrepancies (sometimes called "write-ups") are often created during this period. The relationships amongst the available variables may or may not be evident. An example of the varied relationships amongst aircraft discrepancy and maintenance metrics are shown below:

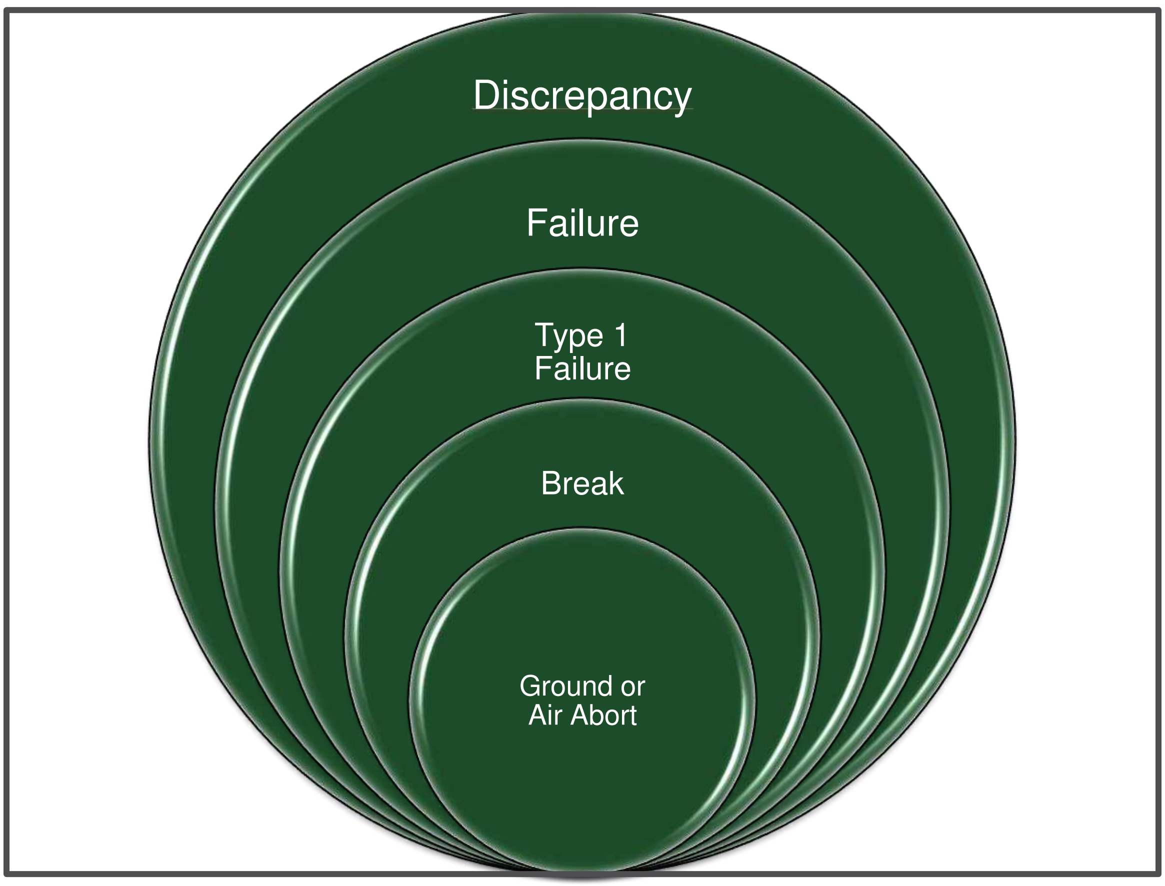


Figure 23: Aircraft Discrepancy Relationships

3.2.6 Supply Metrics

Supply metrics are captured when maintenance puts parts on order. While there are special cases where parts may be ordered without an immediate maintenance need, those instances are special cases and orders generally have a lower priority code than real-time needed parts [137]. For example, a logistician might review historical usage data and determine that the maintenance demand combined with the lead time or other influencing factors may indicate the need to set stock levels as a buffer to keep up with sporadic demand. Supply metrics are captured when a part is requisitioned, regardless of the priority code. Everything starts with a requisition number with additional meta data captured such as date, national stock number, order priority codes, requestor location, etc. The Figure below illustrates the relationship amongst a few of the more closely related supply metrics:

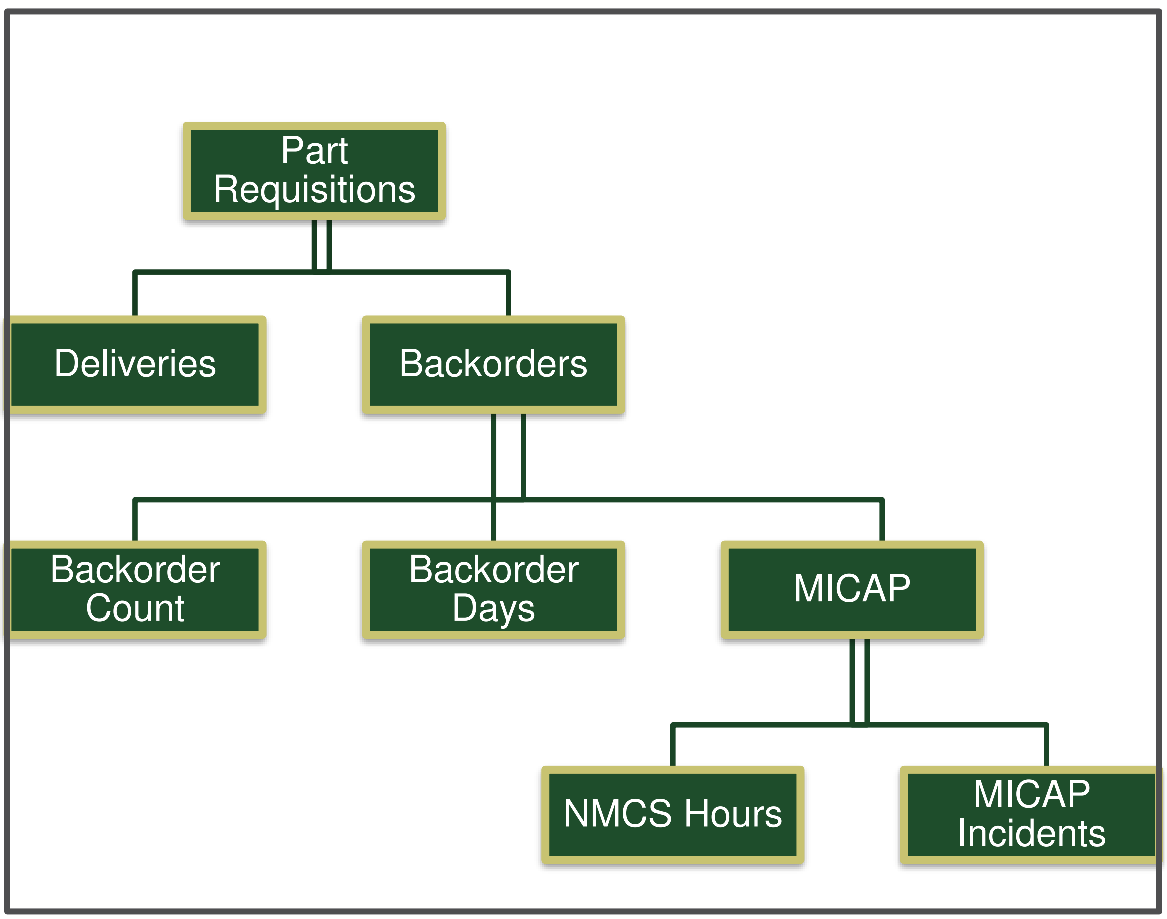


Figure 24: Supply Metrics Relationships

Leading indicators will be reviewed to determine which is the best indicator of supply performance and will serve as the effect variable (dependent variable) in the mathematical model. Lagging indicators will be reviewed to determine which are most likely to help assist systems engineers as an early warning system to prevent downtime and will serve as the independent variables (predictor variables) in the mathematical model. The research question under investigation is to determine whether events maintainers and operators experience in the field can be used as predictors for future supply downtime drivers. Therefore, metrics selected for review as independent variables shall be limited to those that can be reviewed for specific occurrences related to aircraft performance, such that a root cause could be reviewed, analyzed, identified, and resolved.

A review of the data available in LIMS-EV indicated there are thousands of metrics collected across both the logistics, performance, and maintenance. While all these metrics may have some influential relationship on aircraft performance, the overlap of available metrics and complexity of the interactions would require much more study and investigation. Additionally, the purpose of this research is not to create a predictive model, but rather to identify causal relationships that can be exploited to prevent aircraft grounding events. Rather than blindly applying mathematical analyses to all available metrics, a review of the taxonomy of the sequence of events that leads to aircraft downtime will be reviewed first.

To understand the DoD procurement process as it relates to refreshing the stock of subsystem and component parts in supply, one must first understand the National Stock Number (NSN) framework. An NSN is a number that relates to an item of supply that is procured, stocked, and issued. It is a sixteen digit numeric sequence, and is tied through various databases to an item description, name, manufacturer's part number, pricing, and characteristics [139]. Establishing an NSN is a process known as cataloging. Cataloging of an NSN can occur at any point along a system's life cycle. But the most well-known and laborintensive time is when an NSN begins to transition to an operational status. At this stage in the life cycle management process the DoD agency, more specifically the weapon system program office, will identify the spare parts needed to maintain the system throughout its life cycle. One issue that occurs is that all resources necessary to operate and maintain an enterprise system do not necessarily reside within a single program office. This can lead to a mismatch of provisioning for the various support activities that may lead the enterprise system to ultimately fail at a much later date.

Additionally, an NSN is not a manufacturer's part number and does identify as a controlled, configured item. Specific items, that are configuration controlled and available to manufacture, are identified by a part number (P/N) and Commercial and Government Entity (CAGE) identification number. The P/N and CAGE will both be included on any technical data that defines the configuration of an item, such as a drawing or model. There are 17 million active NSNs, identifying items of supply for the DoD inventory. About 10 million additional NSNs are inactive. And the NSNs represent over 42 million part numbers from millions of suppliers all over the world [139]. That is an incredibly large inventory to manage, particularly when DoD mission success is dependent on the ability of logisticians to have parts available whenever the mission dictates.

Aerospace defense policy and guidance dictates what types of logistics data are captured and reviewed. In accordance with the Federal Acquisition Regulation and DoD policies, logisticians are required to review historical usage data prior to establishing the requirement for a purchase of refreshment items for DoD supply. Generally, logisticians review two years of historical purchases to calculate the required quantity of items to last the next two years. While some procedures do exist to procure more stock, such as lifetime buys, justification is required, and a higher-level review and approval process must first be accomplished. While the supply refresh procurement process isn't precisely automated, cursory reviews of supply data prior to sending for rote replenishment stock is part of the process. If the military departments do not submit updated information for NSNs in the database, item managers will continue with replenishment based on past history [126].

One issue that is commonly faced is that highly reliable parts are prone to be listed as "inactive" in the DoD NSN inventory. An inactive part is defined as "an item without a demand in the last 5 years for which no current or future requirements are anticipated" [126]. If a weapon system is in use for 5 years and has component parts that have not failed or required routine replacements, those NSNs are likely to be removed from the active inventory and the stock disposed. On the surface, a policy that automatically removes inventory from supply after a specified period of inactive time may make sense. After all, stocking items that aren't being used can have storage fees as well as taking the time of personnel to manage the inventory, accomplish reviews, and provide periodic data for audits. And the costs are quite high. One report indicated that the Defense Logistics Agency (DLA) disposed of over $1 billion in excess inventory items in a single year, which is about 14% of annual sales in the same period [140].

But issues arise when the flow of data from those providing tactical support to the enterprise system (either operators, maintainers, engineers, or logisticians) doesn't provide the necessary information for strategic logisticians to update their forecasting information. Previous studies have recommended that tighter collaboration with DoD services and DLA supply chain managers could be beneficial in both forecasting existing items and phasing out items that are no longer needed [140]. The study suggested that developing a process or repository for engineering changes could help in supply chain decision making. This information that could be leveraged to help inform the life cycle management process as feedback from system use.

Personnel providing tactical support to the enterprise system, be it as an operator, maintainer, engineer, or logistician, will know exactly when the supply chain failed to provide a part because they are involved in the process above to find a resolution to the issue. After all, the resolutions illustrated in the Logistics Support Flow Chart are documented processes supported by policy [88]. Therefore, there are only a finite number of courses of action that can successfully restore a weapon system to its full capability of a required part is not available.

Requisitions, order history, backorders, etc. are the current method by which the logisticians get feedback from operational units regarding supply issues. This means that the first-time logisticians are informed of an issue that occurs when operators or maintainers order a component part. This can be problematic considering the increasing age of most USAF fleets and the impact of component parts that are nearing their natural end of life. Logisticians and Systems Engineers alike simply do not have the time or manpower to provide an in-depth review of all potential items that may experience increased demand on supply.

3.2.7 Work Around metrics

As aircraft fleets age, issues with supply and the logistics responsibility to provide spare parts and raw material can increase. If a new part is no longer procurable, there are limited options for maintenance and logisticians to resolve the lack of parts. And as parts age and fail in new and interesting ways, the existing technical manuals may not be sufficient to address all the problems faced by maintainers. But the lengthy change process may lead to fielded systems being modified without documentation. If a part is not procured or manufactured, logisticians have no choice but to either repair the part, cannibalize the part, or reverse engineer it to develop new sources. The flow chart below was used to help logisticians and engineers at Robins Air Force Base to resolve parts shortage issues:

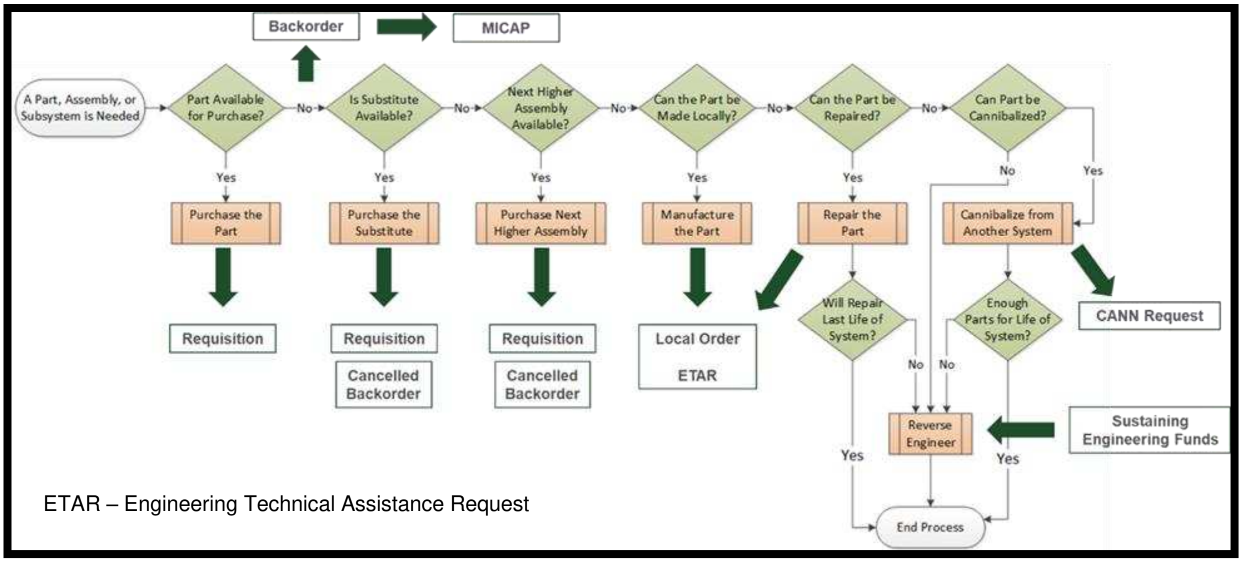


Figure 25: Logistics Support Flow Chart [75]

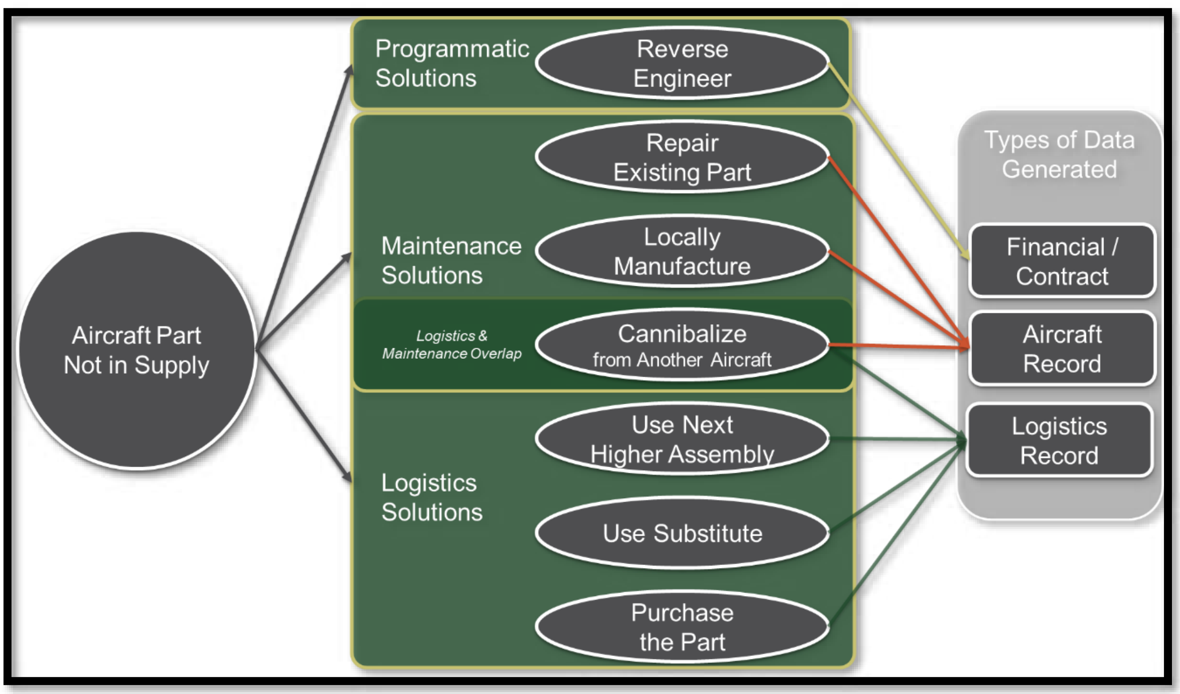


Figure 26: Overview of Parts Shortage Workarounds and Type of Data Generated

Based on this diagram, potential metrics that may make good candidates to include in a mathematical regression are metrics related to Requisitions, Backorders, Cancelled Backorders, and MICAPs since these all correlate to events tied to aircraft discrepancies, operational events, or maintenance actions.

3.2.8 *Variable Reduction*

Of the approximately 200 metrics identified in the LIMS-EV repository related to maintenance, operations, and supply, over one hundred are lagging metrics available for consideration as the dependent variable, although many of these are subsets or related to other metrics in this category. Since the focus of this research are impacts to aircraft downtime caused by lack of supply or component parts (reference the previously discussed research questions), a metric closely related to downtime ***events*** on the aircraft would be the best choice to utilize in a mathematical model. A list of leading indicators was compiled using USAF supply guides and maintenance metric guides in addition to the list of identified records created as a review of supply records, aircraft records, and work around records.

Excluding the lagging indicators removes the majority of the initial data metrics from the candidate list. Additionally, excluding rates and hour metrics whenever possible in favor of counts, occurrences, or incidents also significantly reduces the potential metrics available for mathematical modeling. Finally, some of the leading indicators are not actionable. For example, aircraft sometimes get diverted from their normal flying schedule to participate in exercises related to training or capability demonstrations. While those deviations do impact performance, and they are identified as a leading indicator of poor schedule performance, they are not something that working level personnel can take action to prevent. Therefore, leading indicators that are not actionable by maintenance, operations, or supply personnel will also be removed.

3.2.8.1 *Data Collection Limitations*

The LIMS-EV repository had no linkages between supply data universe and weapon system data universe. This created issues when attempting to collect data for the variables identified in the previous chapter for mathematical modeling. When a maintenance action occurs and a part is ordered, the common linking dataset is the Part Number, which correlates to a National Stock Number (NSN) used by supply to track parts and requisitions, and a Work Unit Code (WUC) used by maintenance to identify the system with the discrepancy.

Unfortunately, there is no Air Force level correlation matrix between WUC and NSN, or even WUC and part number in most cases. WUC's identify a system as described by the maintainer's technical manual. While this sometimes does correlate to a part number, the intent of the system is not to reinvent a part number identification system but rather to allow maintainers to quickly identify the system with the discrepancy for later analysis by engineers. The system is similar to American Transport Association (ATA) coding system and uses a compatible referencing standard. WUC's are defined by MIL-DTL-38769, and definitions unique to each weapon system are identified that systems 00-06 series technical order. WUC's are structured in a 5-digit alpha-numeric format. The first two characters of the WUC identify the end-item or major sub-system of the overarching weapon system, with the remaining 3 digits using zeroes as place holders. For example, 11000 is commonly used as the WUC for airframe structure, 13 for landing gear, 14 for flight controls, and so on. The WUC's primary purpose is to identify all the work that a unit accomplishes with respect to maintenance or action taken against an aircraft. It is not used to order or identify parts. An illustration of how WUC's are broken out is shown below:

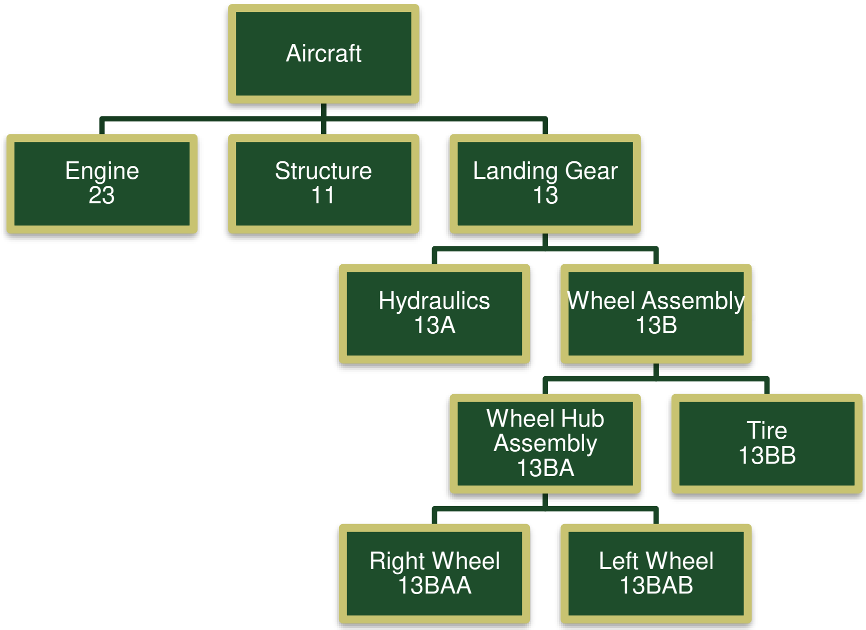


Figure 27: Work Unit Code Taxonomy

Some systems engineers have created their own cheat sheets that link part number or NSN to WUC's as identified by the aircraft maintenance manuals, others have created this list more formally and integrated it into custom analysis software as part of digital transformation efforts. But there is no Air Force level guide that cross references WUC to NSN. Attempts to automate the generation of a WUC to NSN cross-reference proved impossible through LIMS-EV. First, while all weapon systems use WUC's, they do not all use the same codes for the same lower-level sub-system and component parts leading to an inability to aggregate data by WUC across the USAF fleet. Additionally, the information required to determine the cross-reference is frequently in non-searchable scanned engineering reports or technical orders that do not have meta data (the page of the manual is an image, not searchable text). Next, to identify the part number associated with a WUC, the analyst must review the technical manual for the right system and select the associated WUC only by the title (WUC descriptions do not include part numbers). Many times, the part number name/title may not match the WUC designator exactly, and the analyst will make judgement calls as to the appropriate system to use. Finally, as previously stated, the purpose of the WUC was never to track parts and WUC's do not exist for all parts on an aircraft. Rather, major end items, line replaceable units, or larger commodity assemblies typically get their own WUC. But non-repairable disposable items may not.

Another issue was realized in the research of potential supply data available in LIMS-EV. While NSN is the commonly used data item to track parts, most of the supply database architecture is focused on document number, which uniquely identifies each individual requisition. Meta data such as initiation date, order location, and NSN are included as part of that record, but the supply universe in LIMS-EV does not always link this information to performance measures not associated with a specific requisition (mainly lagging indicators such as wait time). It was also discovered that Backorder Cancellations are not a metric commonly tracked. Trends for backorder cancellations could be pulled related to date or timeframe. And single item records could be manually reviewed to determine if the document number had been cancelled. But records related to how many times an order had been cancelled for a unique NSN or WUC could not be generated. Neither did all cancelled backorders have dates associated with the cancellation, further clouding the data.

These issues all had a significant impact on the approach to creating a mathematical model for the aggregated data with the intent to test the results of the model against unique case studies by NSN. The mathematical model will be limited to metric variables where either a WUC or NSN cross reference can be positively determined through a use of aircraft maintenance and supply data in LIMS-EV. This reduces the potential variable list to:

Table 1: Metrics Linked by WUC or NSN

Air Abort (N)	Canns (N)
Backorder Count	Ground Abort (N)
Backorder Days	MICAP (I)
Breaks (N)	

3.2.8.2 Dependent Variable

Since the focus of research is supply performance, a supply or logistics related performance metric should be chosen as the Independent Variable (IV), or effect variable, for the mathematical model. The author interviewed several logisticians at varying levels in the Air Force Life Cycle Management Center (AFLCMC) to request opinions on the best metrics to track logistics performance. All responded that the metric the logistics community tracks most closely related to aircraft performance are TNMCS, NMCS, and current MICAP instances. All identify NMCS, TNMCS and MICAPs as a key indicators to measure overall supply chain health as it relates to the overall goal of Aircraft Availability [141], [101], [104]. A follow-up with the Air Force Sustainment Center's (AFSC's) Director of Engineering (DoE) confirmed that TNMCS trends are a hot topic for the lagging indicator and MICAP occurrences, specific to each weapon system, were frequently reviewed as action items and briefed to senior leaders on weekly status reports. Additionally, the AFSC Data Analytics organization also provided insight into LIMS-EV and confirmed that TNMCS, MICAPS and NMCS were often referred to performance metrics for overall system performance. Additionally, MICAPs are considering the leading indicator for real-time logistics related concerns [24].

MICAP hours are simply an accumulation of the quantity of hours a weapon system has been down for MICAP related parts issues over the queried period. MICAP incidents indicates the number of items that were identified as MICAP incidents during that timeframe. TNMCS is a tempting choice because it is limited to aircraft of operational units and its propensity to be used to determine overall supply health due to its ability to show historical trends. But the TNMCS metric makes it difficult to isolate factors related to only supply issues, since its formula includes NMCB hours (which is a combination of supply and maintenance related issues). NMCS (NA) is also a trending metric and does not indicate negative actions or events on aircraft that could be prevented or resolved. Therefore, for the purposes of this research, the MICAP category will be chosen.

Since the intent is to prevent any downtime hours at all, it logically flows that all MICAP hours should be prevented. However, the documentation of a MICAP hour is not an event by itself. A MICAP incident, MICAP (I) must first occur for hours to accumulate. At this point, it is important to understand how the category of MICAP is applied to parts in supply. A MICAP refers to a specific requisition, or order for parts, in the logistics system. MICAP hours, by the very definition of how the lagging indicators TNMCS and NMCS are calculated, drive supply performance. Based on the review of impacts and drivers to the logistics and maintenance processes, and the comparison of the various MICAP metric types, MICAP (I), will be the chosen dependent variable. By preventing MICAP incidents, systems engineers will be preventing NMC downtime hours associated with logistics.

3.2.8.3 Independent Variables

There are many aircraft operational use and maintenance records and data that tie to a specific serial number or negative event that prevents aircraft operation. But logistics records focus on national stock number (NSN) as the driving identification characteristic and can't be tied directly to policy. In fact, DoD and USAF policies don't even require that logistics processes and data repositories monitor links to aircraft records [6], [53], [75], [77].

The remaining variables, reduced from the original list of 200 and excluding the dependent variable MICAP(I), will serve as the starting point for statistical analyses and become our potential list of influencing variables, or IV's. The next table identifies the final list of all variables and their definitions.

Table 2: Metric Data Dictionary

Metric	Description
Air Abort (N)	An aircraft discrepancy identified by operations during airborne missions; Indicates a sortie could not continue its primary or alternate mission
Backorder Count	Number of requisitions assigned backorder codes, indicating no available stock in supply, calculated per time period or by date
Backorder Days	Sum of days accumulated for requisitions assigned backorder codes, calculated by timeframe or by date
Breaks (N)	Discrepancy assigned by tail number to aircraft that land with a status of Code-3 (Code 3 indicates major discrepancies in mission essential equipment that may require extensive repair or replacement prior to mission assignment)
CANN (N)	Cannibalization, a removal of a serviceable part from a weapon system to replace an unserviceable part on another system
Ground Abort (N)	An aircraft discrepancy categorized by maintenance, operations, HQ, weather, or other factors and occurs preventing a scheduled airborne mission

All these metrics are leading indicators that link to a specific event such as a failure of equipment, a deviation from flying schedule, a recurrence of a failure, a backorder, or other event. The data from LIMS-EV will be reviewed at an aggregated USAF level, to avoid any concerns with operational security.

3.3 Statistical Analyses

This type of data investigation usually starts with a correlation analysis between variables. From there, linear regression, multiple linear regression, and non-linear regression techniques can be used to create a model of the data that is most often used for predictive purposes. For this research, we are exploring the mathematical relationships between the data collected from operational use and maintenance to determine the relationships between aircraft event and weapon system performance as it relates to supply chain and logistics concerns to better understand where feedback loops in the systems engineering process should be added. The analysis software used in this research is a combination of JMP: Statistical Software Version 17, Student Subscription; Microsoft Excel, and STATA 17.0. Graphics, charts, tables, and other information were also created with these software tools.

The statistical analyses used for this research are not new. Therefore, only high-level overviews of the mathematical methods used are covered in this dissertation. There are many textbooks, articles, and websites devoted to the statistics field of study and the references listed for the following methods are just a small sampling of what research is available. Creating a predictive model for aircraft performance is not the purpose of this research. It should be noted that the resulting mathematical model of this data will never be a true model. The assumption that there is no missing data from regression techniques will almost certainly be violated, given the research identified in the previous sections of this report. Factors such as manpower, funding, training, and economic or political factors will almost certainly influence aircraft performance. For the purposes of this study, it is understood that the assumption of no missing information is likely to be violated given the complexity of factors involved that may impact mission capability in the field. Like healthcare industries where data is highly variably and there are many influencing factors on patient health, this acceptance of missing information should not deter the research.

3.3.1 Basic Statistics Characteristics Review

When analyzing data sets, it is prudent to review the basic characteristics of that data set to get an idea for its behavior. Basic statistics include calculations and values such as: maximum, minimum, mean, median, distribution, skewness, kurtosis, constant of variance, standard deviation, etc. Formulas and definitions of these terms abound in textbooks and academic research related to statistics.

3.3.2 Confidence Intervals and Hypothesis Tests

The confidence level is a statistic that represents the chances that the calculated value is correct. In general, confidence intervals are calculated using the mean of the estimated value plus or minus the variation (or error) that occurs in the estimate. Confidence intervals use data from a sample to estimate parameters for a given population or data set. Hypothesis tests use sample data to test a specified hypothesis, and either accept or reject it for that data set. For many statistical calculations, the analyst identifies a null hypothesis and either accepts or rejects it based on the results of the calculations [135]. The alpha statistic, α, is the significance level used to calculate the confidence level. The confidence level is typically calculated as $1- \alpha$. For example, in a statistical analysis where $\alpha = 0.05$, there is a 95% probability of accepting the null hypothesis when the null hypothesis is true, and a 5% probability of rejecting the null hypothesis when the null hypothesis is true. Alpha values range from 0 to 1 [142].

Similarly, p-value is the probability of obtaining a result as extreme as, or more extreme than, the result obtained when the null hypothesis is true. The p-value of a data set is typically calculated based on the test statistic used for the analysis. In general, the analyst will calculate the test statistic based on the data set, determine the critical values of the test statistic (determined from a reference table and usually based on sample size and the selected alpha), calculate the p-value (the percentage of values on the table that fall beyond the test statistic). If the p-value is low, meaning less than the selected alpha level, it indicates that the null hypothesis is not true and must be rejected [135].

The method of applying a confidence level to test statistics opens the door for a small chance that the analyst will get the result incorrect. A Type I error occurs when the analyst rejects the null hypothesis when the null hypothesis is true. Reducing the value of alpha can help avoid a Type I error. A Type II error occurs when the analyst accepts the null hypothesis when the null hypothesis is false. Sample size is a large factor in the occurrence of Type II errors, and a larger sample size will help avoid Type II errors [135].

3.3.3 Correlation Methods

One of the most used methods for reviewing correlation between two variables is the Pearson product moment coefficient of correlation. Correlation measures the strength and direction of linear relationships between two variables [135]. The assumptions when applying Pearson's correlation to datasets are [143] :

- Variables are continuous.
- There is a linear relationship between the two variables.
- Each case (data point) is independent and unrelated to other cases.
- Each variable is normally distributed.
- The data is randomly sampled from the population.
- There are no outliers.

The Pearson's coefficient, *r*, is a numerical descriptive measure of the strength and direction of two variables, x and y, and is computed as follows [135], [143], [144]:

$$\boldsymbol{r_{xy}} = \frac{\sum_{i=1}^{n}(\boldsymbol{x_i} - \overline{\boldsymbol{x}})(\boldsymbol{y_i} - \overline{\boldsymbol{y}})}{\sqrt{(\boldsymbol{x_i} - \overline{\boldsymbol{x}})^2 * (\boldsymbol{y_i} - \overline{\boldsymbol{y}})^2}}$$

Where,

$\overline{x}$ is the mean of the x variable data.

$\overline{y}$ is the mean of the y variable data.

Equation 6: Pearson's Coefficient of Correlation

Analysis of the *r*-value between data sets can provide insight into relationships between those data sets. The closer the *r*-values to zero, the weaker the linear relations. An *r*-value of -1 indicates a perfect negative correlation where values of the two variables are negatively proportional. An *r*-value of +1 indicates a perfect correlation where values are directly proportional to each other. Since Pearson's Correlation method only applies to variables that are linearly related, does not address causal relations, and does not provide insight into the magnitude of influence once variable has on another, this method will only be used as a starting point when reviewing the research data set. Cohen's Rule of Thumb for correlation strength indicates a weak relationship for r-values = +/-0.8, moderate relationships for r-values = +/-0.5, and weak relationships for r-values +/- 0.2 [145].

3.3.4 Multiple Linear Regression

Linear regression is a technique to form models centered on linear correlation between a dependent variable, y, and one or more independent variables x_i. Simple linear regression relates the independent y-variable (IV) to a single dependent x-variable (DV). Multiple regression relates the IV to multiple DV's. The multiple linear regression model is mathematically expressed as follows:

$$y = \beta_0 + \beta_0 x_0 + \beta_1 x_1 + \cdots \beta_k x_k + \epsilon$$

Where, for i = n observations

y = dependent variable

x_k = independent variable

β_0 = y-intercept (constant term)

β_k = slope coefficients for each DV

k = number of independent variables

ϵ = the variation in y that is not explained by the model

Equation 7: Multiple Regression Equation

In multiple regression, each slope coefficient is interpreted as the estimated change in the DV corresponding to a one unit change in the IV, assuming all the other variables are held constant. This technique provides much more insight into relationships between IV and DV's than a simple correlation analysis. However, there are assumptions that must be true to effectively utilize multiple regression as a statistical tool. Those assumptions are:

- Linearity: the relationship between IV and DV is linear

- Multicollinearity: there is little or no multicollinearity or serial correlation; the DV's are not correlated to one another
- Independence: each observation is independent of the others
- Normality: the distribution of the IV and DV is normal, as are their residual error
- Homoscedasticity: the variance in error is constant along the values of the DV

3.3.4.1 Checking for Linearity

Checking for linearity is generally as simple as checking a scatter plot of the residuals vs. the predicted values or the observed vs. predicted values, which is part of the standard regression data output from most statistical software. Scatter plots should show points distributed in a straight line with a slope pattern, with a roughly constant variance (distance from the line) [146] . A typical linear relationship scatterplot will appear as follows:

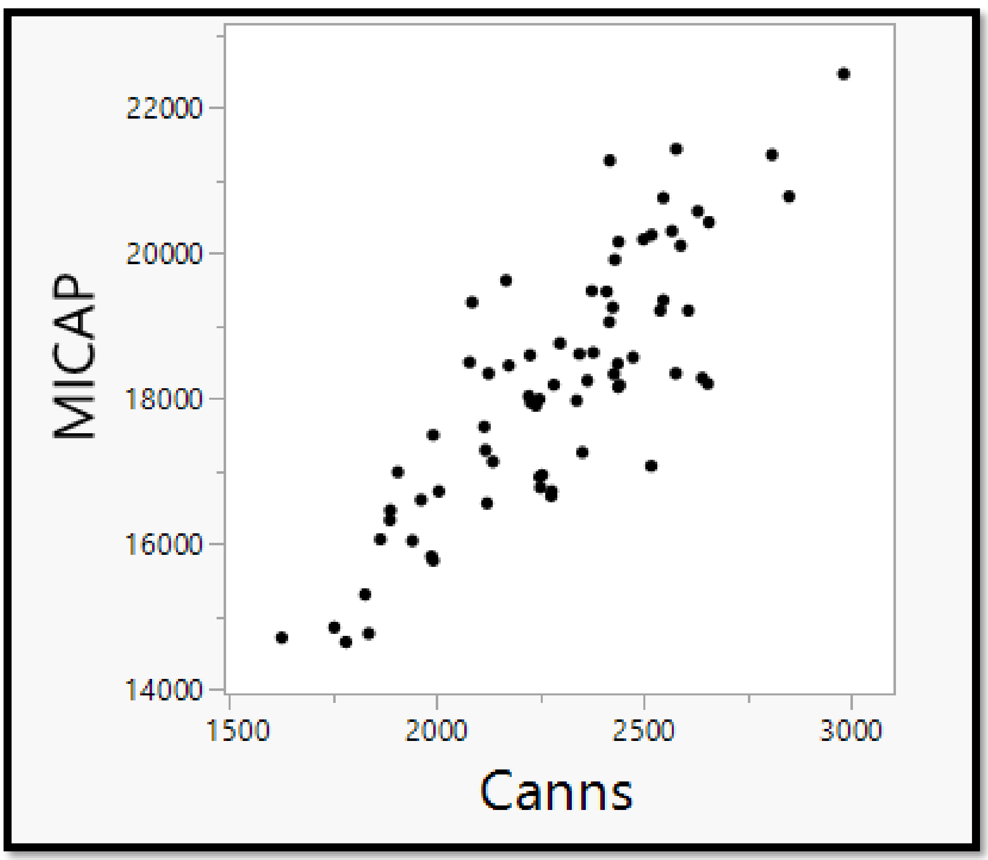


Figure 28: Example Scatterplot Illustrating Linear Relationship

A bowed pattern in the scatter plot indicates a simple slope-intercept model can be improved. If nonlinear characteristics are observed, it is critical that the analyst adjust the model to accommodate the nonlinear relationships. The analyst could consider applying a nonlinear transformation to the dependent or independent variables, such as a logarithmic transformation. Another possibility is to add an additional regressor that is a function of the original, such as squaring the independent variable (so adding x and x^2 into the regression model). Piecewise linear regression is also an approach in some cases. This approach segments the data set to address only the ranges of the independent variable that show linear trends with the dependent variables [135].

3.3.4.2 Checking for Multicollinearity

Sometimes, IV's can be related to both the DV and other IV's. When this occurs, it is called multicollinearity. Multicollinearity is a concerning feature of variables included in a regression model because it can skew the models results. In an ideal world, the IV correlates to all of the DV's, but the DV's do not correlate to each other [135]. Multicollinearity is a problem because it undermines or masks the statistical significance of an IV as it relates to the DV.

Multicollinearity can be tested by calculating the Pearson's Correlation Coefficient which is visually represented with scatter plots of the two variables. Another way to check for multicollinearity is to check for the Variance Inflation Factor (VIF), which identifies how much two variables correlate. The range for VIF starts at 1 and has no upper limit. Therefore, the lower the VIF, the more likely that the model has avoided multicollinearity. A general rule of thumb is a VIF more than 10 indicates a problem with multicollinearity [147]. If multicollinearity is detected, removing variables with higher levels of VIF is one way to eliminate the issue. Other methods include removing the mean of the variable from each observation, a method known as centering the data [135].

Each regression model will be reviewed for VIF, if the value exceeds 10 the correlation matrix will be reviewed for that independent variable to determine which of the other independent variables has the highest Pearson r. Those two independent variables will be compared to the dependent variable by using r-squared values. The variable with the highest r-squared will be kept in the model and the other discarded.

3.3.4.3 Checking for Independence

Independence of observations of each data set is also called autocorrelation. There is nothing inherently wrong with autocorrelation in a data set, but it can be problematic for utilizing linear regression techniques. Autocorrelation can become problematic if the independent observations of a data set are too dependent on one another, thus not providing adequate information to successfully model the system. An example of this is stock market prices. Prices may not vary much day-to-day, but researchers are interested in larger trends over longer periods of time to identify relationships between independent variables and stock prices.

If the assumption of independence is violated, the standard errors of the slope coefficients which relate the IV's to the DV can be underestimated which could lead an analyst to conclude that certain IV's are more statistically significant than they really are [148], [149]. The Durbin-Watson statistic is a test for autocorrelation for statistical models [150]. The test is conducted by checking for correlation amongst the residual error. Visually, the analyst can graph a scatterplot of the residuals vs. time. Randomness in the plot indicates no dependency while patterns indicate that autocorrelation is present. The Durbin-Watson test statistic is:

$$d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2}$$

Where,

T = total number of observations

e_t = the residual for a specific observation from the model

Equation 8: Durbin-Watson Equation

The Durbin-Watson test uses a null hypothesis, H_0, that there is no correlation amongst residuals and the alternative hypothesis, H_A that the residuals are correlated. Durbin Watson tests return a test statistic in the range of 0 to 4, with 2 being the ideal [151]. As a rule of thumb, if *d* is between 1.5 and 2.5, the statistical assumption is that there is not a serious autocorrelation problem [150]. Values related to datasets categorized by number of observations and number of regressor variables can also be utilized using Durbin Watson tables [154]. If the Durbin-Watson statistic is outside of limits, it is assumed that autocorrelation is an issue that must be addressed. There are several options to address autocorrelation: checking for misspecification of pcredictor variables (i.e., identifying a linear relationship when it is exponential), transforming the variables using Cochrane-Orcutt or Hildreth-Lu processes, adding a time-lag variable of the IV or DV to the model, or even restructuring observations to avoid known autocorrelation issues such as with time-series data.

To further evaluate the relationship between time and the various metrics and datasets, the autocorrelation function (ACF) and time series cross correlation values should also be calculated. Autocorrelation is sometimes known as serial correlation in discrete time case, compares the correlated values of a function vs. it's lagged value.

$$r_k = \frac{c_k}{c_0}$$

Where,

c_k = correlation value at lag k

k = the number of time units (e.g. lags)

Equation 9: Autocorrelation Equation [149]

ACF graphs show the correlation values at each lag (1 time period, 2 time periods, etc.) to graphically depict the autocorrelations. The blue curves represent twice lag standard error (± 2 standard errors). Time series cross correlation plots are simply the Pearson's r-value (reference the Correlation Methods section of this dissertation) calculated at each lagged value for the dependent variable. In this way, cross correlation graphs illustrate the correlation at each lag and show the maximum and minimum values. Additionally, any seasonality (repeated trends over a specific cycle timeframe) will be shown. When evaluating time series data, it is important to check for independence and identify any trends that may appear as a result of time-based influence.

3.3.4.4 Checking for Normality

Checking for normality can be as simple as creating a visual representation of the data set via a histogram shown in the following figure.

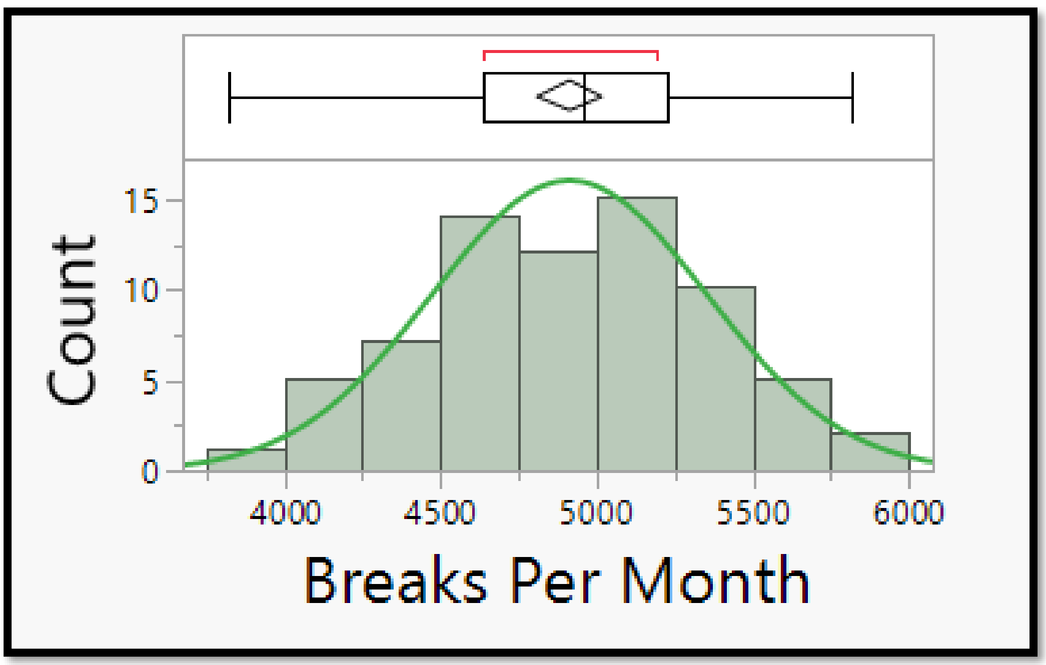


Figure 29: Example Histogram of Normally Distributed Data

Creating a Normal Quantile Plot is another way to visually check for normality. If the data approximates a straight line, the analyst can conclude that the data reasonably approximates a normal distribution [152]. The Shapiro-Wilk Test is a way to mathematically calculate if a random sample comes from a normally distributed data set. The Shapiro-Wilk test uses a null hypothesis, H_0, that a variable is normally distributed in the data population and the alternative hypothesis, H_A that the data set is not normally distributed. The Shapiro Wilk test is calculated using the equation below:

$$W = \frac{(\sum_{i=1}^{n} a_i\, x_i)^2}{\sum_{i=1}^{n}(a_i - \bar{x})^2}$$

Where,

x_i = are the ordered independent variable sample observations

a_i = are constants generated from the covariances, variances, and means

n = the number of observations (sample size)

Equation 10: Shapiro-Wilk Test

The larger the W statistic, the more likely the model is not correct. If the probability, *p*, that W is less than the alpha of our confidence interval, we reject the null hypothesis that the data is normally distributed. If the p-value is greater than alpha, then the null hypothesis is accepted, and we conclude that the data set is normally distributed. The values for skewness (a measure of symmetry to determine if the data is shifted left or right of center) and kurtosis (measures the curve of the data to determine if it is peaked or flattened) are also checked for during this process [153]. While Shapiro-Wilk is generally used for small sample sizes of less than 50, research has shown it can handle sample sizes are large as 2000 [154].

Other indicators of normality include skewness and kurtosis. Skewness is a measure of how symmetrical the distribution is and kurtosis is a measure of the tall or thin (sometimes called the peakedness) the distribution is [153]. Skewness is in between -0.5 and 0.5 and kurtosis values between -1 and 1, indicate data with normal univariate distribution [117], [145].

Violations of normality often occur when the linearity assumption is also made [155], [146]. Data transformations, trimming the data to remove outliers (which then gives the remaining model a reduced range for which it is applicable), ignoring non-normality based on the concept of the Centra Limit Theorem (which states that given a sufficiently large sample size, the sampling distribution of the man for a variable will approximate a normal distribution), and even bootstrapping the dataset (resampling the data to replace outliers) are all ways to address non-normality in a data set [156], [135].

There are several research studies and academic tests that indicate normality distribution for both dependent and independent variable is not a requirement for regression [157][155][158]. The errors after modeling should be normally distributed to draw valid conclusions to include coefficient validity, hypothesis testing, etc. However, the presence of extremely skewed variables or variables with very large tails of outliers could significantly influence distribution of the variables. If the residuals are not normal, the analyst cannot employ the use of t-tests to determine significance of the variable and justify its inclusion in the model. Without normality of residuals, the research analyst cannot conclude that a variable is significant to the outcome, dependent, variable or not [159]. This may make it prudent to transform the data to avoid harmful effects in the model.

3.3.4.5 Checking for Homoscedasticity

Homoscedasticity is the concept of constant variance when reviewing errors. This can be as related to time (in the case of time series data), related the predicted value vs. the actual value, and as it relates to any IV the model uses [146]. Homoscedasticity is diagnosed when reviewing scatter plots of residual values versus predicted values (or residual values versus time). Generating plots of the residuals vs. the independent variables also assists the analyst when looking for consistency. Variance should be constant across these graphs [135]. If the homoscedasticity criteria are violated, the analyst can apply similar methods to resolve as already discussed in the linearity and normality sections of this document.

3.3.4.6 Selecting the Best Model

There are several ways to compare regression models. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Mallows Cp, and R-Squared values. It should be noted that the model with the best R^2 value is the model with the most independent variables, due to the way in which R^2 is calculated [151].

AIC is an estimator of prediction error and is one of the many ways to compare regression models and evaluate their fit. AIC attempts to evaluate models by determining an estimate of a constant plus the relative distance between the unknown true likelihood function of the data and the fitted model [135]. This type of evaluator is called a penalized-likelihood information method. Using this method, the analyst attempts to compensate for a tendency to add independent variables to increase accuracy (resulting in increased R^2 values) which can overfit a model. Generally, the AIC value is calculated as follows:

$$AIC_c = -2\log\mathrm{L} + 2\mathrm{k} + \frac{2k(k+1)}{n-(k+1)}$$

$$where,$$

$$n = the\ number\ of\ observations$$

$$k = the\ number\ of\ estimated\ parameters$$

$$L = the\ \log likelihood\ function\ -2 * \log\mathrm{L} = \mathrm{n} * \ln(\frac{SSE}{n})$$

$$SSE = the\ Sum\ Square\ Error$$

Equation 11: Akaike Information Criterion

A lower AIC score determines superior goodness of fit for model comparison. For goodness of fit, lower AIC values indicate the model is less likely to be overfitted. Overfitting is of serious concern to analysts. Overfitting is a scenario which occurs when using the highest R^2 value as the evaluation method. Overfitting in a regression model results from analysts including as many predictor variables as possible. This serves to help the model match the existing training data, but typically proves less accurate using test or real-world data [153].

BIC is another evaluation statistic and is like AIC. The difference is BIC penalizes models more for additional regressors (independent variables) than AIC does [135]. The BIC value is calculated as follows:

$$BIC = -2\log\mathrm{L} + 2\mathrm{k}ln(n)$$

$where,$

$n = the\ number\ of\ observations$

$k = the\ number\ of\ estimated\ parameters$

$L = the\ \log likelihood\ function\ -2 * \log\mathrm{L} = \mathrm{n} * \ln(\frac{SSE}{n})$

$SSE = the\ Sum\ Square\ Error$

Equation 12: Bayesian Information Criterion

Mallows Cp is another statistic that can also help compare regression models. This evaluator attempts to estimate the size of the bias that is introduced into the model by having an underspecified model (missing regressors). For Mallows C_p calculation

$$C_p = \frac{SSE_p}{MSE_k} + 2(p+1) - n$$

Where,

SSE_p = sum of squared errors for the reduced model

MSE_k = mean square error for the full model (aka $RMSE^2$)

k = # of independent variables present

p = # of independent variables in the reduced model

n = number of observations (data points in for independent variables)

Equation 13: Mallows C_p

For ideal state, Mallows $C_p = p + 1$, Example, if the subset model being evaluated has p=5, the Ideal Mallows $C_5 = 5 + 1 = 6$. Actual models C_p value will vary, but the procedure is to choose the model with the value that gets closest to the ideal. But Mallows values can have some bias. When the C_p value is ...

- Near k+1, the bias is small (next to none)
- Much greater than k+1, the bias is substantial.
- Below k+1, it is due to sampling error; interpret as no bias.
- If all models return a large value, some regressors may be missing from the analysis.
- If several models have close to ideal Mallows numbers, choose the one with the least amount of regressors, since the goal of Mallows is simple models.
- For the largest model containing all the candidate predictors, $C_p = k+1$ (always), therefore it is inappropriate to evaluate a full model with all candidate variables using Mallows C_p

Finally, one of the most common methods to evaluate models is to choose the model with the highest R^2 or adjusted R^2. Generally, R^2 is a good measure of how the model fits dependent variables but does not take into consideration over fitting. Overfitted models may fit the training data very well but will perform badly with testing data. Adjusted R^2 penalizes additional independent variables and adjusts the metric accordingly. In summary, models can be compared using AIC (lowest value is preferred), BIC (lowest value is preferred), Mallows C_p (closest to k+1 is preferred), and adjusted R^2 (highest value is preferred).

3.3.5 Pitfalls to Avoid

An important pitfall to avoid when analyzing data is pre-determining the outcome and drawing weak conclusions from the data to support the hypotheses of the researcher. According to Rumsey, this is called "data mining", where the analyst looks for any possible relationship they can find and then stating their results after the fact [135]. The pitfalls of data mining as a concept are also highlighted in Air Force policy. In the USAF's *Maintenance Metrics* handbook, caution is advised when analyzing metrics [25]. The handbook states that over-emphasizing the improvement of a particular metric while ignoring the root cause of a problem may cause unintended consequences that improve the overall metric, but ultimately do not resolve the issue.

Colloquially, this concept is called "metric-driven behavior". The handbook goes on to say that metrics are indicators that should be viewed in aggregate, used to identify trends, and not necessarily become pass/fail indicators [25]. This author asserts that metrics should be used to understand where potential problem areas may be, and to help identify the resources needed to investigate the root cause of issues that impede system performance.

3.4 Case Study Reviews

Once the mathematical model has identified potential indicators, case study methodology will be utilized to confirm relationships between events in the field and downtime due to supply issues. This method was chosen due to its ability to provide a broader approach to examine the relationship between impediments to aircraft performance, and the supply drivers that contribute to aircraft status. Case studies on 3 separate known supply issues will be reviewed to confirm or reject the mathematical model's selection of the predictor variables. A review of the historical predictor variables prior to the realization of aircraft downtime due to supply issues will be reviewed.

It should once again be noted that the mathematical model resulting from this research will not be used to predict future aircraft downtime. Rather, the predictor variables indicated by the model will be selected in order to help systems engineers and logisticians focus manpower and resources for their already established review methods.

Chapter 4 - Research Results

This chapter details the results accomplished from applying the method described in Chapter 3. Mathematical models were created to identify metrics closely linked to negative supply performance, specifically MICAP Incidents. Due to operational security concerns, the raw data tables will not be published with this research, but the data is available through LIMS-EV. A review of the data available in LIMS-EV based on the list identified in the previous chapter was accomplished. Aggregated data includes metrics that include data from all fielded weapon systems, which utilize data systems that feed into LIMS-EV. It should be noted that new development programs early in the stages of life cycle development typically do not utilize LIMS-EV systems until after the low-rate initial production phase.

4.1 Data Collection

Operational and maintenance data was collected from the LIMS-EV repository over the designated period. Aircraft and Operational metrics are stored in the Weapon Systems View module of LIMS-EV. This data module provides the capability for the user to retrieve metric for any aircraft type, time, location, deployment status, and a multitude of other factors. Data is easily filterable by aircraft model type or timeframe. For the purposes of this analysis, data for all fleets was aggregated over the previously stated timeframe. While the aggregation of this data may skew the results of the regression analyses, it is required to protect operational security concerns. Additionally, the purpose of this research is to identify feedback loops for all aircraft fleets and model types. Aggregating the data helps support the idea that this method will be applicable across the USAF fleets, regardless of model type. Data was pulled from the period of March 2013 through March 2023.

The data was then split into training and test data. The training data (first six years of data) will be used to create the model. The test data (last four years of data) will be used to validate the model with case studies. A custom report was created utilizing LIMS-EV Business

Object (BOBJ) report function. Object queries were then created to gather data from several different data universes. An aggregated report utilizing LIMS-EV OSD and WSV universes returned data query results.

4.2 Mathematical Modeling

4.2.1 Model Limitations

Aircraft performance metrics have many influencing factors, and many cannot be adequately captured in existing metrics. This means that mathematical models will be incomplete or inaccurate. Additionally, the variability in the datasets can produce some extreme outliers. For example, a MICAP is a backorder that causes an aircraft to be mission incapable. If maintenance orders a part which is not immediately available, it gets backordered. The backorder ages as time goes on. If the aircraft is scheduled for a mission and the part is still unavailable, the backorder then gets coded as a MICAP. MICAP orders can vary in measurement from 0 to an infinite (in theory) number of hours. The extraordinarily large variance in this data population may influence and distort the results and error rates of any mathematical models developed from the data set. Given the nature of what a MICAP is, and its presumed influence on downtime due to supply issues, it must be included in any model that is attempting to predict supply performance metrics.

In addition to variance, multicollinearity is expected for the dataset in question. Certain groups of metrics are known to be related, and mathematical methods will help down-select which of each group to utilize in the model. For example, cancelled backorders and MICAPS are both subsets of backorders, which is a subset of the metric total requisitions. The recur metric is a subset of repeat metric, which is a subset of breaks, which is a subset of failures. Backorder lines is the total number of requisitions on backorder (one backorder line may have a quantity of 10 parts), and backorder quantity is the total number of individual parts on order (the sum of the quantities of all the backorder line items). The multicollinearity involved if a model was built from such closely related data would be astronomical.

Therefore, it is critical to once again assert that this model will not be suitable for predictive purposes. Instead, this model will be used to identify potential early warning indicators for specific parts shortages that lie in the future. The purpose is, of course, to give systems engineers, logisticians, and maintainers enough time to execute supply alternatives to parts with long lead times.

4.2.2 Linearity

A simple scatter plot of the available variables against one another was accomplished to determine if linear relationships exist. As expected, the scatter plots indicate that there is an extraordinary amount of variance in the data sets, but some trends do begin to appear. These plots also create a way to visual check which variable more closely approximates a linear relationship to the independent variable.

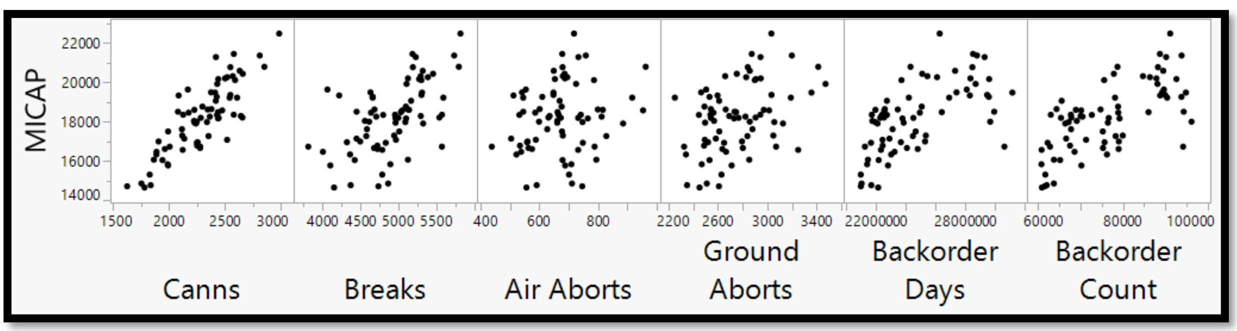


Figure 30: Initial Scatterplot, Linearity Check

As shown in the scatterplot matrix, some of the candidate variables show a linear relationship to MICAP(I), while others appear to have either none or very weak relationships with MICAP(I). None show egregious non-linear curves, although both Backorder Days and Backorder Count may either have some non-linear tendencies or outliers. And both Air and Ground Aborts appear to have very weak relationships with MICAP.

4.2.3 Multicollinearity

A check of the Pearson's coefficient can reveal correlation between the dependent and independent variables, along with any correlated independent variables amongst other independent variables. A heat map of the variables with density ellipses is shown below:

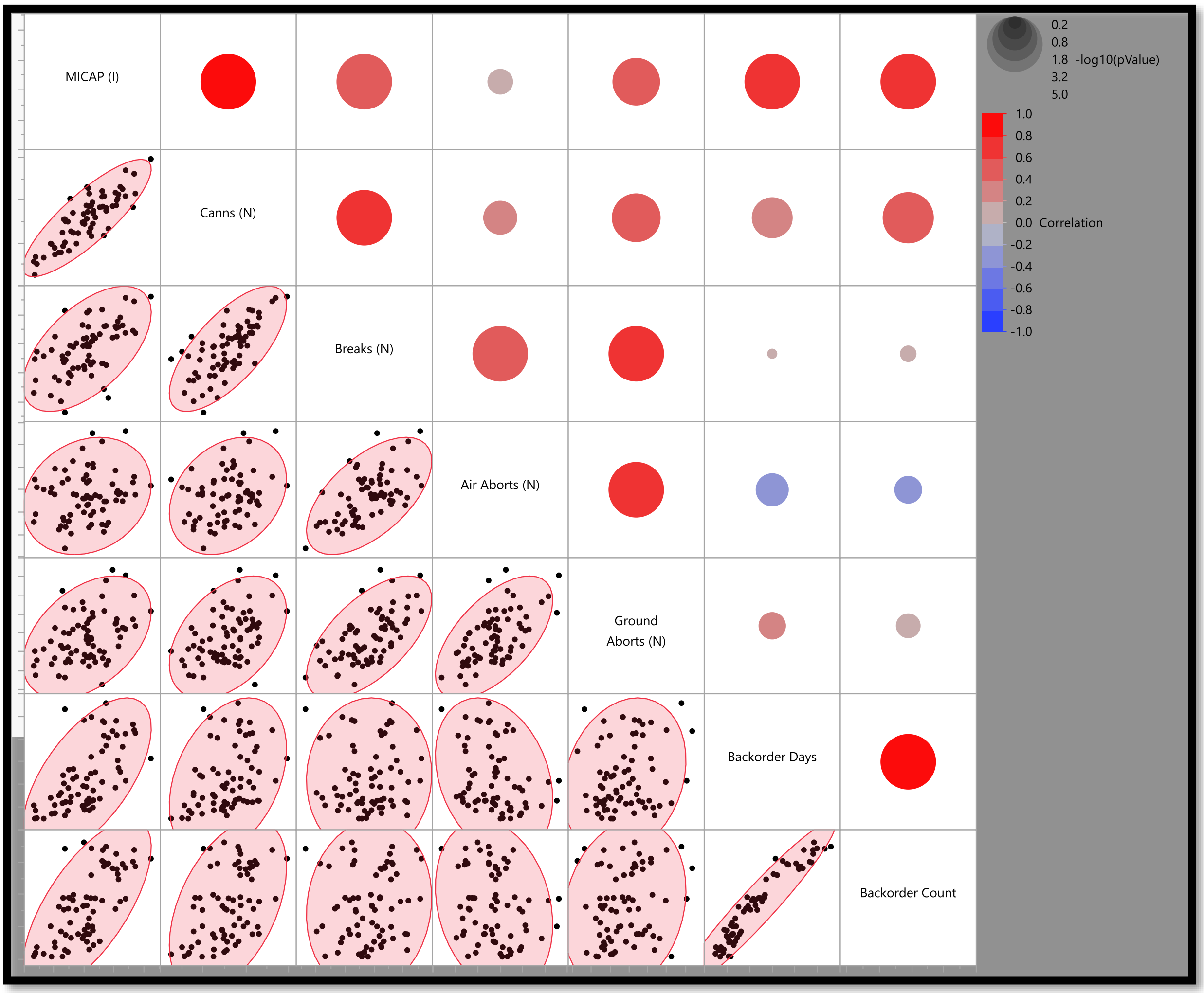


Figure 31: Correlation Matrix and Heat Map

The calculated Pearson's coefficient correlation values are listed in the Appendix. The corresponding correlation matrix for the dependent variables can be found in the appendix. For variables that are correlated with an absolute value greater than 0.8, one of the variables should be excluded from the model, or risk multicollinearity issues. To determine which metric to drop, the correlation values between the independent variable and MICAP (I) was compared for each, and the lowest dropped. In this case, Backorder Days and Backorder Count are highly correlated with a Pearson's Coefficient of 0.947, which confirms the assessment from the initial regression indicated by high VIF values. Backorder Days Pearson R is 0.62, and Backorder Count is 0.68, so Backorder Days was dropped from the model and Backorder Count was retained.

This approach was used to compare the remaining variables, but none reached the 0.8 threshold with each other (although some are very close). This leaves the following candidate list available for regression:

- Air Abort (N)
- Breaks (N)
- Canns (N)
- Ground Aborts (N)
- Backorder Count

4.2.4 Normality

Moving forward with the analysis requires a check for the type of distribution of the dataset variables. As previously discussed, normality is not necessarily required for the distribution of the raw data set, but normality of the residual errors is required. Additionally, datasets with non-normal distributions or extreme skewness or kurtosis may impact the distribution of the residuals. And several of the statistical tests used to validate regression models require normal distributions. Therefore, every attempt will be made to normalize the data prior to including it in the model. The graphical representation of each variable's distribution is shown below.

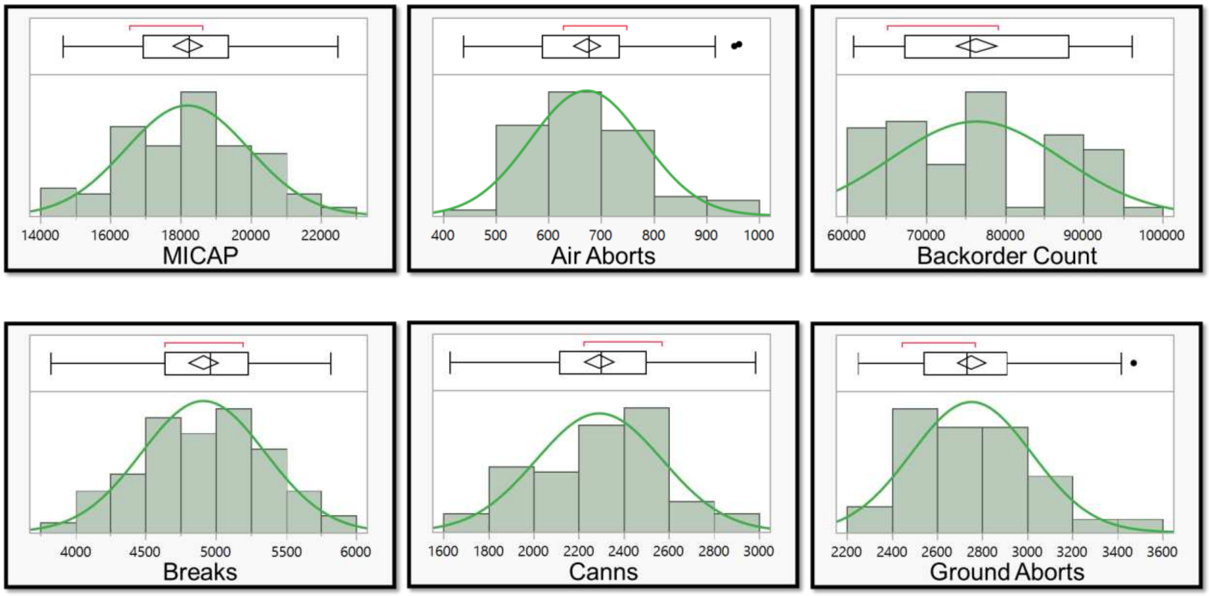


Figure 32: Distribution Plots

The histogram illustrates that MICAP (I) is indeed normally distributed. Skewness and Kurtosis values for each variable were also reviewed. If the skewness is in between -0.5 and 0.5, the data can be assumed to be fairly symmetrical with its positive value indicating that the right tail is slightly larger than the left tail of the distribution [135], [160]. For data with kurtosis values between -1 and 1, the data supports normal univariate distribution [135], [161]. The coefficient of variance indicates there is some variance in the dataset, which was predicted based on the large variety of aircraft and operational patterns that is included. Additionally, the Shapiro-Wilk tests was utilized to verify results. For Shapiro Wilk, high values of p indicate that the null hypothesis (the data is normally distributed) can be accepted. All were identified as within the limits of statistics related to normal distribution of data except for Backorder Count.

Analyses of this type were conducted on all the variables to ascertain normality. Statistical summaries, plots and test results for all variables are in the Appendix. Nearly all the variables show results that indicate normally distributed data. However, both the Shapiro-Wilk and Anderson Darling tests were out of significance limit for p-values, indicating the presence of non-normality for Backorder Count.

It is important to note that according to the Central Limit Theorem (CLT), when the sample size is large enough, the distribution of the errors need not follow a normal distribution. The question of how large sample size should be to apply the rules of the CLT varies by researcher. Ranges of sample size anywhere from 15 to 50 by various researcher [135], [156]. With 72 data points, this dataset clearly exceeds those values. But these rules of thumb should only be applied if the sample size of the dataset accommodates the quantity of independent variables in the model. The issue is that when non-normality is observed, there are two potential reasons. The first is that there is non-normality in errors, in which case the results regarding the relationship and significance of p-values may be inaccurate. Second, the relationship between X and y may not be linear, which means a linear regression is not appropriate. And third, even if the model errors are normal, and the relationship is linear, if the dataset is not normal the tests to ensure regressor predictor variable significance change dramatically, since many of those tests require normal distribution. In the first case, a large enough sample size to apply the CLT overcomes the issue. But in the others, non-normality would continue to be a problem for the model and likely lead to inaccurate inferences.

Additionally, there are approximately 62,000 Backorders per month. Several transformations were attempted including log, square root, inverse, etc. but none changed the distribution significantly towards a normal profile. There are other, more complicated transformations available such as Box-Cox, but it would add complexity to the model. Given that there are about 76,000 backorders per month and only 1200 engineers in the entirety of AFLCMC charged with providing weapon system support, the quantity of backorders is almost insurmountable in terms of being able to review them all [162]. To make Backorders a target metric to track and act upon, there would have to be additional screening criteria to scope the workload. Additionally, MICAP(I) is a subset of Backorder Count, which is adding noise to the model. For these reasons, Backorder Count will be removed from consideration for the model.

4.2.5 Best Subset - Multiple Linear Regression

A best subset evaluation runs all possible models for the regression. It would be nearly impossible to accomplish with larger potential independent variables, but since the candidates were reduced via analysis of process and availability via the data repository, modern statistical software can easily accomplish analysis via this method. The total number of variations is 2^k, where *k* is the number of independent variables. Given the advances in technology, statistical software can run hundreds, or even thousands of possible model simulations. Even on a standard home-use computer, the small quantity of independent variables for this analysis indicates that a Best Subset approach utilizing least squares regression should be attempted. The model results are as follows:

The models were reviewed to determine which had the best AIC_c values, BIC values, Mallows C_p values and R^2 values. It should be noted that the model with the best R^2 value is the model with the most independent variables, due to the way in which R^2 is calculated. The subsequent analysis recommended different models based on the identified independent variables and evaluation criteria. The resulting calculations can be seen in the appendix. The results for the best models are listed in the table below:

Table 3: Model Ranking

	Model	**Ranking**
1	Canns (N), Air Aborts (N), Ground Aborts (N)	Best R^2 and RMSE
3	Canns (N)	Best for AIC_c BIC, and Mallows C_p

Since the statically software makes it convenient, all three models were created. Results are in the appendix. Models did not pass significance tests for all of the independent variables. Specifically, Air Aborts and Ground Aborts were shown to be statistically insignificant. Model 3 passed in terms of significance for the independent variable, but a plot of the residuals by row indicates that autocorrelation is still an issue, as did the Durbin Watson test.

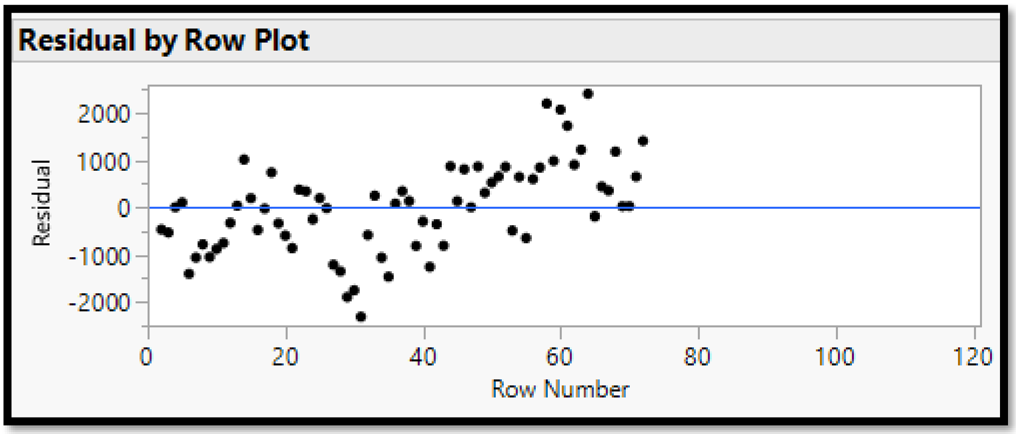


Figure 33: Residuals by Row for Model 1

4.2.6 Independence

The models above indicated auto-correlation is an issue and it must be addressed before proceeding otherwise the model violates the assumption of independent observations. This can be confirmed by accomplishing a statistical test for 1st order autocorrelation, the Durbin-Watson test. Since the values for the Durbin-Watson tests for all three test models are outside the rule of thumb for the test value ($1.5 < d < 2.5$), autocorrelation is confirmed as present in these models.

Since we have a time series dataset, these models violate the independence assumption of linear regression, and the Durbin-Watson test of the model above confirms that theory. Since the Durbin-Watson test returned $d<1$, the is cause for concern of positive serial correlation. Positive autocorrelation means an increase in the previous observation is correlated to an increase in the current observation. To check how severe the autocorrelation is, scatter plots were created of the metrics by row (date) to inspect for patterns:

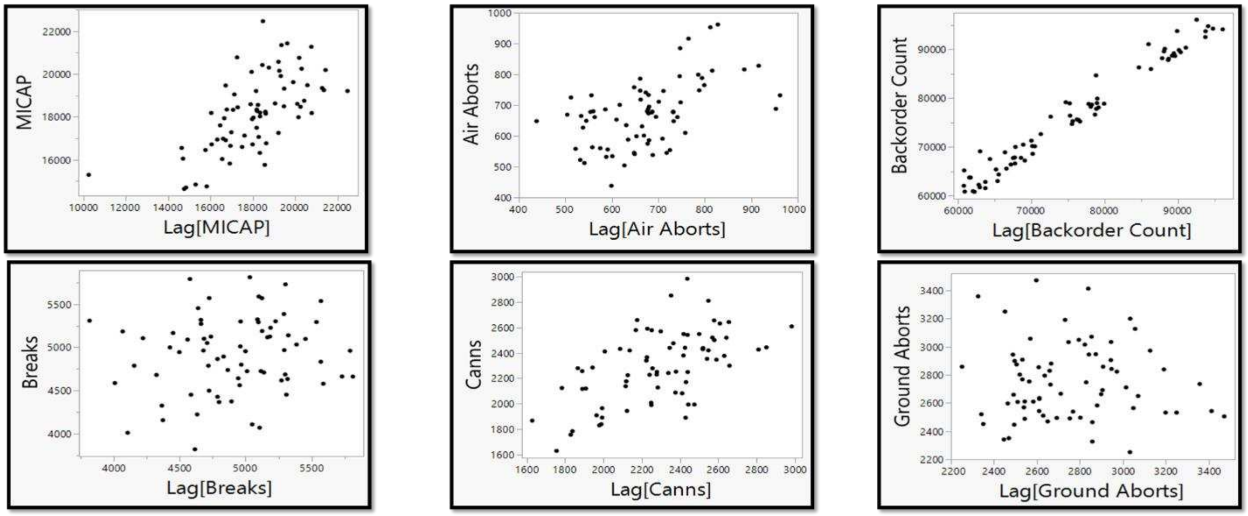


Figure 34: Scatterplots of Variables by 1st Order Lag

These plots indicate MICAP (I) has significant time-based trending, but Canns (N) and Air Aborts also show indication of a linear relationship with time. Breaks and Ground Aborts (N) show little, if any, trending based on time. Another way to determine if autocorrelation exists is to plot the variable against its lag. Below are graphs of the variables against their lags.

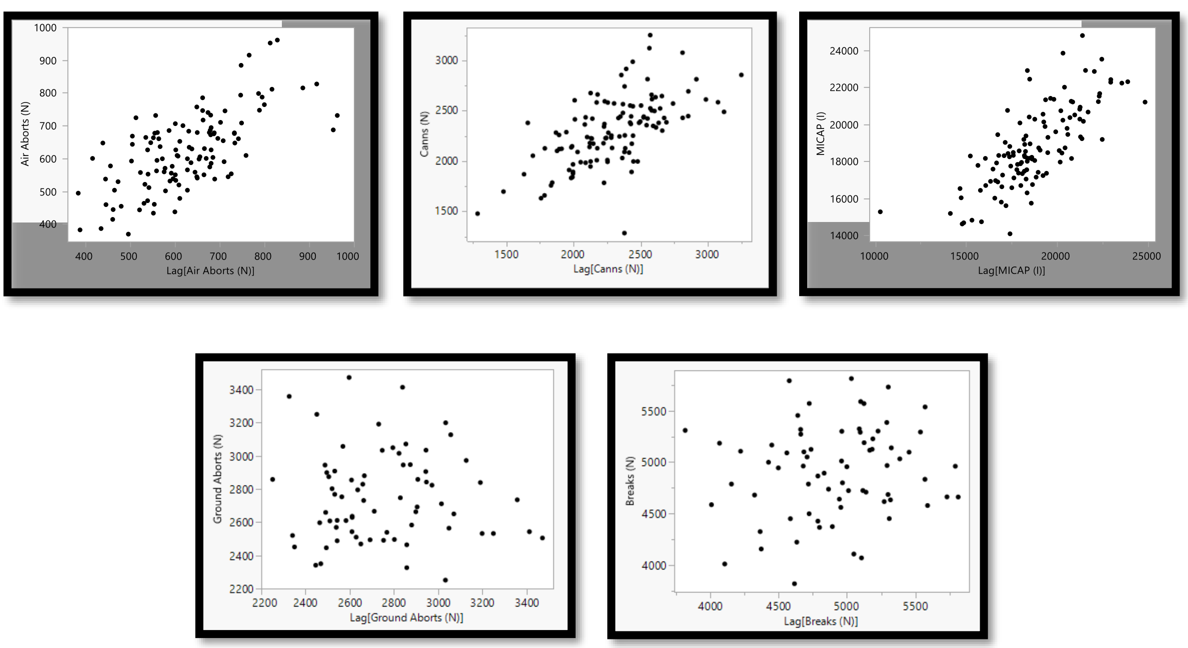
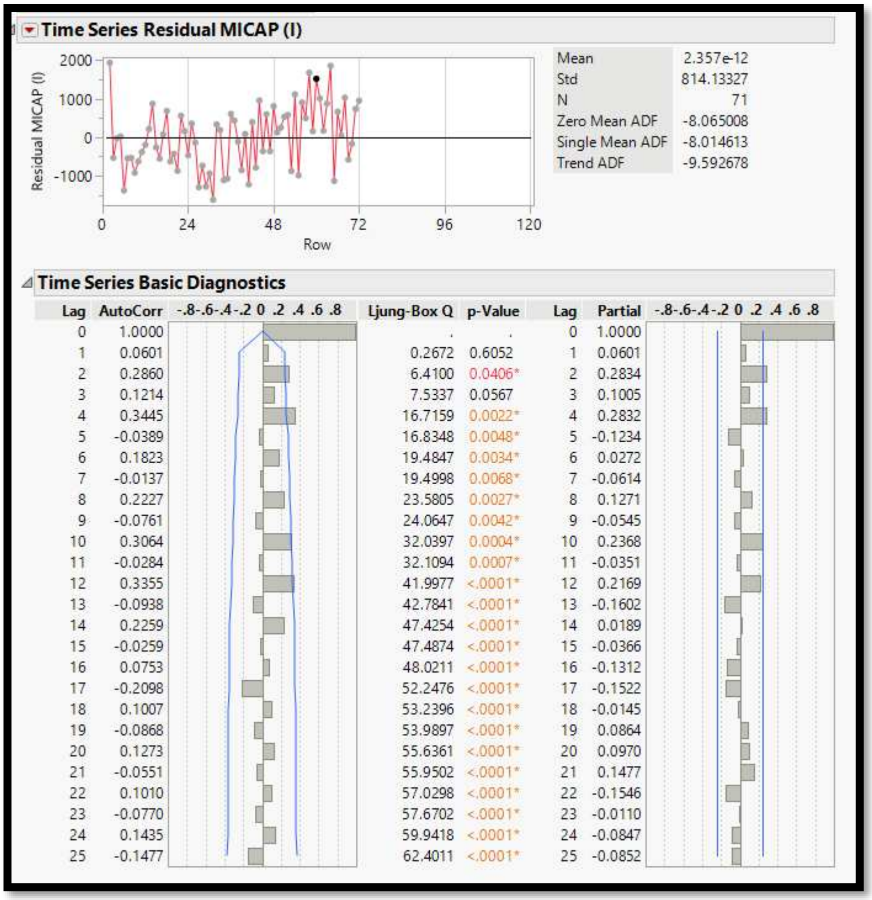


Figure 35: Scatterplots of Variables vs 1st Order Lagged Variable

Again, the graphs confirm that there is significant correlation related to time for Air Aborts (N), Canns (N), and MICAP (I). Ground Aborts (N) and Breaks (N) do not appear to have many, if any, trends related to date or timeframe. Returning to the previously researched taxonomy of how aircraft metrics are related, it is known that maintenance discrepancies occur prior to parts being ordered. Additionally, part requisitions (orders) can turn into backorders, which in turn convert to MICAPs depending on their impact to operations. Given these relationships, it makes sense to explore correlations between MICAP (I) and the lagged values of MICAP, CANN.

Since we have a confirmed autocorrelation, the next step is to determine whether the data is stationary or not. A stationary time series is one whose properties do not depend on the time at which the series is observed [150]. For example, data with seasonal trends is non-stationary. The Augmented Dickey-Fuller (ADF) test is used to determine stationarity by a method focused on the unit-root of the data set [161]. Trends are another concern in time series data. Time series data with trends are constantly increasing or decreasing. Generally trends should be removed from the data prior to modeling or forecasting [163].

To resolve the issue of autocorrelation, the data should be evaluated as time series using Augmented Dickey-Fuller (ADF) testing and by reviewing the autocorrelation function (AC) and partial ACF plots. JMP does this easily with a Time Series capability module, then returns the results of all three parts of the ADF test (Tau values for Zero Mean ADF, Single Mean ADF, and Trend ADF). The estimated critical values of our sample size using Dickey-Fuller Tables are Zero Mean -1.95, Single Mean -2.93, and Trend -3.5. The Zero Mean ADF is checked for the residuals, because their mean is zero, indicates that the test value is much more negative than the critical value (which is expected to be negative) and therefore we can reject the null hypothesis that a unit root exists and conclude that the data is stationary.



Mean	2.357e-12
Std	814.13327
N	71
Zero Mean ADF	-8.065008
Single Mean ADF	-8.014613
Trend ADF	-9.592678

Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	0.0601	0.2672	0.6052	1	0.0601
2	0.2860	6.4100	0.0406*	2	0.2834
3	0.1214	7.5337	0.0567	3	0.1005
4	0.3445	16.7159	0.0022*	4	0.2832
5	-0.0389	16.8348	0.0048*	5	-0.1234
6	0.1823	19.4847	0.0034*	6	0.0272
7	-0.0137	19.4998	0.0068*	7	-0.0614
8	0.2227	23.5805	0.0027*	8	0.1271
9	-0.0761	24.0647	0.0042*	9	-0.0545
10	0.3064	32.0397	0.0004*	10	0.2368
11	-0.0284	32.1094	0.0007*	11	-0.0351
12	0.3355	41.9977	<.0001*	12	0.2169
13	-0.0938	42.7841	<.0001*	13	-0.1602
14	0.2259	47.4254	<.0001*	14	0.0189
15	-0.0259	47.4874	<.0001*	15	-0.0366
16	0.0753	48.0211	<.0001*	16	-0.1312
17	-0.2098	52.2476	<.0001*	17	-0.1522
18	0.1007	53.2396	<.0001*	18	-0.0145
19	-0.0868	53.9897	<.0001*	19	0.0864
20	0.1273	55.6361	<.0001*	20	0.0970
21	-0.0551	55.9502	<.0001*	21	0.1477
22	0.1010	57.0298	<.0001*	22	-0.1546
23	-0.0770	57.6702	<.0001*	23	-0.0110
24	0.1435	59.9418	<.0001*	24	-0.0847
25	-0.1477	62.4011	<.0001*	25	-0.0852

Figure 36: Augmented Dickey Fuller (ADF) Results with Autocorrelation Plots

While confirmation of stationarity is good news because additional more complex transformations are not required, the model still must be adjusted to resolve the autocorrelation. To adjust for the autocorrelation and create a model that can pass the Durbin-Watson test, the lagged value of each variable was created, and regressed using the same stepwise procedure. The best models were generated and evaluated in the same process used previously. The best possible model based on these statistics is:

Summary of Fit

RSquare	0.781576
RSquare Adj	0.771796
Root Mean Square Error	838.0835
Mean of Response	18196.31
Observations (or Sum Wgts)	71

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	168391752	56130584	79.9144
Error	67	47059721	702383.9	Prob > F
C. Total	70	215451473		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	4207.1175	990.5327	4.25	<.0001*	.
Lag[MICAP (I)]	0.4125207	0.085398	4.83	<.0001*	2.8806256
Lag[Canns (N)]	-1.882489	0.618323	-3.04	0.0033*	3.0250911
Canns (N)	4.7306024	0.447513	10.57	<.0001*	1.5693949

Effect Tests

Prediction Expression

4207.1175309

+ 0.412520708 • Lag[MICAP (I)]

+ -1.882488569 • Lag[Canns (N)]

+ 4.7306024266 • Canns (N)

Durbin-Watson

Durbin-Watson	Number of Obs.	AutoCorrelation	Prob<DW
1.7811453	71	0.0601	0.1450

Figure 37: Best Subset, with Lagged Variables

This model shows significance for variables Canns (N), Lag MICAP (I) and Lag Canns (N). To check for autocorrelation, the significance limit is retrieved from Durbin Watson tables, with a k-value of 4 representing the 3 regressor variables, a dL = 1.494 and dU = 1.785, at 5% significant [164]. Since the calculated Durbin Watson values are within the bounds of dL and dU, we can accept the null hypothesis that there are no unit roots, and the model does not have autocorrelation. A plot of the residuals confirms normality for the model, as does the Shapiro-Wilk test. The results of the normality check for this model are in the Appendix.

The resulting equation based on this analysis includes regressor variables for the lag of MICAP(I), the lag of Canns(N) and the basic Canns(N) variable. This yields the following equation:

$$MICAP(I) = 4207.12 + 0.41 * LagMICAP(I) - 1.88 * LagCanns(N) + 4.73 * Canns(N)$$

Equation 14: Final Regression Equation

4.2.7 Mathematical Modeling Summary

The results of the mathematical and statistical analysis resulted in a multiple linear regression model that indicates statistical significance in the relationship between Canns (N) and MICAP (I). While this model is acknowledged as incomplete with missing influential factors, the identification of a relationship between Canns and MICAP will be explored using case studies to validate the relationship and to determine what, if any, alterations to feedback data or process would help prevent MICAPs in the future by preventing Canns. While the lagged variables, adjustment for autocorrelation, normality, etc. are all critical parts of the model building process, those terms exist to help adjust the model to be better at predicting Y values based on independent variables input. Since this research never intended to produce a reliable predictor model, the adjustor variables for lag are not as valuable as the positive identification of the relationship between Canns (N) and MICAP (I).

Chapter 5 - Case Studies and Discussion

To identify appropriate case studies, specific items of supply with high cannibalization quantities were examined. Quantities of Canns (N) and MICAP (I) were graphed over time to visually illustrate sequence of events for cannibalizations and MICAP occurrences. It should be noted that since the testing data was identified for a specific timeframe independent of an item's logistics demand cycle, variations in the cannibalization and MICAP relationships in terms of the graphical illustration are to be expected. For example, the timeframe chosen could potentially begin at a point when MICAPs are high and could potentially exclude the timeframe where Canns first appeared. Similarly, the timeframe chosen may show the start of a trend of cannibalizations, but not extend far enough in the future to show MICAP occurrences.

It is also important that the test data be separate from the training data to preserve data integrity. Therefore, the timeframe used for the original regression model will be excluded from the case study data set (i.e., test data). To combat the ambiguity that visual representations of Canns (N) and MICAP (I) may display as graphed over time, the time series cross correlation values were calculated and graphed for each case study. The maximum correlation at the indicated lag time is the anticipated time gained for logisticians to determine a resolution for the lack of parts in supply.

A 2015 study indicated that the average production lead time for aviation parts is approximately 150 days, which is just less than 4 months [140]. If the correlated lagged value between Canns (N) and MICAP (I) is 4 months or larger, logisticians in theory would have enough time to get parts new parts in supply. Additionally, any amount of positive lag buys time for operators, logisticians, maintainers, and engineers to determine an acceptable resolution to an impending supply issue. Data for specific lead time for each unique item is not available to the public and therefore is not included in this analysis but could be a potential topic for future research.

5.1 Case Studies Selection

The case studies in this section were chosen for their high Canns (N) quantities. It should be noted that the range for “high” can vary from component to component, or weapon system to weapon system and is influenced by characteristics such as fleet size, quantity required per aircraft, life cycle or shelf-life intervals, and maintenance schedules. While the aggregated USAF fleet data analyzed in the previous chapter showed thousands of MICAPs and Canns each month, these numbers are cumulative for the entire USAF fleet. There are millions of component items available for review, and the larger number identified in the previous chapter will be much reduced for specific item analyses.

Additionally, there is a limit to the number of cannibalization requests that units can execute. After all, aircraft need to fly to accomplish their mission and if an item is cannibalized aircraft may be grounded until the item is reinstalled. Therefore, cannibalization occurrences are likely to be limited to the number of aircraft down for otherwise scheduled maintenance, a number which will vary significantly per aircraft model. A cannibalization in an aircraft fleet with only 10 aircraft will have very different impacts to performance than a cannibalization in an aircraft fleet with 100 aircraft. As such, the case studies in this section were selected by utilizing the LIMS-EV top Cann (N) drivers list, which is generated from the supply chain headquarters office as a “hot topic” list under review of senior leaders.

Data for case studies was retrieved from LIMS-EV. This data is independent from the aggregated USAF fleet data used to create the initial regression model. The testing data covers a new timeframe of March 2019 through March 2023, a span which was not included in the original training data set. Since this period covers the COVID-19 pandemic, it is anticipated that not all correlations may be supportive of the results from the statistical model. While the results of the mathematical analysis are important, this research is less concerned with whether the statistical model predicts the MICAP (I) quantities and focuses on whether there is a trend between Canns (N) and MICAP (I), and whether or not monitoring Canns (N) information can be leveraged to prevent negative aircraft events in the future. Case studies are analyses of specific items of supply and their Canns (N) and MICAP (I) data trends over time. For each case study item, LIMS-EV returned results for Canns (N) and MICAP (I) quantities during the specified timeframe. The remainder of this chapter provides the results from that analysis.

5.1.1 Computer Interface Unit

The first component, a Computer Interface Unit, was chosen as a case study due to its listing as a top work unit code driver for Canns (N) occurrences. This graph corroborates a positive relationship between Canns and MICAPs, specifically for this item of supply.

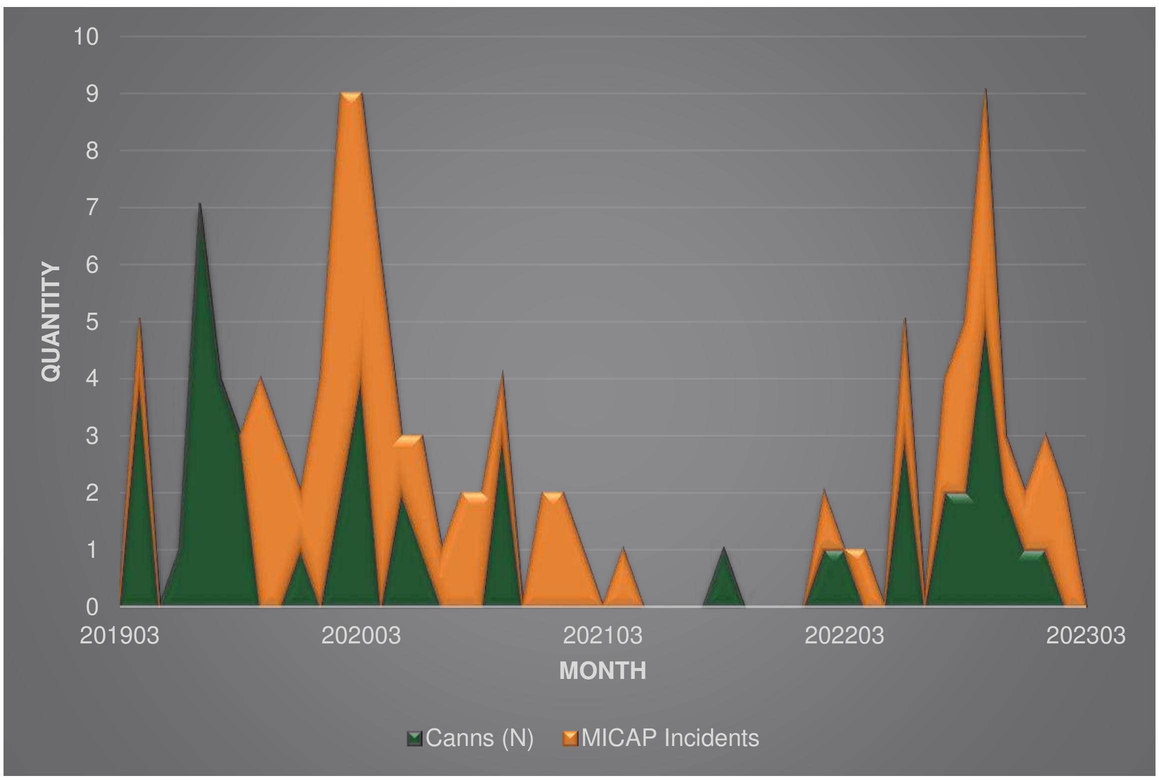


Figure 38: MICAP and Canns Data for Computer Interface Unit

As seen in the figure above, in early 2019 the fleet experiences Canns (N) occurrences and MICAP (I) occurrences which both go to zero before starting a period of sporadic occurrences. After a relatively quiet period starting in late 2021, similar profiling occurs again beginning in 2022 and continuing through 2023. This indicates a cycle of having no parts on the shelf, followed by increases in Canns (N), followed by increases in MICAP (I), followed by a resolution of the parts issue (trends downward until zero) until the cycle repeats itself. This information can be leveraged by the systems engineer and logisticians to create a replacement schedule and demand forecasting for the item.

To validate the trends that are visually illustrated in the previous graph, the correlation coefficient for each lagged timeframe (one month, two months, and so on) was calculated as described in Chapter 4. Using this information, analysts can determine the maximum correlation value between Canns (N) and MICAP (I) and identify time-period lag at which the maximum correlation value occurs. This indicates the most common time delay for this specific item of supply. Results are shown in the table below.

Table 4: Computer Interface Unit Correlation Across Time

Lag	Pearson's Correlation	Correlation vs. Lag
-12	-0.1636	
-11	-0.1737	
-10	-0.2322	
-9	-0.1710	
-8	-0.0298	
-7	-0.0429	
-6	-0.0792	
-5	-0.1182	
-4	0.0281	
-3	-0.0640	
-2	0.0766	
-1	0.1457	
0	0.1563	
1	0.0919	
2	0.1277	
3	0.2271	
4	0.1806	
5	0.0445	
6	0.4305	
7	0.5401	
8	0.2823	
9	0.2649	
10	0.1393	
11	0.0992	
12	0.1062	

Based on the correlation values calculated at each unique lagged time-period, the maximum highest correlation for this data set occurs at a lag of 7 months. In a real-world setting, this information means that engineering analysts and logisticians would have a 7-month delay from the first occurrence of a cannibalization and its corresponding MICAP aircraft grounding event. Compared to the average lead time of 4 months to produce an item, in this specific case if analysts had notified logisticians of the potential for a MICAP occurrence could have prevented an aircraft being listed as Not Mission Capable which would have a positive influence on overall fleet performance.

5.1.2 Antenna Logic Converter

The next item under review is an Antenna Logic Converter.

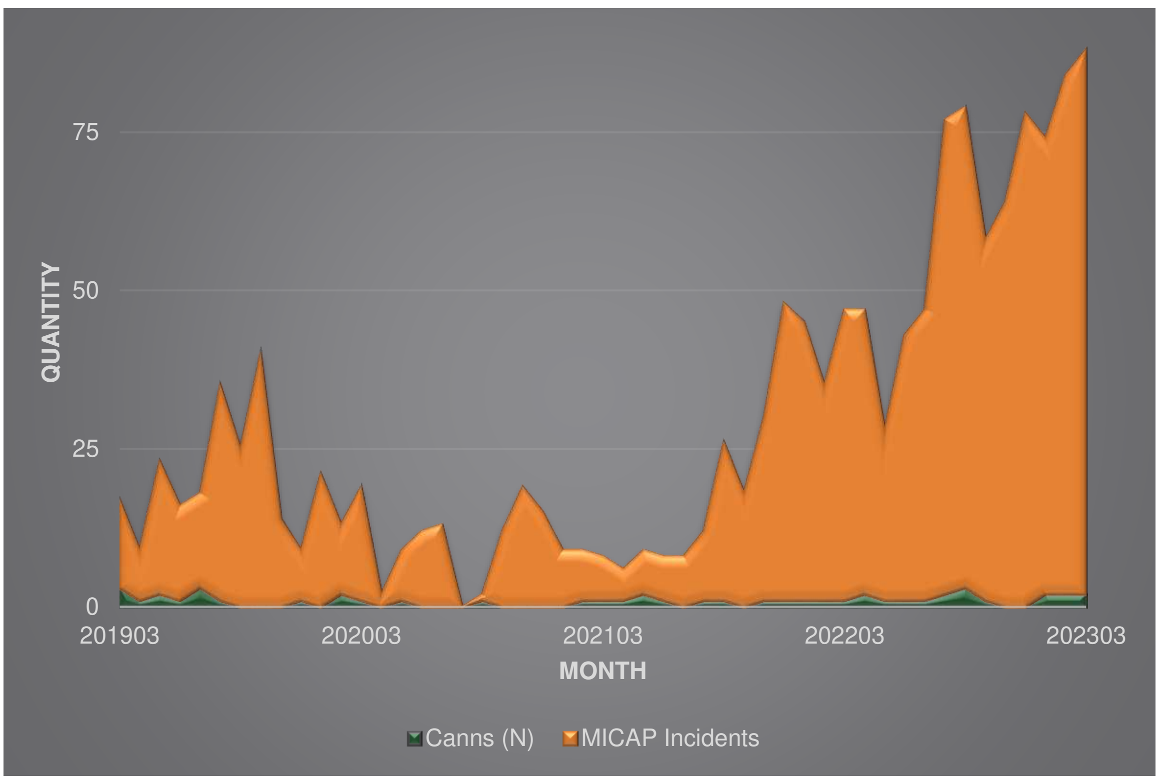


Figure 39: MICAP (I) and Cann (N) for 62AK0,Antenna Logic Converter

This item clearly has had on-going supply issue that began prior to the start of the data set. The overarching trend of MICAP (I) events following Cann (N) events is upheld with this data. The cannibalization rate appears to be mostly steady state, and as a result MICAP (I) begins to accumulate. This indicates that the level of cannibalization events is not enough to keep up with the demand of parts and MICAP (I) begins to outpace Cann (N). This assumption is supported by a very narrow range of Canns (N); the maximum amount never exceeds a quantity of 3, while the number of MICAP (I) is unbounded. The correlation between Cann (N) and MICAP (I) is validated by calculating the correlation values at each time-period lag. The corresponding correlation vs. lag data is shown in the table below:

Table 5: Antenna Logic Converter Correlation Across Time

Lag	Pearson's Correlation	Correlation vs. Lag
-12	0.0376	
-11	0.0282	
-10	0.0382	
-9	0.1072	
-8	0.1140	
-7	0.2420	
-6	0.3214	
-5	0.3196	
-4	0.2741	
-3	0.1819	
-2	0.2549	
-1	0.2878	
0	0.3125	
1	0.2558	
2	0.1914	
3	0.2236	
4	0.2497	
5	0.3452	
6	0.3291	
7	0.2900	
8	0.1807	
9	0.1089	
10	0.1454	
11	0.0664	
12	-0.0061	

The table above verifies that the highest correlation occurs at a lag of 5 months. The information from the graph and table above indicates that there is a lag between cannibalizations and MICAP occurrences at about the 5-month mark. Compared to the average production lead time of 4 months, analysts would have enough time to prepare for the potential demand on supply and work with suppliers to meet the future demand.

5.1.3 Descent Reel

The data below relates the logistics profile of an aircraft descent reel, which is used as emergency egress equipment for aircrew. This type of part typically has a static life limit (i.e., an expiration date) independent of flight hours or functionality of the item. Shelf life or expiration dates will effect the cannibalization profile of items since maintenance cannot cannibalize indefinitely unless new stock with un-expired dates are entered into the supply chain. A graph of Canns (N) and MICAP (I) for descent reels is shown below.

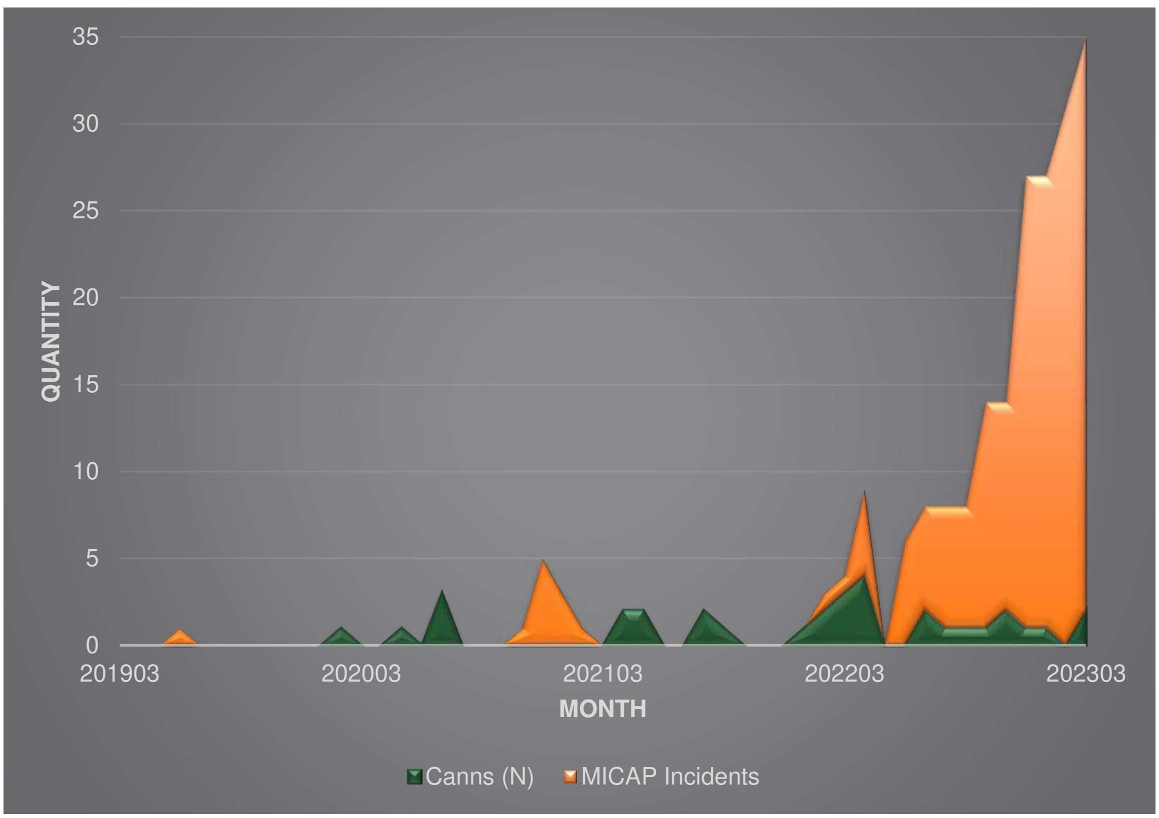


Figure 40: MICAP (I) and Cann (N) for Descent Reel

This profile of MICAP (I) and Cann (N) events does an excellent job of illustrating how cannibalization events tend to be the precursor to MICAP (I) events. There are a few cannibalization events in early 2020 which result in a small blip of MICAP (I) events about 12 months later. Then MICAP (I) events begin to occur more frequently beginning in mid-2022 and accumulate quickly as cannibalization support can no longer keep up with the MICAP (I) demand. This information is supported by the correlation calculations shown below.

Table 6: Descent Reel Correlation Across Time

Lag	Pearson's Correlation	Correlation vs. Lag
-12	-0.0716	
-11	-0.0680	
-10	-0.0868	
-9	-0.0303	
-8	-0.0164	
-7	-0.0093	
-6	-0.0198	
-5	0.0500	
-4	0.0562	
-3	0.1115	
-2	0.0739	
-1	0.1509	
0	0.2045	
1	0.1342	
2	0.2358	
3	0.2790	
4	0.2888	
5	0.2788	
6	0.2744	
7	0.2674	
8	0.3559	
9	0.3107	
10	0.4651	
11	0.5692	
12	0.3044	

The table above clearly shows a maximum correlation value at the 11-month lag time-period. This corresponds to other information logisticians provided about the descent reels, which is that they are check for expiration date once a year, similar to other safety equipment on the aircraft. If the descent reel is within 12 months of expiration, a requisition is submitted to replace the item. While technically the descent reel can be re-installed until the date fully expires, the corresponding requisition will trigger demand on the system and eventually go MICAP if it remains unfulfilled. The logistician involved had a note related to this item stating that several batch purchases had been procured over the last decade, and that Canns and MICAPs tend to occur in batches due to the non-random expiration dates of the most recently procured items.

In a real-world situation, an analyst that identifies a potential MICAP issue based on a cannibalization request 11-months prior to the predicted event could easily beat the average production lead time of 4 months. This would positively impact aircraft performance rates and avoid Not Mission Capable hours for downtime due to MICAP occurrences.

5.1.4 Pneumatic System Valve

The component part reviewed below is a pneumatic system valve. The graph illustrates a significant period of Canns (N) events that occurred for a short time and then were followed by MICAP (I) events.

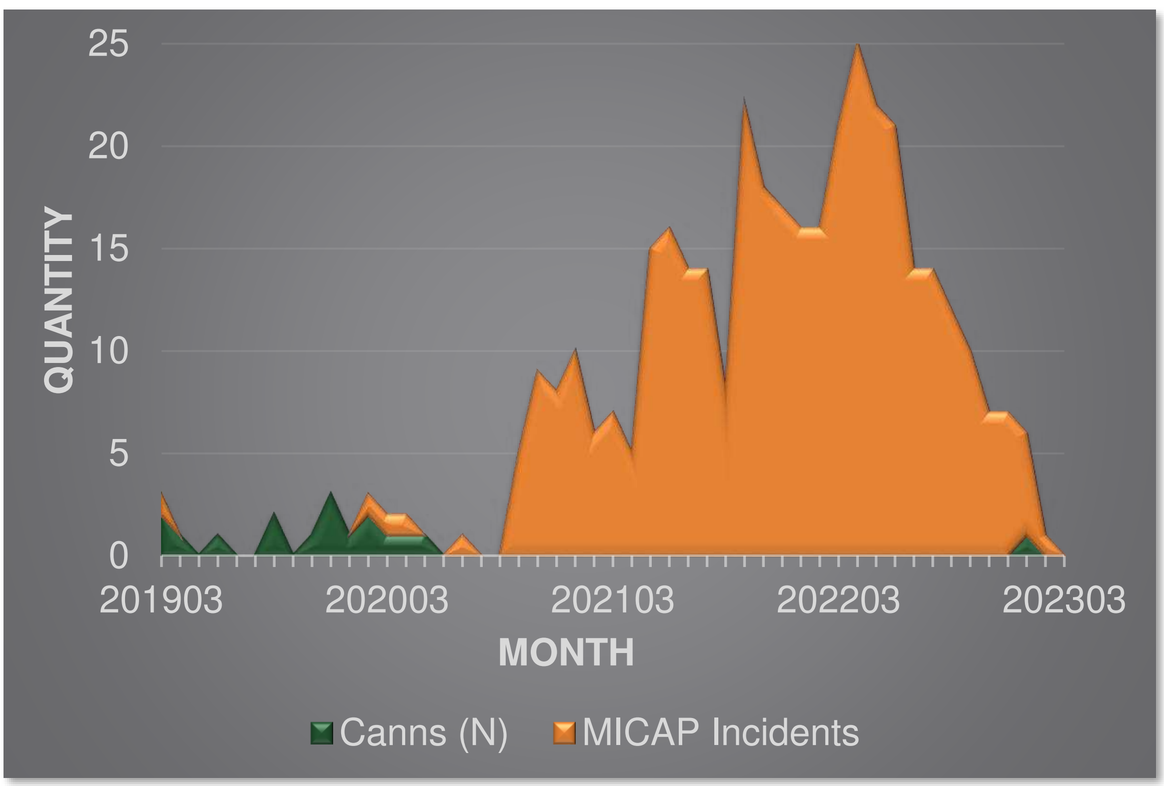


Figure 41: MICAP (I) and Cann (N) for Pneumatic System Valve

It is interesting to note that the quantity of MICAP (I) increased quickly once the Canns (N) events dropped off. If maintainers were unable to cannibalize additional parts due to mission needs, the lack of resolution for MICAPs by fulfilling orders with cannibalized parts would yield an accumulation of MICAP (I) events. The information visually represented in the graph above can be verified with a statistical calculation of correlation values shown in the table below:

Table 7: Valve Correlation Across Time

Lag	Pearson's Correlation	Correlation vs. Lag
-12	0.0195	
-11	-0.1037	
-10	0.1088	
-9	0.1229	
-8	0.1167	
-7	0.0036	
-6	0.0330	
-5	0.0413	
-4	-0.0361	
-3	0.1866	
-2	0.1244	
-1	0.1182	
0	0.1628	
1	0.1894	
2	0.2370	
3	0.0710	
4	0.1899	
5	0.2165	
6	0.2075	
7	0.2697	
8	0.1036	
9	0.3439	
10	0.3559	
11	0.1332	
12	0.2020	

The table above indicates a maximum correlation coefficient at a lag of 10 months. Once again, a lag of this length easily exceeds the average production lead time of 4 months. In a real-world scenario, manufacturers would have more than double the amount of time required to produce parts to fulfill the demand placed on the supply system.

5.1.5 Servo Motor

The graph below illustrates the data for an aircraft servo motor. Cann (N) and MICAP (I) data over the pre-determined time-period is shown in the graph below.

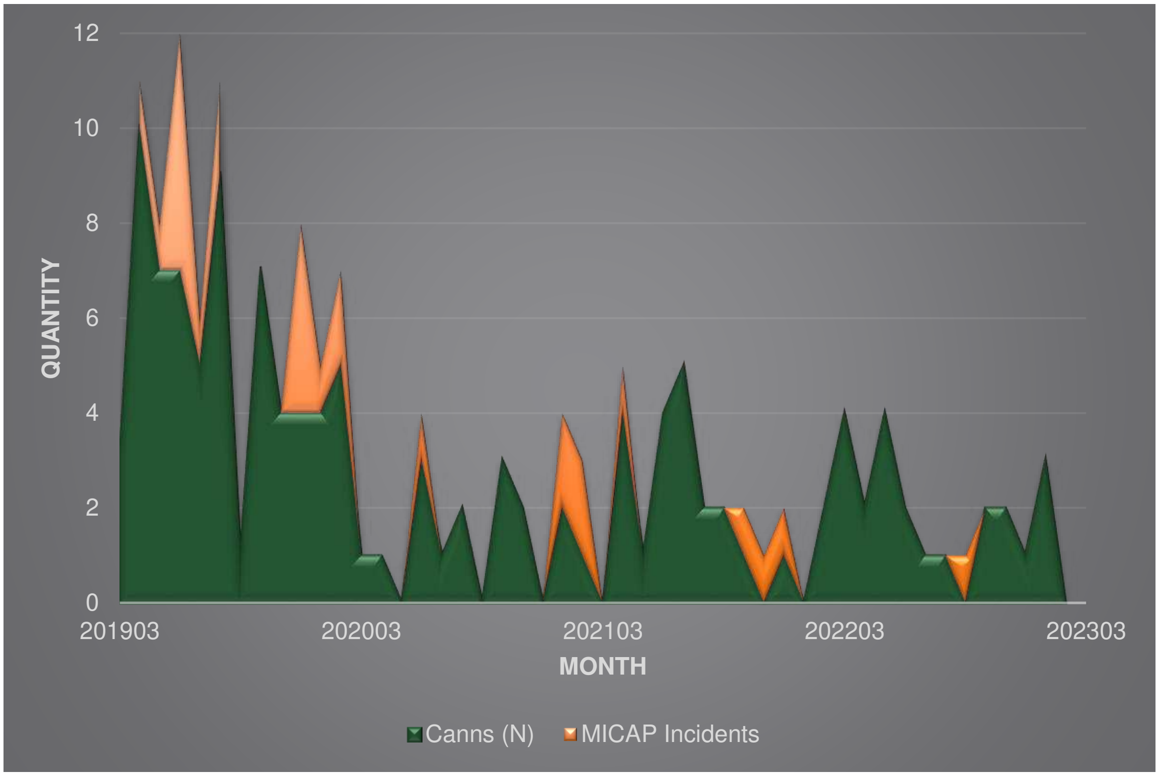


Figure 42: Graph of MICAP and Canns for Servo Motor

While some minor correlation between Cann (N) and MICAP(I) exists in the dataset shown in the previous figure, it is not quite as clear a pattern as in the other case study examples. For this case study example, it is important to note that the pattern of cannibalizations appears to be trending downward at the start of the time-period under review. This may indicate that the item of supply had previously experienced a demand that out-paced the existing supply posture. As with the previous example, this could skew the results of the graphs, although a weak correlation does appear to be visually present. Reviewing the correlation and lag time-period data will help identify whether a mathematical relationship exists and results from that analysis are shown in the table below:

Table 8: Servo Motor Correlation Across Time

Lag	Pearson's Correlation	Correlation vs. Lag
-12	-0.0622	
-11	-0.1564	
-10	-0.0633	
-9	-0.2027	
-8	0.0898	
-7	0.0363	
-6	0.2464	
-5	0.1505	
-4	0.2723	
-3	-0.0138	
-2	0.4062	
-1	0.0898	
0	0.4201	
1	0.2505	
2	0.4678	
3	0.1256	
4	0.3747	
5	0.0529	
6	0.2425	
7	0.1227	
8	0.2568	
9	-0.0578	
10	0.0084	
11	-0.0800	
12	0.0017	

The maximum correlation occurs at a lag of 2-months. The table above also illustrates how short cycle lags can echo in the preceding or following time-periods (lags of 4, 6, 8, respectively. While a 2-month lag time-period does give analysts and logisticians some additional lead time prior to the occurrence of MICAP (I), a lag of only 2 months does not exceed the average production lead time of 4 months for most aircraft parts and therefore would not fully prevent Not Mission Capable hours accumulating when MICAPs occur. However, any warning, regardless of the how far in advance it occurs, could potentially save time on the back end of MICAP hour accumulation. In a real-world scenario knowing a potential issue is pending would still save nearly two months of lead time for working on a resolution to the supply issue.

5.1.6 Avionics Interface Unit

The final item under review is identified as an avionics interface unit (AIU). The occurrences of Canns (N) and MICAP (I) for the AIU are shown below:

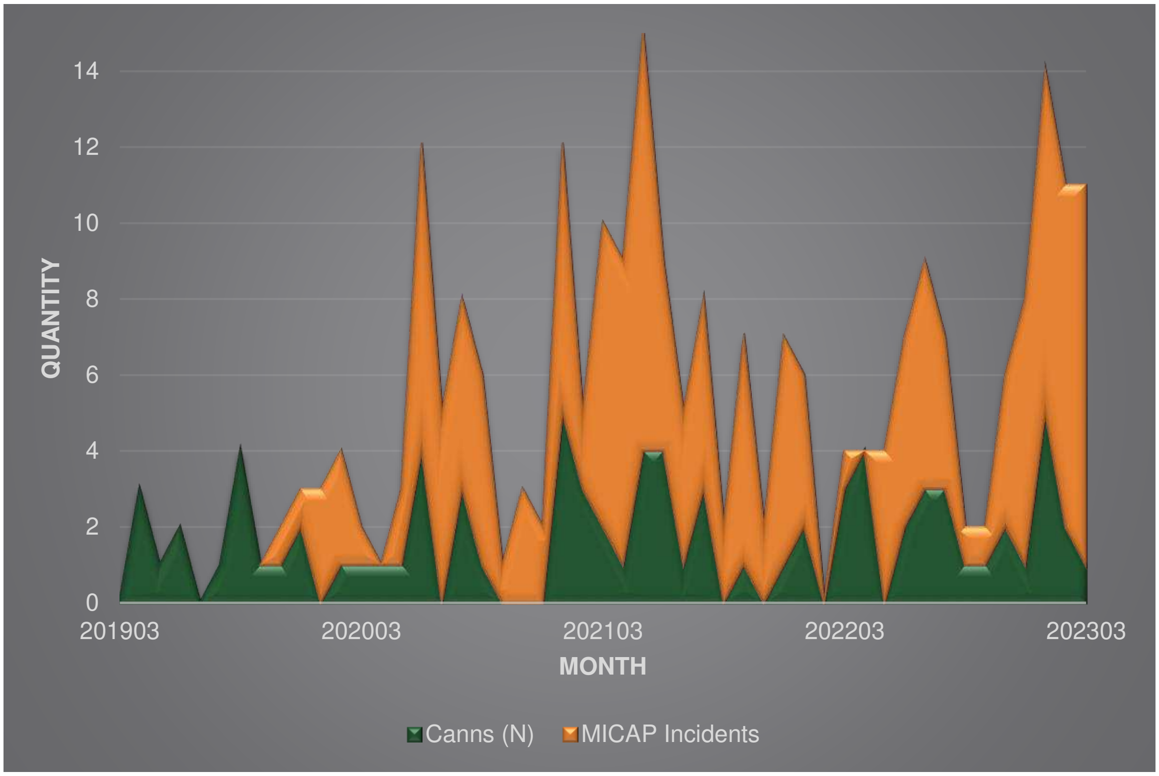


Figure 43: MICAP vs. Canns Data for Avionics Interface Unit

At first glance, the graphical data visually indicates a trend of cannibalizations and MICAPs. Canns (N) began in early 2019 and continued over the next few months until MICAP (I) occurrences began to follow. Since the cannibalizations continued through the entire time-period, the MICAP (I) occurrences also continue throughout the remainder of the time-period. As with previous examples MICAP (I) occurrences tend to accumulate at a quick rate once Canns (N) begin to occur. This indicates an on-going issue getting appropriate quantities of component parts in supply. In this case, the maximum upper boundary of cannibalizations is four, with the total cannibalization amount never exceeding that quantity. MICAP (I) seem to increase and decline frequently during this timeframe. To validate the trends that are visually illustrated in the previous graph, the correlation coefficient for each lagged timeframe was calculated. The results for the dataset with results are shown in the table below.

Table 9: Avionics Interface Unit Correlation Across Time

Lag	Pearson's Correlation	Correlation vs. Lag
-12	0.1611	
-11	0.1443	
-10	-0.0023	
-9	-0.0599	
-8	0.0658	
-7	0.1701	
-6	-0.0131	
-5	-0.0007	
-4	-0.1105	
-3	-0.0224	
-2	0.0848	
-1	0.1461	
0	0.3491	
1	0.0759	
2	0.2607	
3	0.0932	
4	0.1330	
5	0.0047	
6	-0.1488	
7	0.0936	
8	-0.1107	
9	0.1623	
10	-0.0595	
11	0.1346	
12	-0.0304	

Based on the correlation values calculated at each unique lagged time-period, we can conclude that the maximum highest correlation for this testing data set occurs at a lag of 0. This indicates that MICAPs are occurring so frequently that the cannibalization occurrences have very little influence, if any at all on the overall MICAP (I) occurrence rate. This phenomenon can occur when the demand for the item out-paces the availability of aircraft to cannibalization to fulfill demand of aircraft not in a scheduled maintenance status. As stated previously, items that are not good candidates for cannibalization, items that are unique to aircraft with small fleet sizes, or items where demand out paces the availability of cannibalizations may all fall into this category and produce a similar effect. Since this case study was pulled from a list of high

MICAP (I) drivers (not high cannibalizations), it suggests that waiting until MICAPs begin to accrue to address supply issues is not ideal.

In a real-world setting, this information indicates that the on-going demand far outpaces the availability to fulfill that demand with a cannibalized item and system analysts should look for other ways to meet mission needs that include the expected downtime and lack of parts in their considerations. With an average lag of 0 months between Canns (N) and MICAP (I) occurrences waiting until MICAP (I) events occur to act is imprudent.

5.2 Case Study Summary

This section summarizes the findings of the case studies listed in the previous sections. Recall that the average lead time for aircraft components is 4 months. The calculated lag results from each case study are compared to the 4 months average lag to determine whether cannibalization data would be useful in preventing downtime. The findings re shown in the table below.

Table 10: Case Study Summary

Item	Calculated Lag	Is Lag Greater than 4-month Production Lead Time?	Prevent Not Mission Capable Downtime?
Computer Interface Unit	7 months	Yes	Yes
Antenna Logic Converter	5 months	Yes	Yes
Descent Reel	11months	Yes	Yes
Pneumatic System Valve	10 months	Yes	Yes
Servo Motor	2 months	No	Partially
Avionics Interface Unit	0 months	No	No

The results above are clear, in most cases using cannibalization occurrences as a trigger to begin supply workarounds and begin the logistics requisition process would prevent a MICAP from occurring and thus prevent Not Mission Capable (NMC) downtime due to supply (i.e., MICAP occurrences). In 4 out of 6 cases, a MICAP event would have been completely prevented. In 1 out of 6 cases, the logisticians would have gained 2 months, or approximately 50%, of the required production lead time. In 1 out of 6 cases, the MICAP occurrences were already so frequent that the lag between cannibalizations and MICAPs is zero. This illustrates that some parts cannot benefit from this method if there are already on-going sever supply issues where cannibalizations and MICAPs are frequent and consistent occurrences.

However, a four-month period of downtime due to production lead time equates to 2,880 Not Mission Capable Supply (NMCS) downtime hours. With the 4 case studies above, and the 1 case study that partially prevents downtime, a total of 12,960 total NMCS downtime hours could have been avoided. Senior leaders tend to view downtime hours in terms of aircraft availability per year. As an equivalent, 12,960 downtime hours is the equivalent of 1.5 aircraft in service for an entire year.

Chapter 6 - Conclusion, Recommendations, and Future Research

It is nearly impossible to predict every disruption to aircraft operations an enterprise system may face over its lifetime. Working level logisticians and engineers require actionable recommendations for specific supply chain issues to mitigate the issues of changes to supportability element factors. The research presented herein identified a process whereby systems engineers can identify potential supply issues before downtime occurs. This allows decision making at the lowest organizational level to assist operators, maintainers, logisticians, and systems engineers with the ability to adapt to changing environments and execute their mission.

6.1 Summary of Research

Chapter 1 introduced supporting information that identified an issue with DoD systems engineering life cycle management processes. Despite many higher-level efforts to improve both organizational structure and management processes, industry experts agree that the process does not function efficiently. This is primarily due to the fact that the complexity of organizational structure, inflexibility of procurement law and regulations, and long-life spans of enterprise systems all coalesce into a myriad of influencing factors that impact overall aircraft performance. Much of the training or improvement efforts are aimed at improving processes at a higher level, training guidance for the work force, or for realigning organizational structure to facilitate communication issues.

Chapter 2 is built on the research by quantifying the impact of the problem and identifying what improvements had been attempted in the past. Industry experts all agree that weapon system performance is impacted by inefficient organizational structure, acquisition policy, and regulatory processes. This Chapter also identified research for this topic from both third party external to the Government industry organizations as well as the academic community and professional organizations. But most of this research focused on improving lagging indicators in the form of long-term trend performance monitoring. There was very little research on improving leading indicators, and none on specifically leveraging data collected from on-aircraft leading indicator performance events to leading indicator supply metrics.

Chapter 3 provided a detailed methodology to gather data generated during operations, particularly data that spans different career fields, regulatory guidance, and stakeholder ownership. It was surprising to learn that so few performance metrics can be linked directly to negative events on aircraft. And even fewer metrics can be linked to both negative aircraft events and negative supply events. Then, a statistical method was identified to determine potential relationships amongst the various performance metrics, focusing on operational use data and supply chain logistics data. This statistical method was used to determine which metrics to focus manpower and attention on, since resource constraints prevent reviewing all the data all the time. This chapter also identified potential ways to incorporate this information into existing feedback loops for systems engineers to inform supply of impending parts shortages, primarily leveraging the Logistics Requirements Development Process (LRDP) and Reliability Centered Maintenance (RCM) policy and processes which are already required and utilized.

Chapter 4 provided the results of the statistical modeling and data analytics process. The results indicated that there is a link between Cann (N) occurrences and MICAP (I) drivers for negative aircraft downtime events. Evidence suggests that this relationship in the data can be exploited to help working level logisticians and engineers prevent downtime drivers.

Chapter 5 discussed the application of these results. The top drivers for both MICAP (I) and Cann (N) were reviewed to compare results from the proposed model and causal relationship to data utilized in the original statistical analyses. The research upheld the mathematical analysis results that indicated a relationship between Canns (N) occurrences and MICAP (I) drivers. This chapter also recommended real-world steps that working level systems engineers can take to prevent downtime drivers. Finally, the research for each case study that identified the item-unique lag time between cannibalizations and MICAP supply downtime hours was quantified via a time series cross correlation graph which identified the specific lag for each item. This item specific lag time was compared to the average production lead time for aircraft parts procurement to determine whether monitoring cannibalizations would serve as appropriate lead time for logisticians to potentially get parts in supply.

6.2 Recommendations

For immediate action at the working level, systems engineers tasked with the review of maintenance actions under the LRDP framework or with component part analysis under RCM policy should take action to review operational use data as part of on-going life cycle validation procedures. This data can help provide insight into component related downtime and can shed light on any potential supply issues that may be on the horizon. Since analysis of component failure is already within the scope of their normal life cycle management activities, this review of Canns (N) data can be incorporated with ease to existing processes. Once identified, this information should be shared with logisticians through LRDP regularly bill of work reviews, or via the item manager assigned to the NSN. Logisticians should act when they receive this information to update their forecasting levels as part of regular file maintenance and forecasting efforts that happen continually throughout the years.

6.3 Future Research

For future research, process designers and systems architects should review the collection and digital links between operational use data, maintenance data, and supply chain data. It became clear from this research that most supportability elements such as logistics, training, and even maintenance records have performance measures or metrics that do not link to operational need or performance of the physical product (aircraft), let alone are included in the formally documented requirements for that physical system. Going forward, the Air Force needs to recognize that all career fields and supportability elements exist to support the overarching mission, and ultimately provide support to the operators and physical products that execute that mission. The missing relationship links between supportability elements and the Warfighter causes communication issues, lack of understanding of how workload impacts performance, and inefficiencies in life cycle management processes. Future research should explore what the appropriate measures and metrics are that link all areas of operations, logistics, and maintenance to performance of the product (aircraft) or mission (operational need).

As the Air Force develops the next generation of physical products such as aircraft or support equipment, digital systems, intelligence networks, and organizational frameworks it should focus on linking all activities to mission need and enterprise system requirements. The Air Force should look at the enterprise system holistically to develop metrics and data analytics programs that link all supportability elements directly to the performance of the product they are supporting. The Air Force should consider updating its data collection policies to mandate that data collected be tied to the operational need and linked to performance of both the physical products and supportability elements, and the whole enterprise system. There is both process research and database development research that should be accomplished to determine the best path forward to accomplish these goals. While this research has provided a method to work around the gaps in communication between organizations, career fields, and data systems a more holistic approach to weapon system life cycle management from an enterprise system level would benefit all systems within the Air Force.

6.4 Conclusion

The results of the feedback process analysis, operational data, logistics data, and aircraft records along with the results of the mathematical model and case studies show a definitive link between Cannibalizations and parts shortages in the field. This research has accomplished the following:

- Synthesized a useful model for aircraft systems engineering process for operations and sustainment phase activities.
    - Connected Systems Engineering Vee with continuous improvement leveraging existing Government data processes.
- Created a new link between operational and logistics data.
    - Operational Data: Cannibalizations (Cann)
    - Logistics Data: Mission Impaired Capability Awaiting Parts (MICAP)
- Developed an innovative method to prioritize systems engineering manpower for performance data analyses.
    - Prioritize systems or components with the highest Cann rates.
- Demonstrated a novel ability to update supply requirements and leverage the Centralized Asset Management (CAM) process to do so.
    - Engineers analyze parts with large cannibalization occurrences, inform stakeholders of future demand forecasting impacts.
    - Logisticians update appropriate supply inventory requirements.

With the newly developed process for continually monitoring system performance for each supportability element, systems engineers and other stakeholders can investigate their own operational data to tie performance to each support element. In addition to the accomplishments above, the research questions were answered:

- What existing operational data that can be leveraged as feedback to assess or improve performance of fielded systems?
    - Cannibalization data can be used to start parts shortage mitigation earlier.
    - In the example case studies, all examples would either prevent downtime completely or reduce downtime by allowing supply to procure items in anticipation of demand. However, the research concluded that items already

experiencing high levels of MICAPs or cannibalizations would benefit less from this technique.

- What is a process framework for identifying applications of operational and logistics data for performance improvements?
    - Continuous validation of stakeholder requirements as part of the Systems Engineering Vee model. Systems Engineers can utilize cannibalization data to prioritize review of items at risk for causing Not Mission Capable Supply (NMCS) downtime; and can provide this information as feedback to logisticians via the existing Logistics Requirements Development Process (LRDP) which is a required process for all aircraft fleets.
- What performance improvements to fielded systems can be realized by utilizing the operational data and process framework?
    - The Case Studies validate the method of using Cannibalization data to prevent downtime due to parts shortages.
    - In 4 of the 6 case study examples, downtime would have been completely prevented at value of approximately 4 months per item equating to 2,880 downtime hours avoided per item.
    - In 1 of the 6 case studies a gain of two months, which is 50% of the downtime prescribed to production lead time.
    - This equates to 12,960 downtime hours prevented by using the prescribed method (equates to 1.5 aircraft per year).

The methods determined by this research utilize existing DoD processes for logistics forecasting, systems engineering analysis, and data collection. Implementing these methods will improve fleet performance without major changes to organization or regulatory requirements and allows systems engineers to use proven data methods to support logistics requirements.

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Table 11: Operations, Supply, and Maintenance Metrics

Metric	Category	Type
12 Hour Fix (%)	Leading	Mx
12 Hour Fix (N)	Leading	Mx
24 Hour Fix (%)	Leading	Mx
24 Hour Fix (N)	Leading	Mx
8 Hour Fix (%)	Leading	Mx
8 Hour Fix (N)	Leading	Mx
Actions - 6 (No Defect) (N)	Neither	Mx
Adj Sorties Scheduled (N)	Neither	Operations
Administrative Lead Time	Lagging	Supply
Air Abort (%)	Leading	Operations
Air Abort (N)	Leading	Operations
ASD (H)	Neither	Operations
ATC Deviations (N)	Neither	Operations
Available (%)	Lagging	Performance
Available (H)	Lagging	Performance
Available (N)	Lagging	Performance
Available Attain (%)	Neither	Operations
Available Std (%)	Neither	Operations
Backorder Count	Leading	Supply
Backorder Days	Leading	Supply
Breaks (%)	Leading	Mx
Breaks (N)	Leading	Mx
Cann Hours (H)	Leading	Supply
Cann Rate Hours (%)	Leading	Mx
Cann Rate Sorties (%)	Leading	Mx
Cann Rate Sorties Std (%)	Neither	Mx
Cann (N)	Leading	Supply
Cat 1 Hangar Queen (N)	Neither	Mx
Cat 2 Hangar Queen (N)	Neither	Mx
Cat 3 Hangar Queen (N)	Neither	Mx
Customer Wait Time (Avg)	Lagging	Supply
Customer Wait Time (Days)	Lagging	Supply
Cx BO	Neither	Supply
Depot (%)	Lagging	Performance
Depot (H)	Lagging	Performance
Depot (N)	Lagging	Performance
Depot Attain (%)	Neither	Performance
Exercise Deviations (N)	Leading	Operations
Failures - 1 (Inherent) (N)	Leading	Mx
Failures - 2 (Induced) (N)	Neither	Mx
Ferry Count (N)	Neither	Operations
Flying hours / TAI by Month (H)	Neither	Operations
FMC (%)	Lagging	Performance
FMC (H)	Lagging	Performance

Metric	Category	Type
FMC (N)	Lagging	Performance
FSE (%)	Leading	Operations
GAA Deviations (N)	Leading	Operations
GAB Deviations (N)	Leading	Operations
GAC Deviations (N)	Leading	Operations
Ground Abort (%)	Leading	Operations
Ground Abort (MX) (%)	Leading	Mx
Ground Abort (MX) (N)	Leading	Mx
Ground Abort (N)	Leading	Mx
HHQ Deviations (N)	Leading	Operations
Hours Flown (H)	Neither	Operations
Issue Effectiveness Rate	Lagging	Supply
MC (%)	Lagging	Performance
MC (H)	Lagging	Performance
MC (N)	Lagging	Performance
MC Goal (%)	Neither	Operations
MC Std (%)	Neither	Operations
MICAP (H)	Leading	Supply
MICAP (I)	Leading	Supply
MMH / FH (Total) (N)	Lagging	Mx
MMH / FH (Unit) (N)	Lagging	Mx
MTBF - 1 (Inherent) (H)	Lagging	Mx
MTBF - 2 (Induced) (H)	Lagging	Mx
MTBM - 6 (No Defect) (H)	Lagging	Mx
MTBM Total (H)	Lagging	Mx
MTX Deviations (%)	Leading	Mx
MTX Deviations (N)	Leading	Mx
NMC (%)	Lagging	Performance
NMC (H)	Lagging	Performance
NMC (N)	Lagging	Performance
NMCB (%)	Lagging	Performance
NMCB (H)	Lagging	Performance
NMCB (N)	Lagging	Performance
NMCB (NA) (%)	Lagging	Performance
NMCB (NA) (H)	Lagging	Performance
NMCB (NA) (N)	Lagging	Performance
NMCB (NA) Attain (%)	Neither	Performance
NMCBS (%)	Lagging	Performance
NMCBS (H)	Lagging	Performance
NMCBS (N)	Lagging	Performance
NMCBSA (%)	Lagging	Performance
NMCBSA (H)	Lagging	Performance
NMCBSA (N)	Lagging	Performance
NMCBU (%)	Lagging	Performance
NMCBU (H)	Lagging	Performance
NMCBU (N)	Lagging	Performance
NMCBUA (%)	Lagging	Performance

Metric	Category	Type
NMCBUA (H)	Lagging	Performance
NMCBUA (N)	Lagging	Performance
NMCM (%)	Lagging	Performance
NMCM (H)	Lagging	Performance
NMCM (N)	Lagging	Performance
NMCM (NA) (%)	Lagging	Performance
NMCM (NA) (H)	Lagging	Performance
NMCM (NA) (N)	Lagging	Performance
NMCM (NA) Attain (%)	Neither	Performance
NMCMS (%)	Lagging	Performance
NMCMS (H)	Lagging	Performance
NMCMS (N)	Lagging	Performance
NMCMSA (%)	Lagging	Performance
NMCMSA (H)	Lagging	Performance
NMCMSA (N)	Lagging	Performance
NMCMU (%)	Lagging	Performance
NMCMU (H)	Lagging	Performance
NMCMU (N)	Lagging	Performance
NMCMUA (%)	Lagging	Performance
NMCMUA (H)	Lagging	Performance
NMCMUA (N)	Lagging	Performance
NMCS (%)	Lagging	Performance
NMCS (H)	Lagging	Performance
NMCS (N)	Lagging	Performance
NMCS (NA) (%)	Lagging	Performance
NMCS (NA) (H)	Lagging	Performance
NMCS (NA) (N)	Lagging	Performance
NMCS (NA) Attain (%)	Neither	Performance
NMCSA (%)	Lagging	Performance
NMCSA (H)	Lagging	Performance
NMCSA (N)	Lagging	Performance
Off Equip MHs (H)	Neither	Mx
Off Equip MHs General (H)	Neither	Mx
Off Equip MHs Unit (H)	Neither	Mx
On Equip MHs (H)	Neither	Mx
On Equip MHs General (H)	Neither	Mx
On Equip MHs Unit (H)	Neither	Mx
OPS Deviations (%)	Leading	Operations
OPS Deviations (N)	Leading	Operations
OTH Deviations (N)	Leading	Operations
PMC (%)	Lagging	Performance
PMC (H)	Lagging	Performance
PMC (N)	Lagging	Performance
PMCB (%)	Lagging	Performance
PMCB (H)	Lagging	Performance
PMCB (N)	Lagging	Performance
PMCM (%)	Lagging	Performance

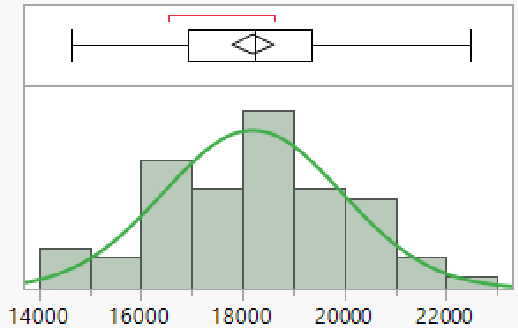
Metric	Category	Type
PMCM (H)	Lagging	Performance
PMCM (N)	Lagging	Performance
PMCS (%)	Lagging	Performance
PMCS (H)	Lagging	Performance
PMCS (N)	Lagging	Performance
PRD (N)	Leading	Operations
Production Lead Time	Lagging	Supply
Recur (%)	Leading	Mx
Recur (N)	Leading	Mx
Repeat (%)	Leading	Mx
Repeat (N)	Leading	Mx
Requisitions	Leading	Supply
Sorties / TAI by Month (N)	Neither	Operations
Sorties Flown (N)	Neither	Operations
Sorties Scheduled (N)	Neither	Operations
Stock Effectiveness Rate	Lagging	Supply
SUP Deviations (N)	Leading	Operations
Support General MHs (H)	Neither	Mx
SYM Deviations (N)	Leading	Operations
TAI (H)	Neither	Operations
TAI (N)	Neither	Operations
TMMHs (H)	Lagging	Mx
TNMC (%)	Lagging	Performance
TNMC (H)	Lagging	Performance
TNMC (N)	Lagging	Performance
TNMCM (%)	Lagging	Performance
TNMCM (H)	Lagging	Performance
TNMCM (N)	Lagging	Performance
TNMCM Goal (%)	Neither	Performance
TNMCM Std (%)	Neither	Performance
TNMCS (%)	Lagging	Performance
TNMCS (H)	Lagging	Performance
TNMCS (N)	Lagging	Performance
TNMCS Goal (%)	Lagging	Performance
TNMCS Std (%)	Neither	Performance
Total Abort (%)	Neither	Performance
Total Abort (N)	Leading	
Total Actions (N)	Neither	Mx
Total Backorders - Lines	Neither	Supply
Total Backorders - Units	Neither	Supply
Total Issues w/Requisition - Lines	Neither	Supply
Total Issues w/Requisitions (Units)	Neither	Supply
Total MAJCOM Deviations (N)	Leading	Operations
Total Repair Cycle Time	Lagging	Supply
TPMCM (%)	Lagging	Performance
TPMCM (H)	Lagging	Performance

Metric	Category	Type
TPMCM (N)	Lagging	Performance
TPMCS (%)	Lagging	Performance
TPMCS (H)	Lagging	Performance
TPMCS (N)	Lagging	Performance
Unit Possessed (H)	Lagging	Operations
Unit Possessed (N)	Lagging	Operations
UNPR (%)	Lagging	Operations
UPNR (H)	Lagging	Operations
UPNR (N)	Lagging	Operations
UPNR Attain (%)	Neither	Operations
USE / FH (H)	Lagging	Operations
USE / Sorties (N)	Lagging	Operations
UTE Adds (N)	Neither	Operations
UTE Cancellations (N)	Neither	Operations
WXX Deviations (N)	Leading	Operations

Table 12: Pearson's Coefficient for Variables

	MICAP (I)	Canns (N)	Breaks (N)	Air Aborts (N)	Ground Aborts (N)	Backorder Days	Backorder Count
MICAP (I)	1.0000	0.8394	0.5788	0.1943	0.4232	0.6212	0.6831
Canns (N)	0.8394	1.0000	0.7060	0.2849	0.4345	0.3568	0.4578
Breaks (N)	0.5788	0.7060	1.0000	0.5923	0.6203	0.0368	0.0962
Air Aborts (N)	0.1943	0.2849	0.5923	1.0000	0.6046	-0.2748	-0.2181
Ground Aborts (N)	0.4232	0.4345	0.6203	0.6046	1.0000	0.2131	0.1849
Backorder Days	0.6212	0.3568	0.0368	-0.2748	0.2131	1.0000	0.9568
Backorder Count	0.6831	0.4578	0.0962	-0.2181	0.1849	0.9568	1.0000

MICAP (I)



Compare Distributions

Show	Distribution		AICc	BIC	-2*LogLikelihood
☑	Normal		1265.3881	1269.737	1261.2116

Quantiles

Summary Statistics

Mean	18196.31
Std Dev	1754.3883
Std Err Mean	208.20758
N	71
Variance	3077878.2
Skewness	0.0235448
Kurtosis	-0.340007
CV	9.6414508
Autocorrelation	0.6262524
Minimum	14643
Maximum	22466
Median	18244
Geometric Mean	18112.238

Fitted Normal Distribution

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Location	μ	18196.31	208.20758	17781.053	18611.567
Dispersion	σ	1754.3883	148.80527	1505.7745	2102.1017

Measures	
-2*LogLikelihood	1261.2116
AICc	1265.3881
BIC	1269.737

Goodness-of-Fit Test

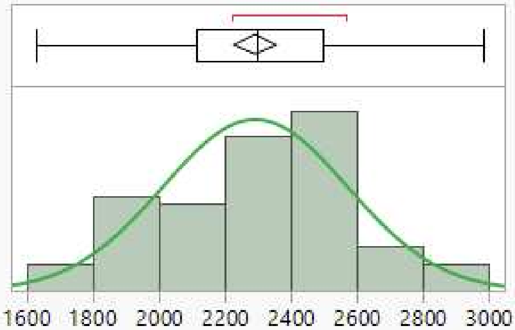
	W	Prob<W
Shapiro-Wilk	0.9878611	0.7288

	A^2	Simulated p-Value
Anderson-Darling	0.2393728	0.7728

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Figure 44: MICAP (I) Normality Check

Canns (N)



Compare Distributions

Show	Distribution		AICc	BIC	-2*LogLikelihood
☑	Normal		1005.0154	1009.3642	1000.8389

Quantiles

Summary Statistics

Mean	2292.0423
Std Dev	280.41339
Std Err Mean	33.278947
N	71
Variance	78631.67
Skewness	-0.134102
Kurtosis	-0.291051
CV	12.234216
Autocorrelation	0.5608651
Minimum	1628
Maximum	2983
Median	2299
Geometric Mean	2274.6714

Fitted Normal Distribution

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Location	μ	2292.0423	33.278947	2225.6695	2358.415
Dispersion	σ	280.41339	23.784353	240.67611	335.99032

Measures	
-2*LogLikelihood	1000.8389
AICc	1005.0154
BIC	1009.3642

Goodness-of-Fit Test

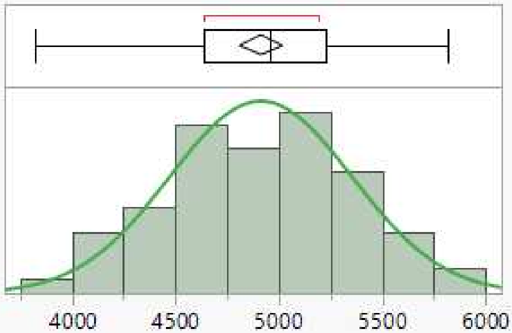
	W	Prob<W
Shapiro-Wilk	0.9877006	0.7193

	A^2	Simulated p-Value
Anderson-Darling	0.3636542	0.4272

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Figure 45: Canns (N) Normality Check

Breaks (N)



Compare Distributions

Show	Distribution		AICc	BIC	-2*LogLikelihood
✓	Normal		1069.2693	1073.6182	1065.0928

Quantiles

Summary Statistics

Mean	4912.9014
Std Dev	440.87329
Std Err Mean	52.322034
N	71
Variance	194369.26
Skewness	-0.199556
Kurtosis	-0.271013
CV	8.9737867
Autocorrelation	0.1282944
Minimum	3817
Maximum	5813
Median	4960
Geometric Mean	4892.9945

Fitted Normal Distribution

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Location	μ	4912.9014	52.322034	4808.5484	5017.2544
Dispersion	σ	440.87329	37.394385	378.39729	528.2528

Measures	
-2*LogLikelihood	1065.0928
AICc	1069.2693
BIC	1073.6182

Goodness-of-Fit Test

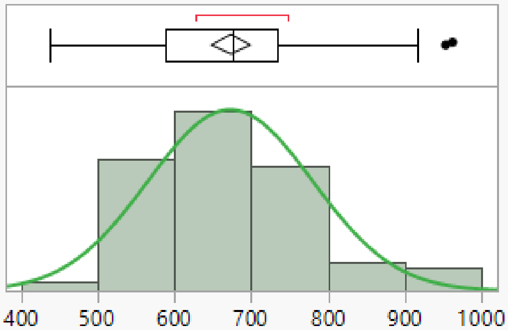
	W	Prob<W
Shapiro-Wilk	0.9892986	0.8115

	A^2	Simulated p-Value
Anderson-Darling	0.2165092	0.8344

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Figure 46: Breaks (N) Normality Check

Air Aborts (N)



Compare Distributions

Show	Distribution		AICc	BIC	-2*LogLikelihood
☑	Normal		868.33857	872.68746	864.1621

Quantiles

Summary Statistics

Mean	672.4507
Std Dev	107.09886
Std Err Mean	12.710296
N	71
Variance	11470.165
Skewness	0.4757811
Kurtosis	0.3425003
CV	15.926648
Autocorrelation	0.5239322
Minimum	438
Maximum	962
Median	676
Geometric Mean	664.1965

Fitted Normal Distribution

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Location	μ	672.4507	12.710296	647.10082	697.80059
Dispersion	σ	107.09886	9.0840066	91.921916	128.32547

Measures	
-2*LogLikelihood	864.1621
AICc	868.33857
BIC	872.68746

Goodness-of-Fit Test

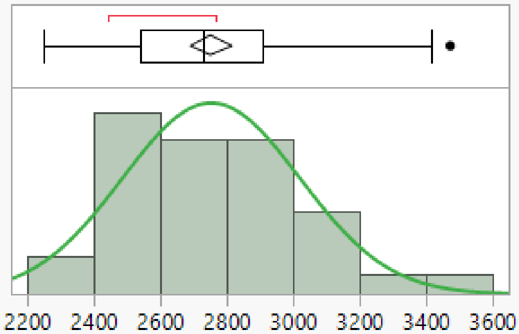
	W	Prob<W
Shapiro-Wilk	0.9737523	0.1425

	A^2	Simulated p-Value
Anderson-Darling	0.5063915	0.1976

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Figure 47: Air Aborts (N) Normality Check

Ground Aborts (N)



Compare Distributions

Show	Distribution		AICc	BIC	-2*LogLikelihood
☑	Normal		997.82001	1002.1689	993.6435

Quantiles

Summary Statistics

Mean	2753.7465
Std Dev	266.55842
Std Err Mean	31.634665
N	71
Variance	71053.392
Skewness	0.6001627
Kurtosis	0.0303596
CV	9.6798461
Autocorrelation	-0.037621
Minimum	2251
Maximum	3472
Median	2731
Geometric Mean	2741.3754

Fitted Normal Distribution

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Location	μ	2753.7465	31.634665	2690.6531	2816.8398
Dispersion	σ	266.55842	22.60919	228.78452	319.38935

Measures	
-2*LogLikelihood	993.64354
AICc	997.82001
BIC	1002.1689

Goodness-of-Fit Test

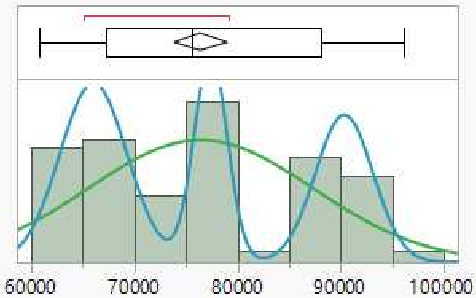
	W	Prob<W
Shapiro-Wilk	0.9668264	0.0572

	A^2	Simulated p-Value
Anderson-Darling	0.6904896	0.0664

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Figure 48: Ground Aborts (N) Normality Check

Backorder Count



Compare Distributions

Show	Distribution	AICc ^	AICc Weight	BIC	-2*LogLikelihood
☑	Normal 3 Mixture	1495.5569	0.653	1511.3357	1477.2343
☐	Johnson Sb	1496.8309	0.3453	1505.2755	1488.2248
☐	Normal 2 Mixture	1507.7124	0.0015	1518.1027	1496.7893
☐	SHASH	1511.8192	0.0002	1520.2639	1503.2131
☐	Lognormal	1522.3917	0	1526.7406	1518.2152
☐	Gamma	1522.7841	0	1527.133	1518.6076
☑	Normal	1524.3727	0	1528.7216	1520.1962
☐	Student's t	1526.6665	0	1533.0963	1520.3082
☐	Weibull	1528.2806	0	1532.6295	1524.1041
☐	Exponential	1740.7386	0	1742.9433	1738.6806
☐	Cauchy	2804.1278	0	2808.4767	2799.9513

Quantiles

Summary Statistics

Mean	76437.563
Std Dev	10869.445
Std Err Mean	1289.9658
N	71
Variance	118144840
Skewness	0.2454775
Kurtosis	-1.256202
CV	14.220031
Autocorrelation	0.9501897
Minimum	60783
Maximum	96120
Median	75637
Geometric Mean	75683.74

Fitted Normal Distribution

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Location	μ	76437.563	1289.9658	73864.808	79010.319
Dispersion	σ	10869.445	921.93431	9329.14	13023.73

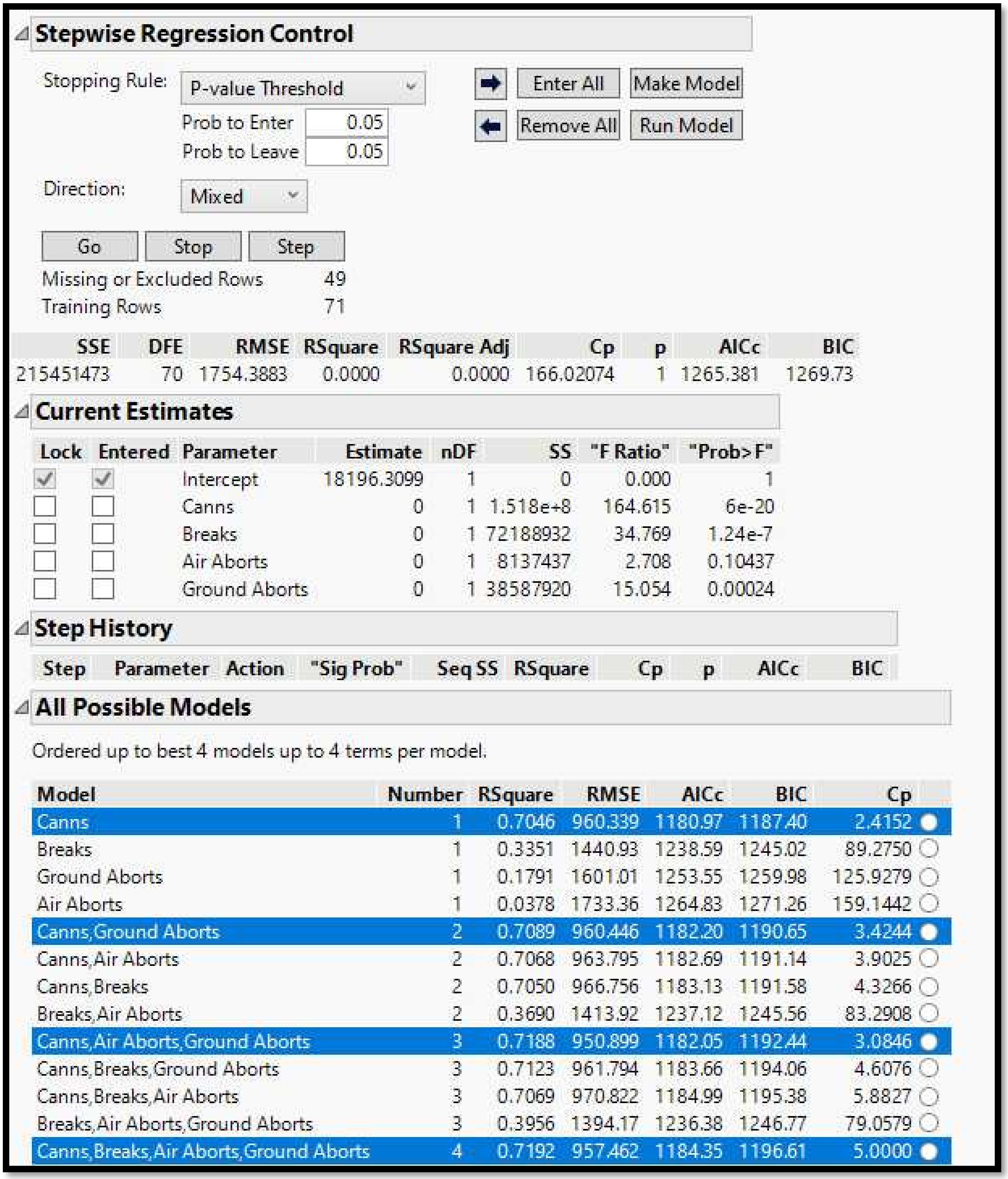
Measures	
-2*LogLikelihood	1520.1962
AICc	1524.3727
BIC	1528.7216

Goodness-of-Fit Test

	W	Prob<W
Shapiro-Wilk	0.9284318	0.0006*

	A^2	Simulated p-Value
Anderson-Darling	1.5585166	<.0001*

Figure 49: Backorder Count Normality Check



Stepwise Regression Control

Stopping Rule: P-value Threshold

Prob to Enter 0.05

Prob to Leave 0.05

Direction: Mixed

Enter All | Make Model | Remove All | Run Model

Go | Stop | Step

Missing or Excluded Rows 49

Training Rows 71

SSE	DFE	RMSE	RSquare	RSquare Adj	Cp	p	AICc	BIC
215451473	70	1754.3883	0.0000	0.0000	166.02074	1	1265.381	1269.73

Current Estimates

Lock	Entered	Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
✓	✓	Intercept	18196.3099	1	0	0.000	1
☐	☐	Canns	0	1	1.518e+8	164.615	6e-20
☐	☐	Breaks	0	1	72188932	34.769	1.24e-7
☐	☐	Air Aborts	0	1	8137437	2.708	0.10437
☐	☐	Ground Aborts	0	1	38587920	15.054	0.00024

Step History

Step	Parameter	Action	"Sig Prob"	Seq SS	RSquare	Cp	p	AICc	BIC

All Possible Models

Ordered up to best 4 models up to 4 terms per model.

Model	Number	RSquare	RMSE	AICc	BIC	Cp
Canns	1	0.7046	960.339	1180.97	1187.40	2.4152
Breaks	1	0.3351	1440.93	1238.59	1245.02	89.2750
Ground Aborts	1	0.1791	1601.01	1253.55	1259.98	125.9279
Air Aborts	1	0.0378	1733.36	1264.83	1271.26	159.1442
Canns,Ground Aborts	2	0.7089	960.446	1182.20	1190.65	3.4244
Canns,Air Aborts	2	0.7068	963.795	1182.69	1191.14	3.9025
Canns,Breaks	2	0.7050	966.756	1183.13	1191.58	4.3266
Breaks,Air Aborts	2	0.3690	1413.92	1237.12	1245.56	83.2908
Canns,Air Aborts,Ground Aborts	3	0.7188	950.899	1182.05	1192.44	3.0846
Canns,Breaks,Ground Aborts	3	0.7123	961.794	1183.66	1194.06	4.6076
Canns,Breaks,Air Aborts	3	0.7069	970.822	1184.99	1195.38	5.8827
Breaks,Air Aborts,Ground Aborts	3	0.3956	1394.17	1236.38	1246.77	79.0579
Canns,Breaks,Air Aborts,Ground Aborts	4	0.7192	957.462	1184.35	1196.61	5.0000

Figure 50: Best Subset Model Comparisons

Response MICAP

Regression Plot

Effect Summary

Source	Logworth	PValue
Canns	19.219	0.00000

Remove Add Edit FDR

Lack Of Fit

Summary of Fit

RSquare	0.704642	AICc	1180.973
RSquare Adj	0.700362	BIC	1187.403
Root Mean Square Error	960.3385		
Mean of Response	18196.31		
Observations (or Sum Wgts)	71		

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	151816219	151816219	164.6150
Error	69	63635254	922250.06	Prob > F
C. Total	70	215451473		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	6158.8754	945.1053	6.52	<.0001*	.
Canns	5.251838	0.409333	12.83	<.0001*	1

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Canns	1	1	151816219	164.6150	<.0001*

Prediction Expression

6158.8753647 + 5.2518379519 • Canns

Effect Details

Durbin-Watson

Durbin-Watson	Number of Obs.	AutoCorrelation	Prob<DW
0.8125675	71	0.5765	<.0001*

Response MICAP

Effect Summary

Source	Logworth	PValue
Canns	16.405	0.00000
Ground Aborts	1.019	0.09563
Air Aborts	0.892	0.12822

Remove Add Edit FDR

Summary of Fit

RSquare	0.718814	AICc	1182.047
RSquare Adj	0.706223	BIC	1192.437
Root Mean Square Error	950.8989		
Mean of Response	18196.31		
Observations (or Sum Wgts)	71		

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	154869487	51623162	57.0921
Error	67	60581986	904208.74	Prob > F
C. Total	70	215451473		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	5286.5086	1267.936	4.17	<.0001*	.
Canns	5.0772783	0.450221	11.28	<.0001*	1.2338928
Air Aborts	-2.053058	1.332974	-1.54	0.1282	1.5777642
Ground Aborts	0.9634311	0.569994	1.69	0.0956	1.7871225

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Canns	1	1	114995292	127.1778	<.0001*
Air Aborts	1	1	2145004	2.3722	0.1282
Ground Aborts	1	1	2583270	2.8569	0.0956

Prediction Expression

5286.5085841

+ 5.0772783489 • Canns

+ -2.05305789 • Air Aborts

+ 0.9634310969 • Ground Aborts

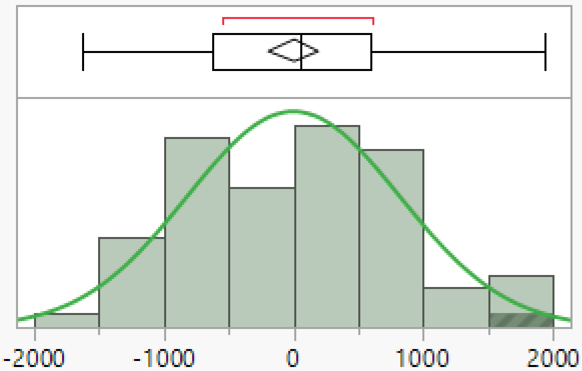
Effect Details

Durbin-Watson

Durbin-Watson	Number of Obs.	AutoCorrelation	Prob<DW
0.9592384	71	0.5088	<.0001*

Figure 51: Best Subset Results: Model 1 and Model 2

Residual MICAP (I)



Compare Distributions

Quantiles

Summary Statistics

Fitted Normal Distribution

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Location	μ	2.357e-12	97.307537	-194.0738	194.07376
Dispersion	σ	819.92788	69.545375	703.73619	982.43465

Measures	
-2*LogLikelihood	1153.198
AICc	1157.3745
BIC	1161.7234

Goodness-of-Fit Test

	W	Prob<W
Shapiro-Wilk	0.983161	0.4590

	A^2	Simulated p-Value
Anderson-Darling	0.2897531	0.6312

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Figure 52: Normality Check, Model 4 (Lagged Variables)