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COST ESTIMATING RELATIONSHIPS FOR RECURRING T100 FLYAWAY COSTS

Thesis

Kyrie M. Rojo, Captain, USAF

AFIT-ENV-MS-23-M-228

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY
AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

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AFIT-ENV-MS-23-M-228

CREATING A COST ESTIMATING RELATIONSHIP FOR RECURRING T100 FLYAWAY COSTS

THESIS

Presented to the Faculty

Department of Mathematics and Statistics

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Cost Analysis

Kyrie M. Rojo, BS

Captain, USAF

March 2023

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COST ESTIMATING RELATIONSHIPS FOR RECURRING T100 FLYAWAY COSTS

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AFIT-ENV-MS-23-M-228

Abstract

This research investigates a dataset of over 80 Air Force and Navy aircraft and applies regression techniques to create two cost estimating relationships (CERs) for predicting recurring T100 flyaway costs, depending on where in the acquisition lifecycle the estimate takes place. The first CER explains 89 percent of the variation in the dataset and can be applied prior to Milestone B (MS B). The second CER explains 88 percent of the variation in the dataset and can be applied between MS B and MS C. Significant cost drivers identified include stealth, cohort, empty weight, the natural log of speed, legacy aircraft, fighter aircraft, and Engineering and Manufacturing Development costs. This research is the largest aircraft regression study to date for recurring T100 flyaway costs and can be used by cost analysts as a reliable cross-check in early estimates.

Acknowledgments

I would like to express my genuine appreciation to my research advisor, Dr. Edward "Tony" White, for his continuous support, guidance, and expertise throughout this entire journey. I would also like to thank my other committee members, Dr. Jonathan Ritschel and Dr. Brandon Lucas, for their time and counsel in improving my thesis. Furthermore, I would like to thank my sponsor, Mr. Shawn Valentine, and the entire FCC team at the Air Force Life Cycle Management Center for their rigorous data consolidation efforts, which without this thesis could not be possible. Finally, and most importantly, I would like to thank my husband for his patience and unwavering support.

Table of Contents

List of Figures

List of Tables

CREATING A COST ESTIMATING RELATIONSHIP FOR RECURRING T100 FLYAWAY COSTS

I. Introduction

Background

The Air Force is preparing for the future of air superiority with the introduction of new aircraft such as the B-21, T-7, E-7, and the Next Generation Air Dominance (Department of the Air Force, 2021). With these current acquisition efforts, the foundation of a successful program lies in a credible and accurate lifecycle cost estimate. In the Department of Defense (DoD), flyaway costs constitute a majority of the procurement costs in aircraft acquisition. A flyaway cost includes all of the costs that go into manufacturing the aircraft i.e., prime mission equipment, systems engineering and program management (SEPM), and engineering changes (Department of Defense, 2022). For aircraft, unit costs are given in constant dollars typically at the 100th unit, which is also referred to as UC100, the T100 unit cost, or simply T100 (Department of Defense, 1992). A T100 flyaway cost then looks specifically at the flyaway costs associated with the T100 unit cost.

The four main cost estimating methods employed by cost estimators are analogy, engineering build-up, extrapolation from actuals, and parametric (Department of Defense, 2022). Determining which method to use for a cost estimation depends on which phase of the acquisition life cycle you are in 1) Materiel Solutions Analysis 2) Technology Maturation and Risk Reduction 3) Engineering and Manufacturing Development (EMD) 4) Production and Development (P&D) and 5) Operations and Support (O&S) (Department of Defense, 2020). As actual flyaway costs occur during production (phase

4), in order to estimate T100 flyaway costs prior to the P&D phase, the favored approach is the parametric method (Department of the Air Force, 2007). The parametric method involves identifying cost drivers and creating a cost estimating relationship (CER) based on historical data (Government Accountability Office, 2020).

Due to the level of uncertainty of cost estimates early in a program's life cycle, which is when parametric methods are most prevalent, RAND recommends the continued expansion and utilization of historical cost data to help manage risks (Light et al., 2017). In an effort to enhance cost estimations for all future aircraft programs and contribute to a strong foundation, this study endeavors on employing historical data and creating a CER model specifically for T100 flyaway costs.

Problem Statement

The intent of this thesis is to identify which variables are cost drivers for recurring T100 flyaway costs. The manner in which T100 flyaway costs are calculated is via a learning curve applying actual production costs. This paper aims to establish a cost estimating relationship that can predict T100 flyaway costs early in the acquisition life cycle, prior to actual costs.

For a cost estimate to be reliable it must be comprehensive, well-documented, accurate, and credible (Government Accountability Office 2020). This can make establishing a CER challenging as it requires statistical rigor, meticulous documentation, and access to historical data (Naval Center for Cost Analysis, 2018). As best as can be ascertained, the novelty of this research is that it is the largest aircraft regression study to date for recurring T100 flyaway costs. Therefore, the comprehensive analysis conducted in this thesis could provide a useful starting point for early cost estimates, or at the very least be a consistent cross-check.

Research Questions

The primary objective of this thesis is to develop a CER that can forecast recurring T100 flyaway costs. To achieve this objective, several prospective cost drivers are assessed, and the following research questions are investigated:

1. What type of effect, if at all, does an aircraft's system type have on recurring T100 flyaway costs?
2. What is an adequate proxy for complexity in estimating recurring T100 flyway costs?
3. Which calculation of weight (empty weight, airframe unit weight, or aircraft density) best predicts recurring T100 flyaway costs?
4. How does an aircraft's contractor influence recurring T100 flyaway costs?

Methodology

The dataset and methodology described in this thesis was curated for the development of two models that are discussed further in Scope and Limitations, and with even greater description in Chapter III. The dataset for the first model consists of 82 aircraft and the second model consists of 59. Data was obtained from Cost Data Summary Reports (CSDRs) and weight statements via the Cost Assessment Data Enterprise (CADE), with additional information provided by the Air Force Life Cycle Management Center (AFLCMC).

Once all of the potential exploratory variables are established, they are individually assessed and entered through a stepwise regression approach. Next, they are trimmed based on the Bonferroni correction and their vulnerability from overinfluential datapoints is investigated. Once a model is specified it is validated by evaluating diagnostics and assumption tests, followed by conducting a robustness check. As mentioned, the manner in which data was collected and the methodology for analysis is heavily expanded upon in Chapter III.

Scope and Limitations

Figure 1 displays the decision points and where the three milestone decisions (A, B, and C) occur amongst the five previously mentioned acquisition phases. With the goal of creating a model that can predict costs in the P&D phase, all potential exploratory variables must contain data that is accessible prior to Milestone C. In fact, most of the variables investigated in this thesis have data that is available prior to Milestone B, with the exception of EMD costs (which occur during the EMD phase). As a result, two CER models are created: one with data available around Milestone A (all variables minus EMD), and the second with data available after Milestone B (all variables including EMD).

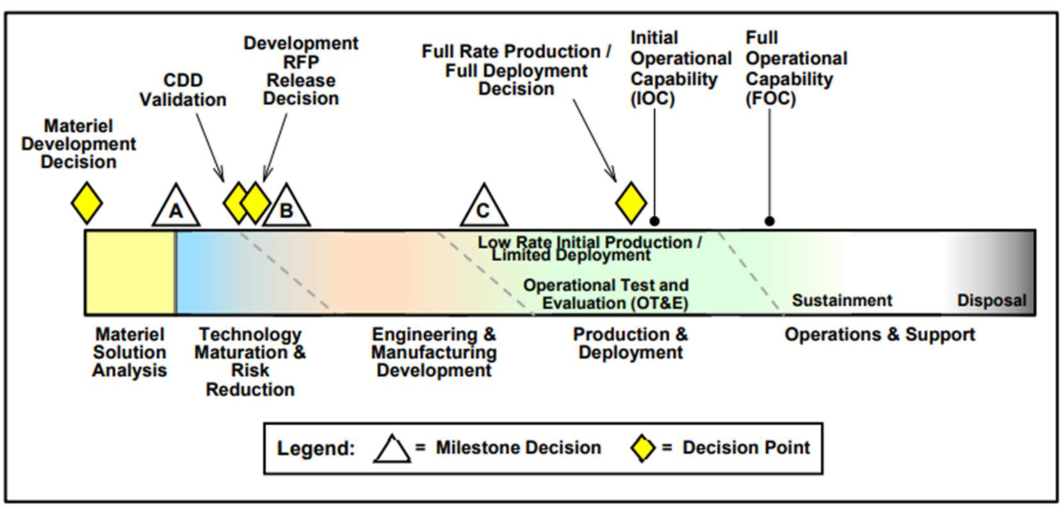


Figure 1. Major Capability Acquisition Model (Department of Defense, 2020)

Additional limitations are the exclusion of certain variables in this thesis due to their negative effect on the size of the dataset. This consists of aircraft material, material mixes, and manufacturing techniques, which requires data that is simply not available for most of the aircraft included in our analyses. Furthermore, since they are a different commodity, helicopters are also not included in the dataset.

Preview

This thesis is ordered as follows. Chapter I is an introduction of the thesis and contains the background, problem statement, research question, and brief methodology. Chapter II is the literature review and covers relevant information required to understand the topic including program cost categories, how T100 flyaway costs are calculated, cost estimating methodologies, how CERs are developed, and what previous research has discovered. Chapter III is the methodology section which describes the data and provides a detailed outline of how to conduct the analysis. Chapter IV presents the analysis and the results inferred by them. Lastly, Chapter V concludes the thesis by summarizing the thesis findings and providing recommendations on future research.

II. Literature Review

Chapter Overview

The DoD Instruction 5000.4-M "Cost Analysis Guidance and Procedures" recommends that in the absence of actual cost data, a parametric approach should be used for cost estimates (Department of Defense, 1992). This recommendation emphasizes the value of the analysis in this thesis that seeks to create a CER for T100 flyaway costs. Enhancing knowledge of what flyaway costs are, how they are calculated, and where they fall into the scope of an entire life cycle cost estimate is essential background for the content of this research. Furthermore, an understanding of cost estimating methodologies, specifically the parametric technique, will explain why a CER is a useful process for estimating flyaway costs. Therefore, this literature review lays the groundwork for such awareness, as well as assesses what studies have been done in the past to identify cost drivers and build CERs for T100 flyaway costs.

Program Cost Categories

Under the umbrella of the total ownership cost of an aircraft program are five program cost categories: life-cycle cost, acquisition cost, procurement cost, weapon system cost, and flyaway cost (Department of Defense, 2022). The relationship between the different cost categories is displayed in Figure 2. A life-cycle cost includes all costs of a program throughout the four phases of its cost life cycle: research and development (R&D), production/investment, operations and support (O&S), and disposal (Mislick & Nussbaum, 2015). An acquisition cost is a life-cycle cost minus O&S and disposal costs; a procurement cost is an acquisition cost minus development costs and the cost of system-specific facilities; a weapon system cost is a procurement cost minus the costs of initial spares; a flyaway cost is a weapon system cost minus support items costs. A flyaway cost is the core of all cost categories and consists of prime mission equipment, SEPM, test and evaluation, warranties, engineering changes, nonrecurring startup costs, and government-furnished equipment (GFE) (Department of Defense, 2022). Flyaway costs are the focus of our research for which we are trying to predict, specifically recurring T100 flyaway costs, whose distinction is explained in the next section.

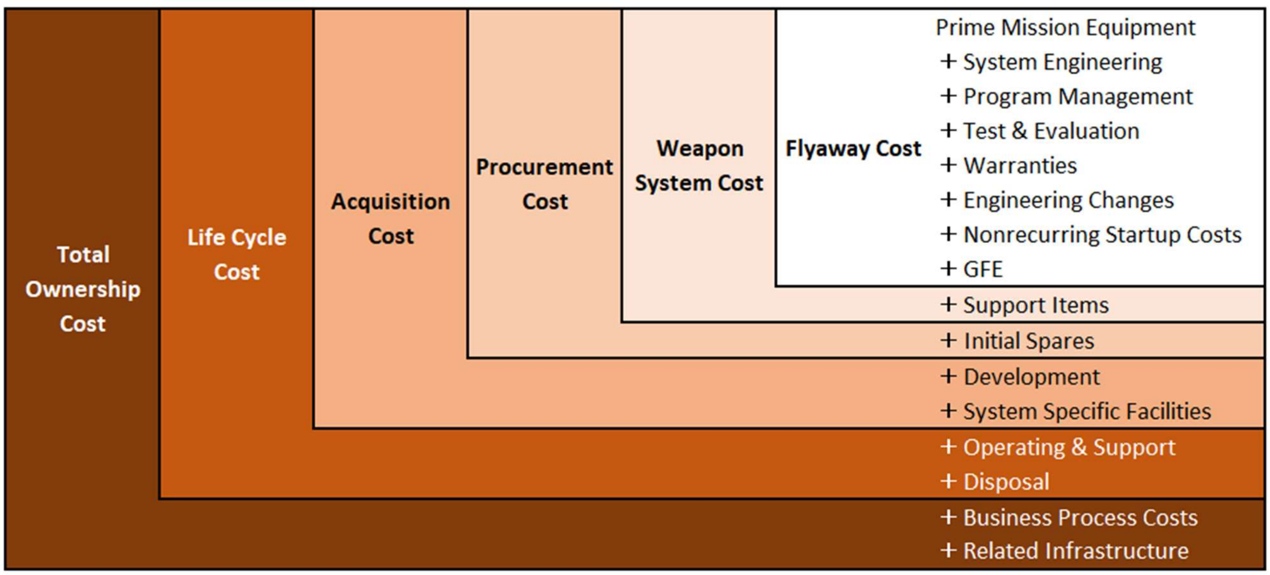


Figure 2. Total Ownership of Cost Composition (Department of Defense, 2022)

T100 Flyaway Costs

The term “flyaway cost” refers to a single aircraft. However, since the cost of each aircraft produced is not equal, how do you determine which cost represents an aircraft’s flyaway cost? Is it the flyaway cost of the first aircraft produced? The last? Maybe an average? What is used by practitioners in the field and therefore also used in this thesis, is the T100 flyaway cost.

When investigating cost data for historical programs, it is important to use unit costs as a standard of comparison. There are two ways to characterize unit data, either by lot or unit of production (Department of Defense, 2022). Using the cost of an aircraft at the 100th unit is useful because it standardizes data and allows costs to be referenced at the same point of the production process (Mislick & Nussbaum, 2015). The DoD Cost Estimating Guide refers to the unit cost of the 100th unit as UC100, but the Joint Agency Cost Estimating Relationship (CER) Development Handbook refers to it as T_{100}, which is also how it has historically been referenced. Therefore, T100 is the verbiage that we use henceforth.

Flyaway costs occur during the production phase of an aircraft, also known as the investment phase (Mislick & Nussbaum, 2015). During this phase, a build-up technique is often used for cost estimation because actual cost data is available. However, when calculating unit costs such as the T100, a cost estimator should use a cost improvement curve (CIC) (Government Accountability Office, 2020). The first CIC (also referred to as a learning curve when calculations are in hours versus dollars) was introduced in 1936 by Theodore Paul Wright while studying production costs in aircraft (Wright, 1936). A cost improvement curve addresses the phenomenon that as tasks are repeated, learning occurs making the task more efficient and therefore cost less (Department of Defense, 2022).

There are two leading theories on CICs: Unit Theory and Cumulative Average (CUMAV) Theory. Both theories address the learning phenomenon previously mentioned, but unit theory assumes a reduction in unit costs while CUMAV assumes a reduction in cumulative average costs. The Department of Defense Cost Estimating Guide's only stipulation on deciding which theory to choose is to consistently use only one throughout the model. Since T100 costs are unit costs and it is the predominant approach amongst Air Force practitioners, the unit theory cost improvement curve is the one we will be applying. While a cost improvement curve is useful for determining the production unit costs of an aircraft, it should only include recurring costs to prevent skewing the results (Department of Defense, 2022). Therefore, the term flyaway cost is in reference to recurring flyaway costs as opposed to total flyaway costs.

Since a CIC is intended to only estimate recurring costs, the dependent variable predicted in this thesis is the sum of the recurring costs for Air Vehicle (element code 1.1 of the Cost Data Summary Report (CDSR), or 1921) and Systems Engineering/Project Management (element code 1.2), plus the cost of the engines which typically have their own separate 1921. This is still fundamentally the same breakdown as shown in Figure 2, but excludes the nonrecurring costs.

The following steps demonstrate how to calculate T100 flyaway costs with data from a typical program in our dataset:

<u>Step 1.</u> <u>Normalize the data.</u> When applying a CIC to analyze unit costs, the data must first be normalized to remove the effect of escalation. The DoD Inflation and Escalation Best Practices for Cost Analysis state that the best practice for normalizing costs in a CIC is to base them on constant price (CP$), which removes the effect of inflation and real price change (OSD CAPE, 2021). The precise index that was utilized in this thesis as well as by practitioners in the Air Force and civilian aircraft industry, was the Produce Price Index (PPI) 3364, which details price changes in aerospace products and parts (Bureau of Labor Statistics, 2022).

Step 2. Calculate the average unit cost (AUC). The AUC for each lot is calculated by dividing the lot's recurring flyaway costs by the total number of units produced (Equation 1).

$$AUC\ of\ Lot_t = \frac{Recurring\ Flyaway\ Costs\ in\ Lot_t}{Number\ of\ Units\ in\ Lot_t} \tag{1}$$

Step 3. Calculate the lot midpoint (LMP). The most simplistic approach to calculating the LMP consists of two equations, one for the first lot and one for each proceeding lot. The LMPs for the first lot are computed by dividing the lot size by two if the lot size is less than 10, or by dividing the lot size by three if the lot size is greater than or equal to 10 (Equation 2).

$$LMP\ of\ Lot_1 = \begin{cases} For\ Lot\ Size < 10, Lot\ Size\ \div 2 \\ For\ Lot\ Size\ \geq 10, Lot\ Size\ \div 3 \end{cases} \tag{2}$$

For all subsequent lots, the LMP is calculated by adding the first (F) and last (L) unit number in a lot, plus two times the square root of F times L, and then dividing the total by four (Equation 3).

$$LMP\ of\ Lot_{t>1} = \frac{F + L + 2\sqrt{F * L}}{4} \tag{3}$$

Step 4. Perform a linear regression. In order to perform a linear regression, the data needs to be made linear by taking the natural logs of the AUC and LMP.

Then, ln(LMP) (the X variable) is regressed on ln(AUC) (the Y variable) to derive a simple linear equation (Equation 4). Figure 4 displays a scatterplot of these points with its fitted regression line.

$$\hat{Y}_X = \hat{\beta}_0 + \hat{\beta}_1 * X \qquad (4)$$

When applied to one of our programs in our dataset, Program A (for security issues we cannot reveal this program or it's derivative data), the regression output results in the following linear equation:

$$\ln(AUC) = 12.548 - 0.1996 * \ln(LMP)$$

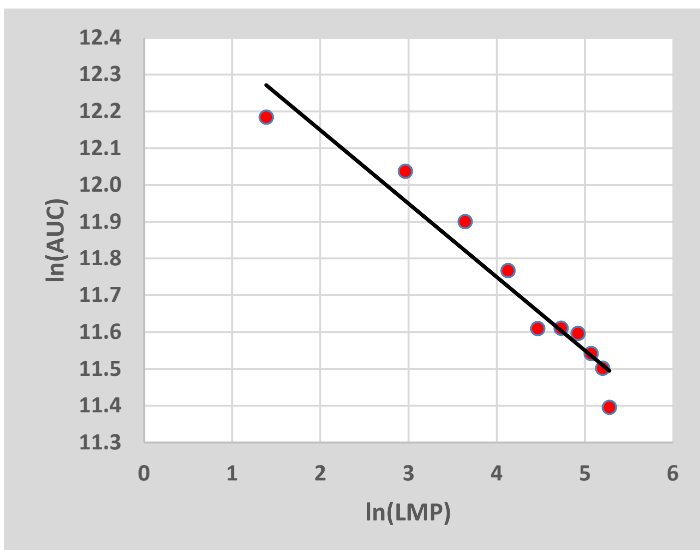


Figure 3. Scatterplot of ln(AUC) versus ln(LMP) with a Fitted Regression Line

<u>Step 5.</u> <u>Transform from log space.</u> To eliminate the natural logs in Equation 4, take the natural exponent of each side to arrive at the standard learning curve (Equation 5).

$$Y_X = A * X^{-b} \qquad (5)$$

Where:

- Y_x = the flyaway cost of unit X
- A = the theoretical cost of unit one (T1)
- X = the unit number
- b = the theoretical slope of the learning curve

When we transform our Program A example from log space to the original space, our estimated learning curve equation becomes:

$$Y_X = \$281{,}531.61 * X^{-0.1996}$$

Step 6. Calculate T100 flyaway cost. Once all calculations are made and the learning curve equation is computed, evaluate the equation at X = 100 or Y_{100}. This is the flyaway cost of unit 100 or the T100 flyaway cost. The T100 flyaway cost for our Program A data (prior to adding the engine costs) is then:

$$T100 = Y_{100} = \$281{,}531.61 * 100^{-0.1996} = \$112{,}286.40$$

This process results in an approximation of the recurring flyaway cost at the theoretical 100th unit while considering the learning effect. Roughly one quarter of our dataset has less than 100 quantified units, but their T100 flyaway costs are still inferred via the same method. Appendix A lists the number of aircraft produced for each aircraft in the dataset.

Cost Estimating Methodologies

Now that it is shown how T100 flyaway costs are estimated when actual production costs are known, the method for estimating them prior to the production phase needs to be addressed. As mentioned earlier, there are four common cost estimating methodologies: analogy, engineering build-up, extrapolation from actuals, and parametric.

The Department of Defense Cost Estimating Guide states that there is no preference for which method to select as it depends on the circumstance, but it does clarify which method is often appropriate during each phase of the system's life cycle as demonstrated in Figure 4. The analogy cost estimating method is preferred when the system the cost analyst is developing a cost estimate for has a similar system. To employ this method, the analyst will adjust the costs of the analogous system to account for the differences in the new system, and then apply it to the estimate. This method can be applied throughout a program's life cycle, but it is most appropriate if an applicable analogy is available and if the program is in its early stages before actual costs are available.

The build-up method estimates the lower elements of a system and aggregates these to arrive at a comprehensive estimate. This method is appropriate when there is a stable configuration of the system, typically after the technology maturation and risk reduction (TMRR) phase. The extrapolation from actuals method is when the entire cost estimate of a system is extrapolated from actual costs that occurred earlier in its program. This method is appropriate once actual production or O&S data is available (Department of Defense, 2022).

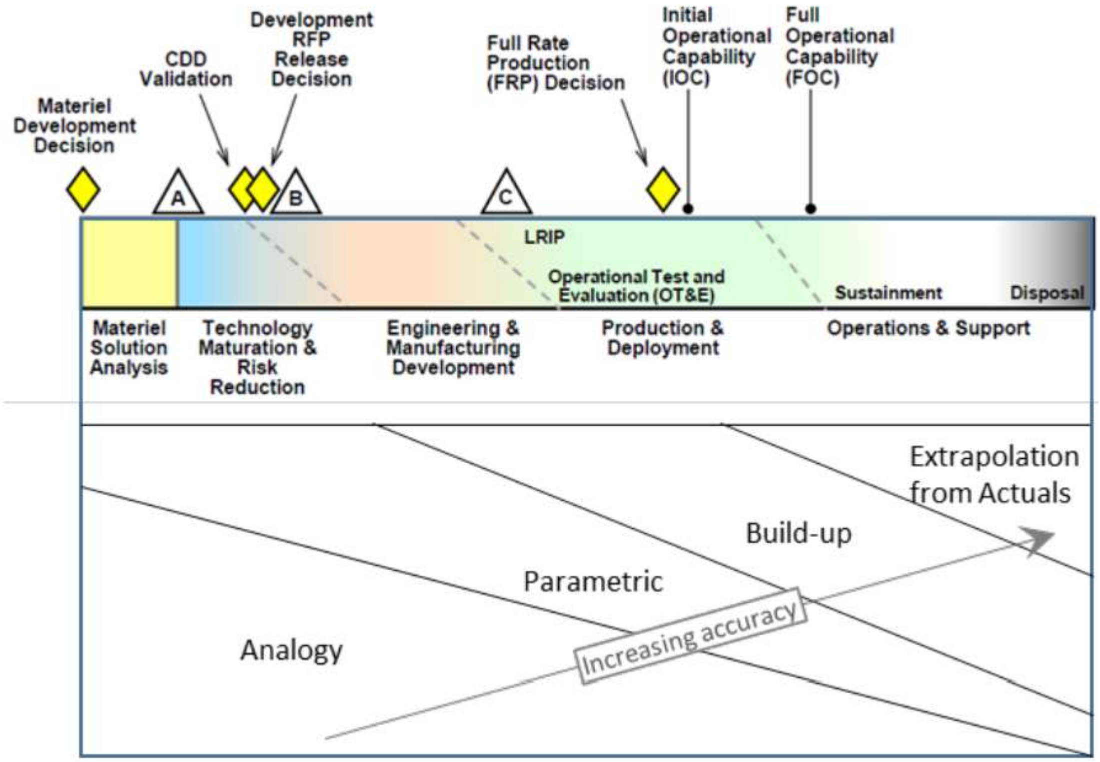


Figure 4. Estimating Method Applicability (Department of Defense, 2022)

The fourth common cost estimating method and the one utilized in this thesis is the parametric estimating method. The parametric method analyzes historical data to create an algebraic equation that relates cost to characteristics within a system. Similar to the analogy method, the parametric method can be utilized throughout a program's life cycle, but it is especially useful in early cost estimates before all of the system's details are completely developed (Department of Defense, 2022). This is why the parametric method is chosen for this particular research where the goal is to estimate T100 flyaway costs prior to a fully developed system or one with observed production costs, which rules out the build-up and extrapolation from actuals methods. This research also analyzes the data from several different aircraft, effectively excluding the analogy method that relies on a single data point.

Developing a Cost Estimating Relationship (CER)

The parametric cost estimating method involves applying regression techniques to estimate the relationship between a dependent variable (T100 flyaway costs) and independent variables (cost drivers) to produce a parametric CER. The *Joint Agency Cost Estimating Relationship Development Handbook* (JACERDH) (2018), provides extensive details on the process for creating CERs, and will therefore be the primary reference for this section of the literature review as well as drive methodology. The JACERDH describes the following six steps required to develop a CER:

Step 1. Purpose, Scope, Collect, Validate, and Normalize Data. Defining an estimate's purpose drives its scope, which then determines the data that needs to be collected. After all of the required data is collected, it must be validated and normalized to reduce the noise in the data.

Step 2. Analyze Normalized Data. The goal of this step is to understand the data by assessing descriptive statistics. Then once the possible variable sets are identified, the analyst can hypothesize the function form and error term of the CER.

Step 3. Generate CER. To generate a CER, an analyst must determine what regression method is suitable for their data. Essentially, a cost analyst begins their analysis by assuming their model is in the linear form before running an ordinary least squares (OLS) regression as a baseline method. Then, based on whether or not the assumptions for OLS are met, the analyst will either assess different regression methods or move on to model diagnostics.

Step 4. Validate CER. Once a model is created, it must be tested to identify any potential weaknesses as well as to measure the fit of the model and overall prediction strength. Chapter III of this thesis goes into further details on what tests need to be conducted to validate a model.

Step 5. Characterize Uncertainty. After a model is validated, the performance of the model must be assessed. This involves generating a confidence interval, prediction interval, S-curve, and a histogram illustrating the cumulative distribution function (CDF) and probability distribution function (PDF).

Step 6. Document CER. Documentation should have been accomplished for each step in the CER's development to the degree that the entire process can be replicated. If steps 1-5 are successful, then the final step is to complete the documentation.

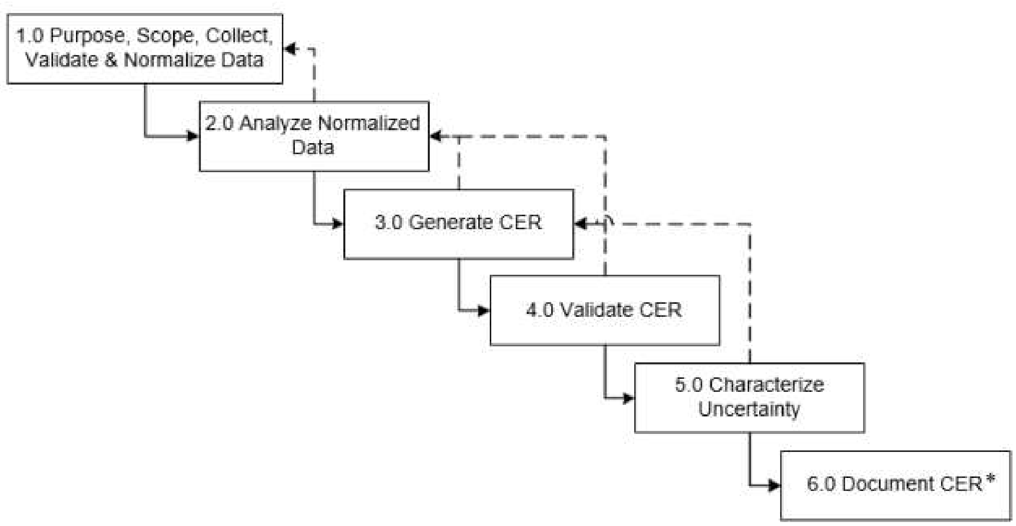


Figure 5. CER Development Process (Naval Center for Cost Analysis, 2018)
***The final step should be completion of the documentation since documentation should be completed at each step.**

The flow of the previously described CER development process is shown in Figure 5. Dark solid lines indicate the flow that is taken once a step is successful, and the dotted lines represent the route to take in the event one is unsuccessful. The methodology and analysis sections of this research expand on developing a CER as creating one to predict T100 flyaway costs is the goal of this thesis.

Previous Research

Since it has been established which cost estimating methodology will be chosen to predict T100 flyaway costs, relevant prior research on the subject must be examined. To be clear, there were no prior studies found that attempted to predict recurring T100 flyaway costs (nor any type of flyaway cost for that matter). Therefore, the most similar type of study conducted was a series of papers by RAND from 1972 to 2001 that investigated cost drivers for different elements of aircraft airframes. For aircraft, the element code 1.1, Air Vehicle (which constitutes a majority of flyaway costs), consists mostly of costs from the sub element Airframe. This deduces that a cost driver for an airframe would be a reasonable cost driver for air vehicle and consequently a flyaway cost. In an attempt to cast a broader net for research related to flyaway costs, a quest for studies that focused on production costs was conducted, but resulted in only one report from 1991 that created cost models for production support elements. Altogether, there are five prior studies explored in this section, followed by a summary in Table 1.

i.) <u>Levenson, Boren, Tihansky, and Timson: 1972</u>. *Cost-Estimating Relationships for Aircraft Airframes* is a report that was prepared for the United States Air Force Project RAND by the RAND Corporation. The Levenson, Boren, Tihansky, and Timson (1972) report supersedes their 1966 report and included additional data points as well as an analysis of the documented CERs' prediction intervals. The report applied regression techniques to analyze 29 aircraft and provided a set of relationships for estimating costs of airframe cost elements. At the time of the report, airframe cost elements were divided into two categories: development and production of operational airframes. Development cost elements consist of engineering, development support, flight test aircraft, flight test operations, and test facilities; and production cost elements consist of manufacturing labor, manufacturing material, engineering (sustaining), tooling, quality control, and manufacturing facilities.

The seven cost elements that the report ultimately developed estimating equations for were engineering, development support, flight test operations, tooling, manufacturing labor, manufacturing material, and quality control. These final CERs were expressed in exponential form. While other variables were included in a single equation, such as production rate and the number of flight test vehicles, there were only three variables present in all equations that best [1]explained variations in the cost elements: aircraft quantity, maximum speed, and Aeronautical Manufacturers' Planning Report (AMPR) weight.

ii.) <u>Large, Campbell, and Cates: 1976</u>. *Parametric Equations for Estimating Aircraft Airframe Costs* is a report that was prepared for the Assistant Secretary of Defense (Program Analysis and Evaluation) (now the Director of Cost Assessment and Program Evaluation (CAPE)) by the RAND Corporation. The Large, Campbell, and Cates (1976) report was a follow on to Levenson, Boren, Tihansky, and Timson (1972), that aimed to

[1] The authors measure best with the unadjusted coefficient of correlation and the coefficient of variation. No level of significance was presented.

discover additional characteristics that could explain cost variations amongst individual aircraft. The report analyzed 25 military aircraft through multiple-regression techniques and developed a set of exponential equations for total airframe cost and eight cost elements: engineering, tooling, nonrecurring manufacturing labor, recurring manufacturing labor, nonrecurring manufacturing material, recurring manufacturing material, flight test operations, and quality control. The study considered 17 characteristics in its analysis, but like previous research, weight and speed were the only significant factors. For all equations developed, not a single one was consistently within 20 percent of their actual cost. This concluded the authors to suggest further research on performance characteristics (versus physical characteristics) to predict costs such as schedule, contractor's experience, efficiency, economic conditions, and labor scarcities.

iii.) Hess and Romanoff: 1987. *Aircraft Airframe Cost Estimating Relationships* is a report that was prepared for the United States Air Force Project RAND by the RAND Corporation. The Hess and Romanoff (1987) report followed up Large, Campbell, and Crates (1976) study with nine additional aircraft and an assessment of 29 characteristics including those suggested in the 1976 report. The authors utilized a multiple least-squares analysis to derive a set of exponential equations for engineering, development support, flight test operations, tooling, manufacturing labor, manufacturing material, quality control, and total program cost. Out of the 29 potential explanatory variables, each set of equations was allowed to have at most four independent variables, one from each of the following categories: size, technical/performance factors, construction, and program.

Additionally, this study investigated subsamples of the dataset by mission designation (fighter, bomber/transport, and attack), but only found an acceptable estimating relationship for the fighter subsample. Overall, speed and empty weight were the only two variables that were statistically significant, credible, and improved the quality of the equations. Finally, despite having 34 aircraft in their dataset, Hess and Romanoff recommended a final equation set containing a subset of only 13 aircraft that had first flight dates post-1960. The rationale behind this was, it is more useful to have relevant and recent aircraft in predicting the costs of future aircraft.

iv.) Owens, Allard, Ellison, Hofmann, Gahagan, and Valaika: 1991. *Estimating Relationships for Aircraft Production Support Elements* is a report that was prepared for the Air Force Cost Center (now the Air Force Cost Analysis Agency) by the Management Consulting and Research, Inc. (MCR). MCR was contracted out to improve upon prior methodologies for estimating the aircraft production support cost elements data, peculiar support equipment (PSE), training, and initial spare parts. This study only selected eight aircraft to be analyzed because of the broad range they represented and assessed 14 potential independent variables that were sorted into three categories: cost, programmatic, and technical data. Each equation set had a different combination of independent variables that were tested via calculus concepts and determined causal if they took on a certain form.

The report then regressed this set of explanatory variables onto their corresponding cost element to create four equations. This included maximum speed, airframe unit weight, maintenance man hours per flying hour (MMHPFH), and aircraft type for the PSE dependent variable; MMHPFH, avionics type, and time of arrival for training; avionics type and time of arrival for data; and maximum speed, MMHPFH, and avionics type for initial spare parts. Future study recommendations by MCR were to expand the dataset by including development costs and additional aircraft, and to validate additional support element costs such as SE/PM.

v.) Younossi, Kennedy, and Graser: 2001. *Military Airframe Costs: The Effects of Advanced Materials and Manufacturing Processes* is a report that was prepared for the United States Air Force Project RAND by the RAND Corporation. The Younossi, Kennedy, and Graser (2001) report is an updated extension of prior RAND cost-estimating studies that utilized the historical airframe database MACDAR (Military Aircraft Cost Data Archive and Retrieval). This study assessed five fighter-class aircraft to approximate the effect of material mix, manufacturing technique, and part geometric complexity on the following recurring cost elements: engineering, tooling, manufacturing, and quality assurance. There was no official level of statistical significance that was assigned to the analysis in this research, as the “estimates were derived in a series of meetings between RAND researchers and industry with much discussion on clarifying ground rules and definitions” (Younossi et al., 2001 p.68). The resulting regression equations were expressed in exponential form and the selected independent variables were weighted material cost factor (WMCF), aircraft quantity per lot, cumulative aircraft quantity, average airframe unit weight per lot, recurring labor hours, and a dummy variable for whether or not the aircraft occurred during engineering and manufacturing development (EMD). The inclusion of distinctive independent variables like cumulative aircraft quantity allows for future aircraft estimates to be tailored for a broader range of factors.

Table 1 summarizes the previously discussed studies and highlights key points such as which dependent variables were analyzed and what independent variables were selected to estimate them. However, as valuable as the previous research is, they do expose several gaps that this thesis addresses. First, as mentioned at the beginning of this section, this thesis is the first to endeavor in creating a CER specifically for recurring T100 flyaway costs. Secondly, this thesis fills the two decades plus time gap between 2001, when the last study of this kind was conducted, and now. Lastly, due to this time gap, this thesis analyzes the largest dataset (with 82 aircraft) for a study of this kind.

Table 1. Summary of Previous Research

Study	Number of Aircraft in Dataset	Costs Estimated	Dependent Variables	Independent Variables Selected for Equations	Synopsis
Levenson, Boren, Tihansky, and Timson: 1972	29	Aircraft Airframes	1. Engineering 2. Development Support 3. Flight Test Operations 4. Tooling 5. Manufacturing Labor 6. Manufacturing Material 7. Quality Control	1. Aircraft Quantity 2. Maximum Speed 3. AMPR Weight	An earlier set of CERs for the development and production costs of aircraft airframes. All seven CERs included aircraft quantity, maximum speed, and AMPR weight.
Large, Campbell, and Cates: 1976	25	Aircraft Airframes	1. Engineering 2. Flight Test Operations 3. Tooling 4. Nonrecurring Manufacturing Labor 5. Recurring Manufacturing Labor 6. Nonrecurring Manufacturing Material 7. Recurring Manufacturing Material 8. Quality Control 9. Total Airframe Program Cost	1. Maximum Speed 2. Airframe Unit Weight	Attempted to improve upon prior CERs from the 1972 study by investigating 17 new independent variables (IVs) and developing an additional CER for the total airframe costs. Ultimately, maximum speed and AUW were still the only variables tested that could explain variations in cost.
Hess and Romanoff: 1987	34	Aircraft Airframes	1. Engineering 2. Development Support 3. Flight Test Operations 4. Tooling 5. Manufacturing Labor 6. Manufacturing Material 7. Quality Control 8. Total Airframe Program Cost	1. Maximum Speed 2. Empty Weight	A follow-up to the 1976 study with a larger dataset that assessed 19 IVs from four categories: size, performance, construction, and program. Size (empty weight) and performance (maximum speed) were the only characteristics selected for the final set of CERs.
Owens, Allard, Ellison, Hofmann, Gahagan, and Valaika: 1991	8	Production Support Elements	1. Peculiar Support Equipment 2. Training 3. Data 4. Initial Spares	1. Maximum Speed 2. Airframe Unit Weight 3. Maintenance Man Hours Per Flying Hour 4. Time of Arrival 5. Aircraft Type 6. Avionics Type	A report that created CERs for production support elements. No single IV was present in all four CERs, and weight is actually only present in the peculiar support equipment equation.
Younossi, Kennedy, and Graser: 2001	5	Aircraft Airframes	1. Recurring Engineering 2. Recurring Tooling 3. Recurring Manufacturing 4. Recurring Quality Assurance	1. Weighted Material Cost Factor 2. Lot Size 3. Cumulative Aircraft Quantity 4. Average Airframe Unit Weight per Lot 5. Recurring Labor Hours 6. EMD	The most recent study to create CERs for airframe costs, with an emphasis on the role of material properties. The final equations were in a complex exponential form that require a comprehensive knowledge of an aircraft's material mix and manufacturing techniques.

Summary

This chapter presented a framework for what defines a flyway cost and how to calculate a recurring T100 flyaway cost. Additionally, it explained common cost estimating methodologies and the process to develop a cost estimating relationship. Lastly, Chapter II examined previous research on the topic of estimating costs related to the production phase of an aircraft's lifecycle and gaps this thesis fills. Next, Chapter III explains the dataset for this thesis and the methodology techniques used for analysis.

III. Methodology

Chapter Overview

This chapter describes the process for how the final dataset utilized in this thesis was arrived at and provides the roadmap for how it is analyzed in Chapter IV. First, the sources of the data collected are discussed in addition to the criteria for an aircraft's inclusion or exclusion. Next, the potential explanatory variables are described and a justification for their selection is explained. Finally, the method for developing our cost estimating relationship is presented including regression analysis, statistical tests, and validation techniques.

Data

Most of the data gathered in this thesis was acquired through the Cost Assessment Data Enterprise (CADE). Contractor, quantity, and cost data, such as the lot costs required to calculate T100 flyaway costs, were collected via Cost Data Summary Reports (CDSRs), also known as 1921s, within CADE's Defense Automated Cost Information Management System (DACIMS). Aircraft weight data was obtained by accessing CADE's Data & Analytics application, entering in the Air Force library, and typing "weight statement" into the Keyword Search bar. Speed data and some of the cost data that is not available in CADE was consolidated and provided by the Air Force Life Cycle Management Center (AFLCMC).

Once all available data was captured, the number of aircraft in the dataset was filtered based on whether or not an aircraft had complete data. For an aircraft to have complete data and be included in the dataset it had to contain at least one weight statement, aircraft cost data, and engine cost data. For aircraft, engines typically have their own production and 1921s separate from the aircraft itself, which was limited in CADE. The AFLCMC provided most of the engine cost data analyzed in this dataset, but this limitation did exclude several aircraft, most of which are retired.

Furthermore, a separate criterion was created to investigate EMD costs as a cost driver, which only had data available for 59 aircraft. This complication along with when in an acquisition's lifecycle EMD costs occur, necessitated the development of two CER models. More information on the two separate models is discussed in the *EMD Costs* section of this chapter. The total number of aircraft that was eliminated due to the inclusion criteria are displayed in Table 2, and the full list of aircraft analyzed for both models is in Appendix A.

Table 2. Aircraft Inclusion and Exclusion Table

Inclusion/Exclusion Criteria	Aircraft Removed	Remaining Aircraft
Aircraft in CADE with Weight Statements Available		516
Aircraft with Aircraft Cost Data Available	329	187
Aircraft with Engine Cost Data Available	105	82
Total Aircraft in Dataset for First CER		**82**
Aircraft with EMD Costs	23	59
Total Aircraft in Dataset for Second CER		**59**

Data Variables

The dependent variable that is explored in this thesis and for which the CER will be developed for is recurring T100 flyaway costs. Chapter II defined what a T100 flyaway cost is and detailed how to calculate it. The conditions that were established for a variable to be considered in this thesis are prior research had to recommend it or it met the following criteria:

1. Must be available pre-production (all variables have data available pre-EMD except for EMD costs).
2. Must be reasonably related to cost.
3. Must have historical data accessible.

The list of independent variables that are analyzed in Chapter IV along with their descriptions are described in Table 3.

Table 3. Potential Explanatory Variables

Variable	Name	Description
ST	System Type	Ten dummy variables that represent the different system types of aircraft in this dataset. Table 4 provides a breakout of each one.
Qt	Quantified Units	Total number of aircraft in lot production that was applied to calculate T100 flyaway cost.
AF	Air Force	Dummy variable where 1 = aircraft was produced solely for the Air Force and 0 = it was not.
EC	Engine Count	The total number of engines in an aircraft.
Ct	Contractor	Six dummy variables that represent the current contractors who developed and produced the aircraft in this dataset.
EW	Empty Weight	The weight of the aircraft (in pounds) minus fuel, ordnance, and personnel.
AUW	Airframe Unit Weight	Empty weight (in pounds) minus propulsion, avionics, and government furnishings and equipment.
Speed	Max Speed	Maximum speed (in knots).
AD1	Aircraft Density 1	Airframe unit weight divided by empty weight: (AUW/EW)
AD2	Aircraft Density 2	Empty weight minus airframe unit weight then divided by empty weight: (EW-AUW)/EW
Stealth	Stealth	Dummy variable where 1 = aircraft has stealth technology and 0 = it does not.
Legacy	Legacy	Dummy variable where 1 = legacy aircraft and 0 = modern aircraft.
EMD*	EMD Costs	EMD costs for the mission design series (MDS) A-model
***Will not be tested in first regression analysis due to number of aircraft with this data, and when in a program's lifecycle this data is available.**		

The variables included in this analysis that were included in prior research's final equations are quantity, empty weight, airframe unit weight, and speed. All other potential explanatory variables represent data that can be attained before a Milestone C decision (pre-production), can reasonably be associated with an aircraft's flyaway cost, and are historically accessible. The following subsections further explain the variables analyzed in this thesis, and how they are tied to the research questions from Chapter I.

Research Question 1

The first research question is: *What type of effect, if at all, does an aircraft's system type have on recurring T100 flyaway costs?* To answer this, the variable System Type is assessed.

System Type

Hess and Romanoff (1987) attempted to create separate equations for three different system types and only found a significant model for fighter aircraft. This thesis expands that effort and investigates ten system types, but as dummy variables within one equation instead of separately. Table 4 presents a summary of each system type variable.

Table 4. System Type Breakdown by Aircraft

System Type Variable	System Type	Number in Dataset	Aircraft in Dataset
ST1	Attack	11	A-10A, A-3A/B, A-4A, A-5A/RA-5C, A-6A, A-6E, A-7A/B, A-7D, EA-6B, S-3A, S-3B
ST2	Bomber	11	B-1B, B-2A, B-36A, B-47A, B-52A, B-52D, B-57A, B-58A, B-66B, RB-57D, RB-66B
ST3	Electronic Attack	1	ES-3A
ST4	Fighter	33	F-117A, F-22A, F-35A, F-35B, F-100A, F-101A, F-102A, F-104A, F-105A, F-106A, F-111A, F-14A, F-14D, F-15A, F-15C, F-15E, F-16A/B, F-16C/D, F-16C, F-4B, F-4C, F-4D, F4D-1, F-4E, F-4F, F-4J, F-5E, F-5F, F-80A, F-80C, RF-4B, RF-4C, RF-4E
ST5	Fighter/ Attack	4	EA-18G, F/A-18A, F/A-18C, F/A-18E/F
ST6	Patrol	2	P-3C, P-8A
ST7	Reconnaissance	2	E-3A, E-6A
ST8	Trainer	3	T-38A, T-39A, T-45TS
ST9	Transport/ Tanker	12	C-123B, C-130A, C-130J, C-131A, C-141A, C-17A, C-27J, C-5A, C-5B, HC-130J, KC-135A, MC-130J
ST10	UAV/Drone	3	MQ-1C, MQ-9A, RQ-4A

Research Question 2

The second research question is: *What is an adequate proxy for complexity in estimating recurring T100 flyway costs?* To answer this, three variables are assessed, Stealth, Legacy, and EMD.

Stealth

Prior datasets did not statistically assess the significance of a stealth variable, which could be a proxy for complexity due to its advanced technology. The Stealth variable is a dummy variable where 1 indicates a stealth aircraft, and 0 indicates it is not. This dataset has five aircraft with stealth technology: B-2A, F-117A, F-22A, F-35A, and F-35B.

Legacy

The Legacy variable is intended to capture the age and complexity of an aircraft and is defined by whether or not the weapon system is completely integrated or not. Legacy aircraft do not consist of an integrated weapon system, but rather separate components contained within an aircraft weapon system. If an aircraft at the Mission Design (MD) level was defined as a legacy aircraft, then all modifications of this aircraft were also defined as a legacy aircraft because their technology is based on legacy aircraft. For example, the C-5A was produced in the 1960s when weapon systems were not fully integrated yet and is therefore a legacy aircraft. The C-5B on the other hand was produced in the 1980s when weapon systems were being fully integrated but is still based on the same C-5A aircraft, and is therefore also a legacy aircraft.

There are 46 legacy aircraft in this dataset, with first flight dates that range from 1944 – 1968 at the MD level. Alternatively, modern aircraft are wholly integrated weapon systems whose production began in the 1970s. There are 36 modern aircraft in this dataset, with first flight dates that range from 1972 – 2007. Identification of whether or not an aircraft is legacy or modern was verified by a subject matter expert from the AFLCMC, and the breakdown between the two classifications is displayed in Table 5.

Table 5. Aircraft Breakdown by Legacy vs Modern

Legacy vs Modern Aircraft	
Legacy Aircraft	A-3A/B, A-4A, A-5A/RA-5, A-6A, A-6E, EA-6B, A-7A/B, A-7D, B-36A, B-47A, B-52A, B-52D, B-57A, RB-57D, B-58A, B-66B, RB-66B, C-123B, C-130A, C-131A, KC-135A, C-141A, C-5A, C-5B, F-100A, F-101A, F-102A, F-104A, F-105A, F-106A, F-111A, F4D-1, F-4B, F-4C, F-4D, F-4E, F-4F, F-4J, RF-4B, RF-4C, RF-4E, F-80A, F-80C, P-3C, T-38A, T-39A
Modern Aircraft	A-10A, B-1B, B-2A, C-130J, HC-130J, MC-130J, C-17A, C-27J, E-3A, E-6A, ES-3A, EA-18G, F/A-18A, F/A-18C, F/A-18E/F, F-117A, F-14A, F-14D, F-15A, F-15C, F-15E, F-16A/B, F-16C, F-16C/D, F-22A, F-35A, F-35B, F-5E, F-5F, MQ-1C, MQ-9A, P-8A, RQ-4A, S-3A, S-3B, T-45TS

EMD Costs

Engineering and Manufacturing Development (EMD) costs are the costs incurred during the EMD phase of the acquisition lifecycle. The goal of the EMD phase is to complete a weapon system's engineering development, so a system may proceed to the production and development (PD) phase, which is where the recurring T100 flyaway costs occur. Therefore, it is fair to suggest that the more complex a weapon system is, the more costs it will incur during its engineering and manufacturing development.

A caveat to investigating this variable that was discussed during the inclusion/exclusion criteria earlier in this chapter is that there are only 59 aircraft with EMD cost data available. Additionally, unlike all of the other potential variables in this thesis, EMD is the only variable with data not available pre-Milestone B. Due to this, there will be two CER models created. The first CER development incorporates all variables discussed in this section, excluding EMD costs; this results in a sample size of 82 and is applicable early in an aircraft's acquisition lifecycle. Then, a second CER is developed that analyzes all variables including EMD costs; this results in a sample size reduction to 59. If EMD is found significant, then the second CER can only be applied around Milestone C once all EMD costs are calculated.

Research Question 3

The third research question is: *Which calculation of weight (empty weight, airframe unit weight, or aircraft density) best predicts recurring T100 flyaway costs?* To answer this, two variables for weight are assessed, empty weight (EW) and airframe unit weight (AUW). Additionally, a third variable which is based off of weight is assessed, aircraft density (AD).

Weight

There are over 1,000 weight statements in the CADE library for approximately 516 different mission design series (MDS). This means for certain MDSs, such as the F-117A and P-3C, there is only one weight statement. While other MDSs, such as the A-10A and C-17A, have over a dozen weight statements. Out of the 82 aircraft in this dataset, 53 have only one weight statement in CADE and 29 have more than 1. For the EW and AUW variables listed in Table 3, if there was more than one weight statement available then the weight statement that reflected production units that occurred around the 100^{th} unit was selected. However, to rigorously investigate when in a program's life cycle weight is the most predictive of T100 flyaway costs, four additional variables are analyzed: EW1 and AUW 1 which represents data from the first (or only) weight statement for an aircraft, and EW2 and AUW2 which represents the last.

Aircraft Density

Aircraft density is intended to capture how tightly packed an aircraft is. Typically, volume is required to calculate density, but since the volume of the aircraft in the dataset are not available, weight is used as a substitute (Hess and Romanoff, 1987). There are two forms of aircraft density that is tested in this thesis, and their formulas are defined in Table 6.

Table 6. Aircraft Density Formulas

Aircraft Density Variable	Formula
AD1	$\frac{Aircraft\ Unit\ Weight}{Empty\ Weight}$
AD2	$\frac{Empty\ Weight - Aircraft\ Unit\ Weight}{Empty\ Weight}$

Research Question 4

The fourth research question is: *How does an aircraft's contractor influence recurring T100 flyaway costs?* To answer this, the variable Contractor is assessed.

Contractor

Large, Campbell, and Cates (1976) suggested contractor experience as a potential variable to investigate further, and Hess and Romanoff (1987) created a contractor experience dummy variable that did not produce a significant result. However, most of those contractors either merged to form new corporations, were acquired, or are completely defunct altogether. Out of the 19 contractors that produced the aircraft in this dataset, only six are still currently operating. This thesis assesses whether or not these six current contractors, shown in Table 7, are significant predictors of T100 flyaway costs.

Table 7. Current Contractor Breakdown

Contractor Variable	Contractor (Year Founded)	Number in Dataset	Aircraft in Dataset
Ct1	Boeing (1916)	8	B-47A, B-52A, B-52D, E-3A, E-6A, EA-18G, KC-135A, P-8A
Ct2	General Atomics Aeronautical Systems, Inc (1955)	2	MQ-1C, MQ-9A
Ct3	General Dynamics (1899)	4	F-111A, F-16A/B, F-16C/D, F-16C
Ct4	Leonardo Aviation (1948)	1	C-27J
Ct5	Lockheed Martin (1995)	6	C-130J, F-22A, F-35A, F-35B, HC-130J, MC-130J
Ct6	Northrop Grumman (1994)	1	RQ-4A

Other Potential Variables

There are four additional variables assessed in this thesis that are not linked to any of the four prior research questions but fit the criteria to be an exploratory variable. Speed (S) and quantified unit (Qt) were found to be predictive of airframe costs in prior research and will therefore be included in Chapter IV's analysis. The other two variables, Air Force (AF) and engine count (EC), are simply for exploratory purposes.

Air Force

The Air Force (AF) variable is assessed to determine if aircraft developed and produced for the Air Force, could potentially be a predictor of flyaway costs. While it has not been previously identified as a cost driver, it does meet the criteria outlined at the beginning of this chapter. This dataset has 50 aircraft that are solely Air Force, and 32 that are not as demonstrated in Figure 6.

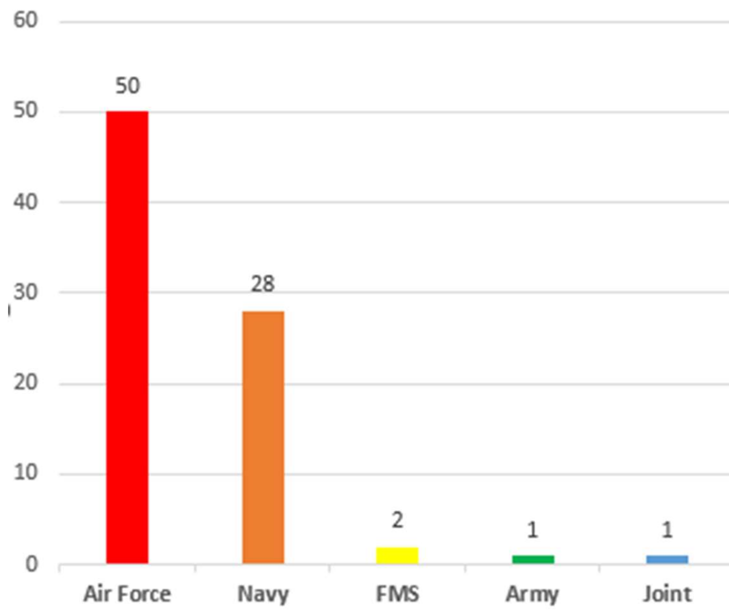


Figure 6. Total Number of Aircraft by Service

Engine Count

Engine count is the total number of engines each aircraft has, and in this dataset, there are five different engine counts an aircraft can possess: 1, 2, 4, 6, or 8. The most common engine count is 2, representing exactly half of the dataset, and the least common are 6 and 8 with only two aircraft each. Figure 7 breaks down the total number of aircraft by engine count.

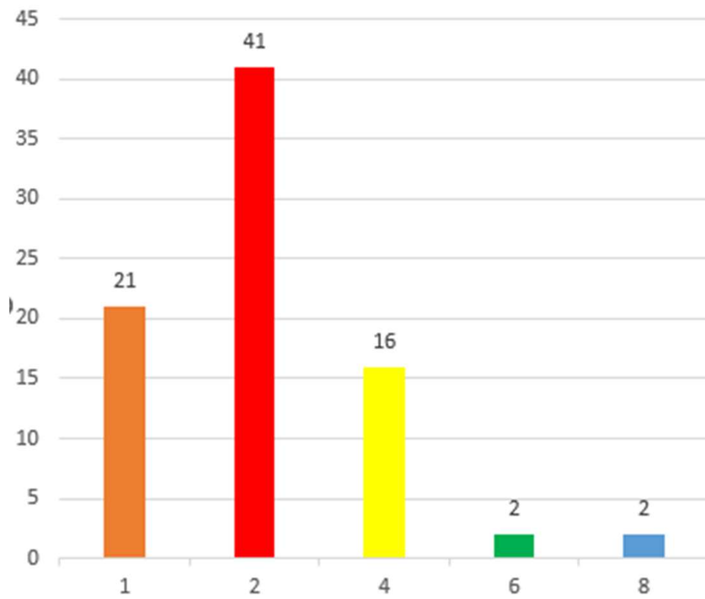


Figure 7. Total Number of Aircraft by Engine Count

Data Analysis

Descriptive Statistics

Once all data were collected and calculated, descriptive statistics were assessed for each variable. First, a boxplot and summary statistics were compiled for the dependent variable, recurring T100 flyaway costs, to capture a quick snapshot of the data this thesis is trying to predict. Next, scatterplots and boxplots were created for each independent variable depending on whether or not the variable possesses qualitative or quantitative data. For the quantitative variables, such as weight and aircraft density, scatterplots were examined. For the qualitative variables, such as contractor and system type, boxplots were examined. The purpose of this step is to identify any trends in the data and to determine if any variables should be transformed (i.e., if they appear non-linear).

Statistical Analysis

The descriptive and statistical analysis performed in this thesis is accomplished with JMP® Pro 15, and a 10% level of significance are used for all statistical tests. After each independent variable is visually assessed, they are individually regressed on the dependent variable to statistically test their significance in predicting T100 flyaway costs. To accomplish this, a *t*-test is conducted for the following hypothesis:

H_o: *The variable is not predictive of recurring T100 flyaway costs*

H_a: *The variable is predictive of recurring T100 flyaway costs*

If while assessing the descriptive statistics an independent variable appears to take on a different form (i.e., non-linear), then the alternative form is also tested in this step. Additionally, if a trend is noticed and a cohort emerges, then the *t*-test is also conducted on the cohort as a dummy variable. If the cohort variable is found to be predictive, then inclusion criteria for the cohort is established by scrutinizing the members of the cohort, and determining what characteristics they (and only they) share that make them unique.

Generate CERs

The following process of developing a CER is completed twice to create two models. One with all independent variables except for EMD costs, and a second with all independent variables including EMD costs. After each independent variable is statistically assessed, they are analyzed together through stepwise regression. Stepwise regression is an automatic process that screens potential independent variables to determine their best combination in predicting the dependent variable (McClave et al., 2014). When screening the potential independent variables, there are three routines a stepwise regression can take: forward, backward, or mixed. The forward routine adds variables that are significant at a specified *p*-value, but does not move backwards to recheck the significance of previously entered variables. The backwards routine begins with all variables in the model and eliminates those that do not meet the *p*-value threshold. The mixed routine combines the two methods and adds in variables like the forward routine, but then moves backward to recheck that previously entered variables are still significant and then removes them if they are not. For the stepwise regression performed in this thesis, the mixed direction is applied due to its thoroughness, and a *p*-value of 0.10 is set as the individual threshold for variables to enter and leave the model. We later prune this for individual significance by adopting the Bonferroni method to maintain familywise significance when conducting multiple hypotheses tests.

Once stepwise regression produces the combination of explanatory variables that are individually significant at the 0.10 *p*-value threshold, the variables are fitted through the standard least squares function to create a preliminary model. The preliminary model is then trimmed by saving Cook's D and assessing which aircraft are overinfluencing the model. The aircraft that are flagged during the Cook's D assessment are then removed from the dataset, and the stepwise regression is reran with the same independent variables from the preliminary model. When the results from the new stepwise regression produce a trimmed model, the aircraft that were removed from the Cook's D assessment are included back into the dataset and the trimmed model is validated. The logic behind building a model this way, where Cook's D is utilized to trim variables, is to produce a stable model without sacrificing datapoints that can overly predict the response. At the same time, the method of stepwise regression and subsequent trimming of the variables, helps to create a parsimonious model that is less likely to overfit the data.

After the preliminary model is trimmed, it must be tested for statistical significance, diagnostics, and assumptions. The first step is to ensure that each explanatory variable is predictive of recurring flyaway costs by testing them at a 10% level of significance. To do so, a *t*-test is conducted and the comparisonwise error rate (or Bonferroni correction) that each variable is tested against is the level of significance, 0.10, divided by the number of explanatory variables in each model. The hypothesis for each *t*-test is:

H_o: *The variable is not predictive of recurring T100 flyaway costs*

H_a: *The variable is predictive of recurring T100 flyaway costs*

Next, multicollinearity and diagnostics are evaluated to determine if any explanatory variables are strongly correlated with one another, or if any datapoints are outliers and overinfluencing the model. To ensure there is not high multicollinearity amongst the independent variables, variance inflation factors (VIF) are evaluated. If a VIF score is equal to one then it has zero multicollinearity, and high multicollinearity exists if an independent variable has a VIF score greater than four. To identify any outliers or overinfluencing datapoints, a histogram of the studentized residuals and Cook's D overlay plots are analyzed. When assessing the studentized residuals, if a datapoint is outside of three standard deviations then it is deemed an outlier. For the Cook's D assessment, if a datapoint is far from the other datapoints and greater than 0.5, then it is considered to be overinfluencing the model. If an independent variable has a high multicollinearity or if a datapoint is identified as an outlier and as overinfluential, then it will be investigated and addressed during analysis in Chapter IV.

After the diagnostics detect any possible problems with the model, there are seven assumptions that must be met which are presented in Table 8. The first six assumptions are required for a model to be considered the best linear unbiased estimate (BLUE) (Hilmer & Hilmer, 2014). A BLUE model is deemed the gold standard for estimators, because it is a linear estimate that has zero bias and minimum variance.

The seventh assumption is the condition of normality. Since the *t*-test follows a *t*-distribution, in order to utilize it the data must be normally distributed. For this condition to be met, the residuals are examined for normality and constant variance. For the assumption of normality, a histogram of the residuals is created, and an Anderson-Darling test is conducted for the following hypothesis:

H_o: *The residuals have a normal distribution*

H_a: *The residuals do not have a normal distribution*

To test the residuals for constant variance, a graph of the predicted values versus residuals is assessed. For the statistical analysis, a Breusch-Pagan test is conducted to test the following hypothesis:

H_o: *The residuals have constant variance*

H_a: *The residuals have nonconstant variance*

It is important to not only test the residuals but to also assess the residuals' distribution and variance visually, because in the event one assumption fails it can determine where the failure occurred. Some failures are considered good, and the failure of either of these assumptions does not necessarily disqualify the validity of the *t*-tests. Same as the diagnostics, if an assumption is not met it will be addressed in Chapter IV. The following table, Table 8, summarizes the seven assumptions and how to test for each.

Table 8. Model Assumptions and How to Test for Each

Assumption	How to Test
1. The model is linear in the parameters.	Tested by assessing the regression model and verifying that the parameters ($\beta_1,\ldots,\beta_n$) are linear, and therefore define a linear relationship between y and $x_1,\ldots,x_n$. $y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon$
2. The data are collected through independent, random sampling.	Assumption already met because each aircraft program is independent of one another.
3. The data are not perfectly multicollinear.	If the data does not have high multicollinearity, which is already tested, then it cannot be perfectly multicollinear.
4. The error term has zero mean.	Assumption met with the inclusion of an intercept in the model.
5. The error term is uncorrelated with each independent variable and all functions of each independent variable.	Assumption already met by including all independent variables possible within the scope of this thesis.
6. The error term has constant variance.	Conduct a Breusch-Pagan test (previously shown)
7. The data must be normally distributed.	Conduct an Anderson-Darling test (previously shown)

Validate CERs

In addition to testing assumptions and running diagnostics, the model must also be validated. The metrics employed in this thesis to explain the model's performance are the R^2, adjusted-R^2, and PRESS R^2 statistics. The coefficient of determination (R^2) is a commonly used metric that explains how much variability in recurring T100 flyaway costs are accounted for in the model. The R^2 is calculated by dividing the explained sum of squares (ESS) by the total sum of squares (TSS), and because of this the R^2 will always increase with the addition of a new independent variable. The adjusted R^2 corrects this drawback by considering the number of explanatory variables included in the model, and therefore will only increase if the new explanatory variable adds to the predictability of the model. The predicted residual error sum of squares (PRESS) R^2 statistic is recommended in evaluating a model's prediction ability (Naval Center for Cost Analysis, 2018). When PRESS R^2 is compared with the adjusted R^2, results can determine if the model is over-fitted and therefore inflated.

Characterize Uncertainty

After the model is validated and determined to be stable, its applicability and uncertainty must be defined. First, the absolute values of the standardized betas are ranked from highest to lowest, and a Pareto chart is created to demonstrate which variables have the largest and smallest effect on the response. Next, the boundaries of each explanatory variable for applying the model are established to prevent extrapolation. Finally, an example for how to apply the model utilizing Program A data is presented. The results of the example provide a comparison of the predicted costs versus the actual costs as well as create a 95% confidence interval.

Summary

This chapter explained how and why the final dataset was built and defined each variable while linking them to the research questions. Then it described the process for how to analyze the data and to develop a CER. The next chapter, Chapter IV, applies the methods presented in this chapter and display their results.

IV. Analysis and Results

Chapter Overview

This chapter details the analysis and subsequent results from the methodology described in Chapter III and is broken down into four sections. The first section describes the dataset and provides descriptive statistics for each variable investigated in this thesis to identify any trends. The second section inferentially tests any trends and the effects that each variable has on the response. The third section develops the first CER model, validates it, and characterizes its uncertainty. The fourth and final section repeats the process as indicated in the third section, but in relationship to the second CER model.

Descriptive Statistics

The summary statistics for the dependent variable, recurring T100 flyaway costs, are presented in Table 9 and displayed in Figure 8. These give an overview of the recurring T100 flyaway costs and show the typical value as well as the large variation in cost among the various aircraft.

Table 9. Summary Statistics of Recurring T100 Flyaway Costs

Summary Statistics of Dependent Variable (in $K)	
N	82
Median	$26,914.42
Mean	$51,297.87
Std Dev	$60,533.158
IQR	$44,118.01

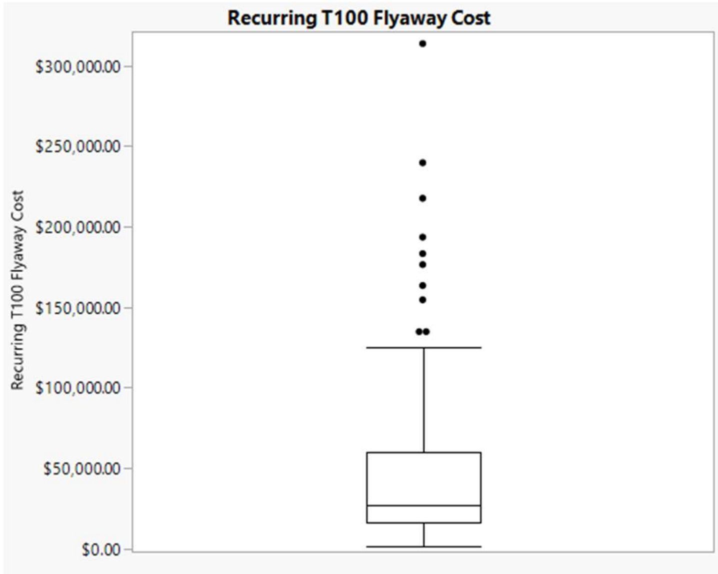


Figure 8. Boxplot of Recurring T100 Flyaway Costs

Figures 9 and 10 display scatterplots of the weight data for the 82 aircraft in this dataset. Recall that AUW and EW represent the airframe unit weight and empty weight of an aircraft with weight data selected from weight statements that were submitted approximately around the 100th unit of production, while AUW1 and EW1 represent data from the first (or only) weight statements submitted, and AUW2 and EW2 represent data from the last ones. Figure 9 compares the scatterplots of AUW, AUW1, and AUW 2 against the T100 flyaway costs, and there appears to be no major differences between the three variables. There seems to be a relationship between the dependent and independent variables with the data displaying a natural log trend and flaring effect. Figure 10 produces similar results with the empty weight variables.

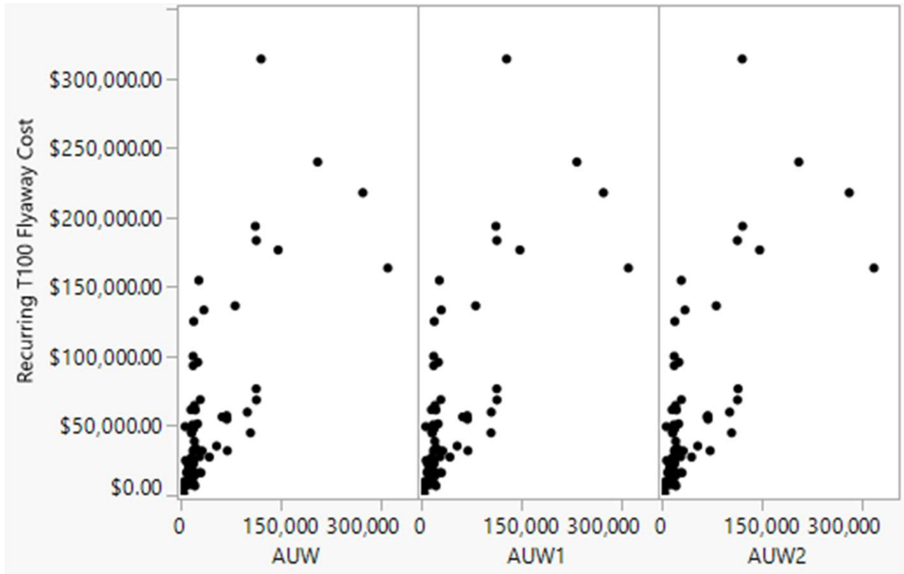


Figure 9. Scatterplot of Recurring T100 Flyaway Cost vs Airframe Unit Weight, AUW1, and AUW2

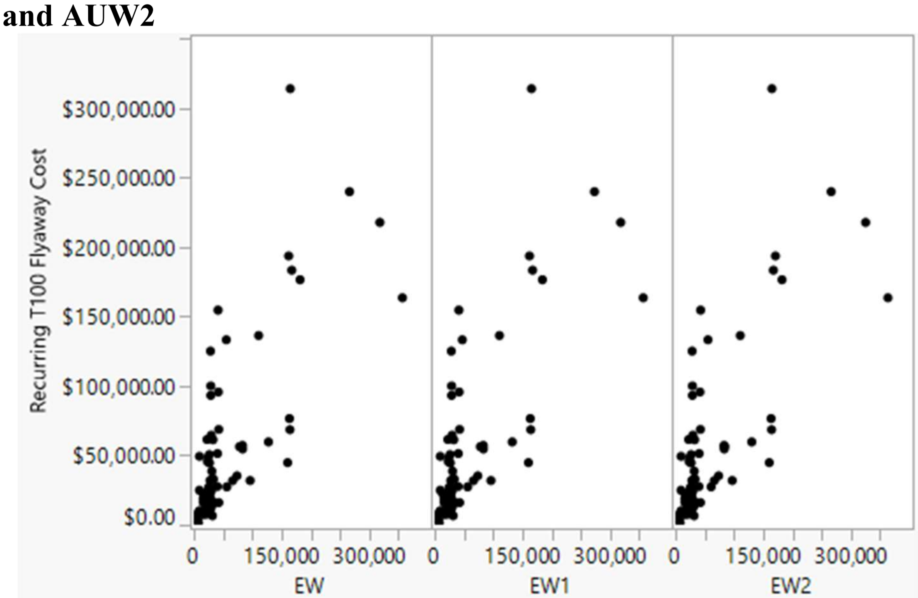


Figure 10. Scatterplot of Recurring T100 Flyaway Cost vs Empty Weight, EW1, and EW2

Figure 11 is a scatterplot of an aircraft's quantified units versus its T100 flyaway costs. The graph does suggest that a relationship between the variables exist, but it seems to be in the form of an exponential decay.

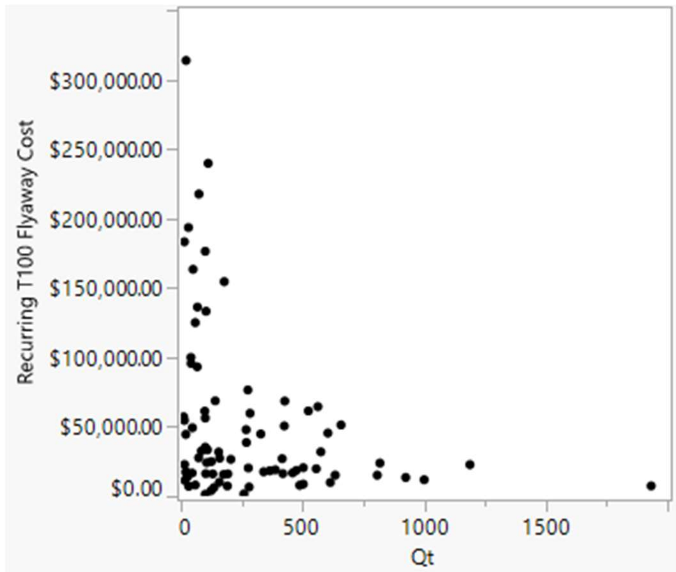


Figure 11. Scatterplot of Recurring T100 Flyaway Cost vs Quantified Unit

Figure 12 is a scatterplot of an aircraft's speed versus its T100 flyaway cost. Most of the data looks to follow a pattern of positive correlation between speed and cost, with the exception of seven datapoints that are circled in red. When investigating these datapoints in JMP® Pro 15 (the software utilized in this thesis' analyses), they account for seven out of the nine heaviest aircraft in the dataset: E-3A, E-3B, B-1B, B-2A, C-17A, C-5A, and C-5B. Therefore, they were identified as a potential cohort that is tested in the statistical analysis section of this chapter.

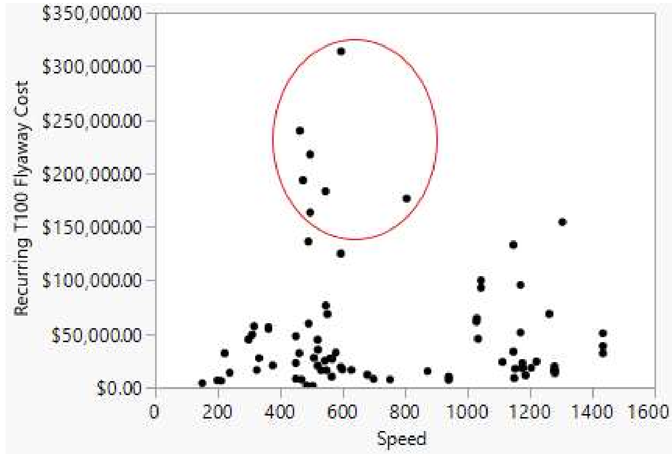


Figure 12. Scatterplot of Recurring T100 Flyaway Cost vs Speed with Potential Cohort Circled

Figure 13 is a scatterplot of the two aircraft density variables versus T100 flyaway costs. There is not a strong pattern in the graphs, but it does appear both variables have opposing relationships with the dependent variable, albeit weak ones.

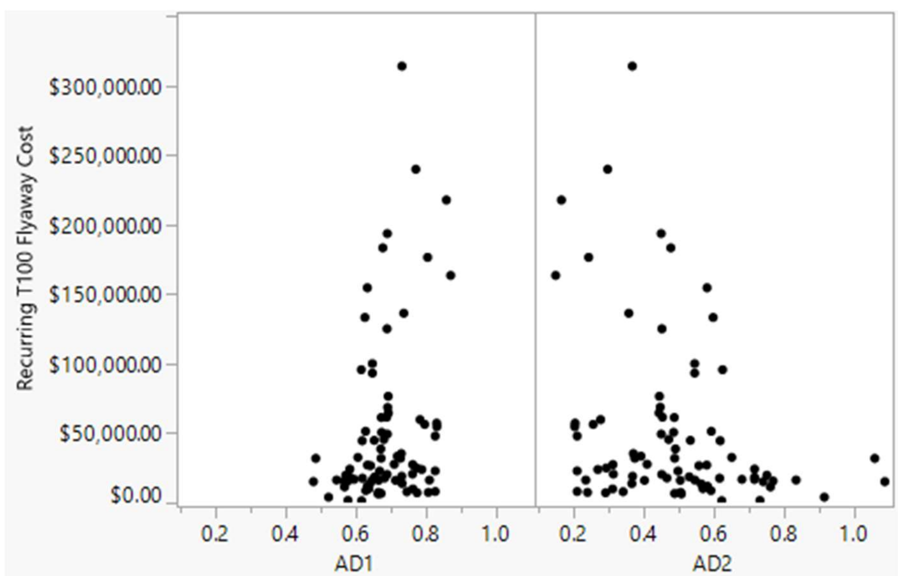


Figure 13. Scatterplot of Recurring T100 Flyaway Cost vs Aircraft Density 1 and 2

Figures 14 and 15 are box plots with respect to two dummy variables, Air Force and stealth technology, versus T100 flyaway costs. In Figure 14 there appears to be similar means between Air Force and non-Air Force aircraft, with the Air Force aircraft having a greater variance. On the other hand, in Figure 15, the boxplots of the aircraft with stealth technology and the ones without it have almost no overlap (with the exception of outliers) and seem to be different.

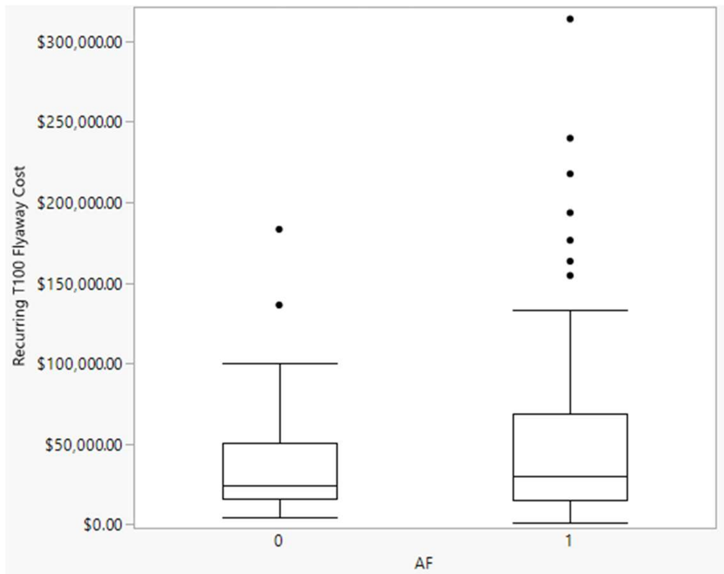


Figure 14. Boxplots of Recurring T100 Flyaway Cost vs Air Force Aircraft

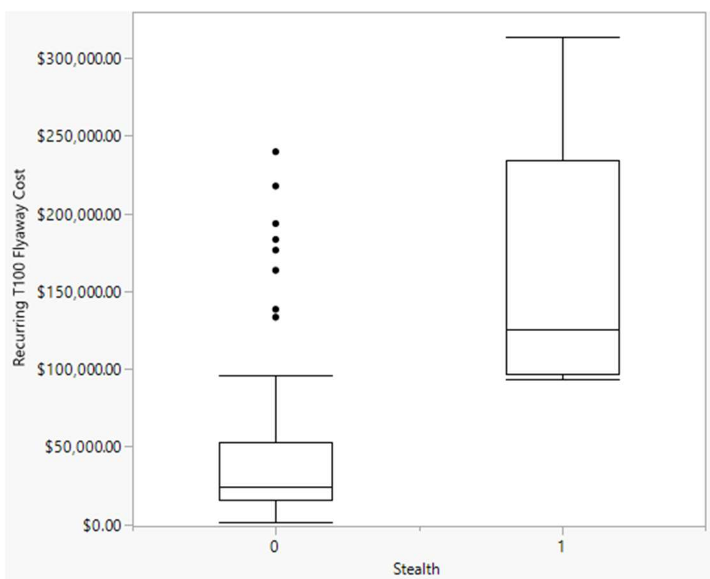


Figure 15. Boxplots of Recurring T100 Flyaway Cost vs Stealth Technology

Figures 16 and 17 are boxplots of two categorical variables, system type and contractor, versus T100 flyaway costs. When performing the actual analysis of the two categorical variables, each category is transformed into several dummy variables; so, there is a variable for each system type and contractor. However, for descriptive purposes all system types are displayed together versus T100 flyaway costs as shown in Figure 16, and all contractors are treated in the same manner in Figure 17. Visually, each system type and contractor appear to have their own unique distribution and spread.

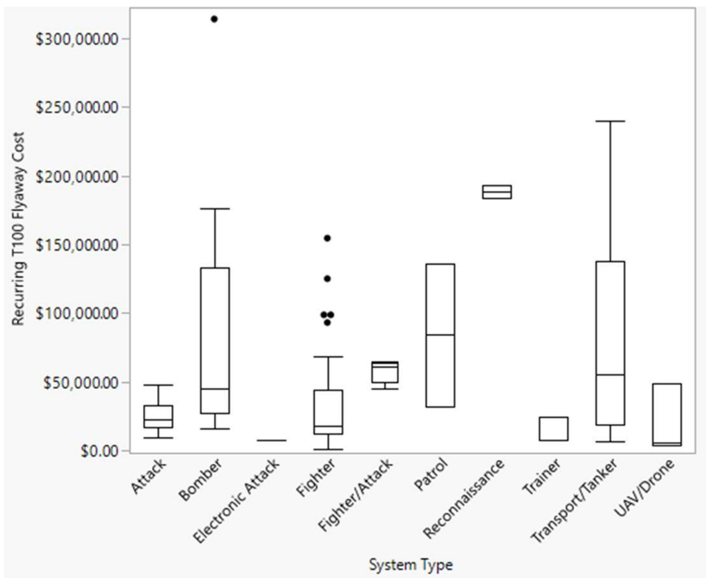


Figure 16. Boxplots of Recurring T100 Flyaway Cost vs System Type

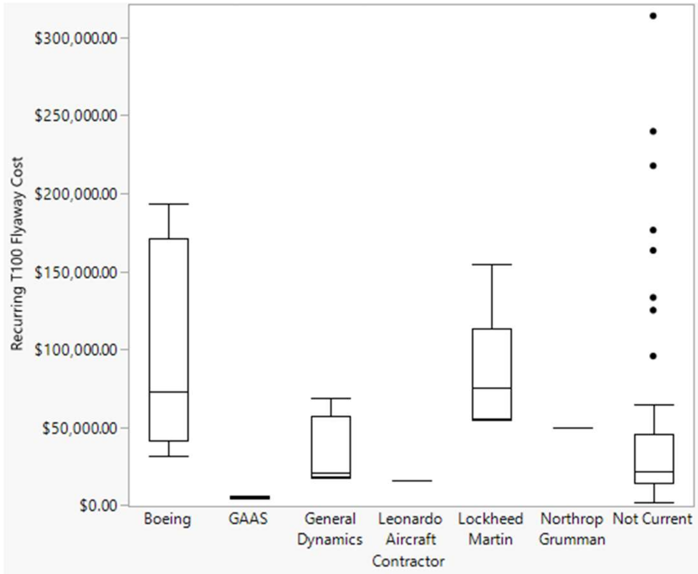


Figure 17. Boxplots of Recurring T100 Flyaway Cost vs Contractor

Figures 18 and 19 are boxplots of another dummy variable, Legacy, and the variable Engine Count. The boxplot of legacy aircraft in Figure 18 (represented by 1), is much shorter than modern aircraft (represented by 0), indicating that the legacy aircraft seem to overall have cheaper recurring T100 flyaway costs. Furthermore, in Figure 19, the aircraft with a 4-engine count have a much higher threshold of recurring T100 flyaway costs than any other engine count, including the four aircraft with six and eight engines.

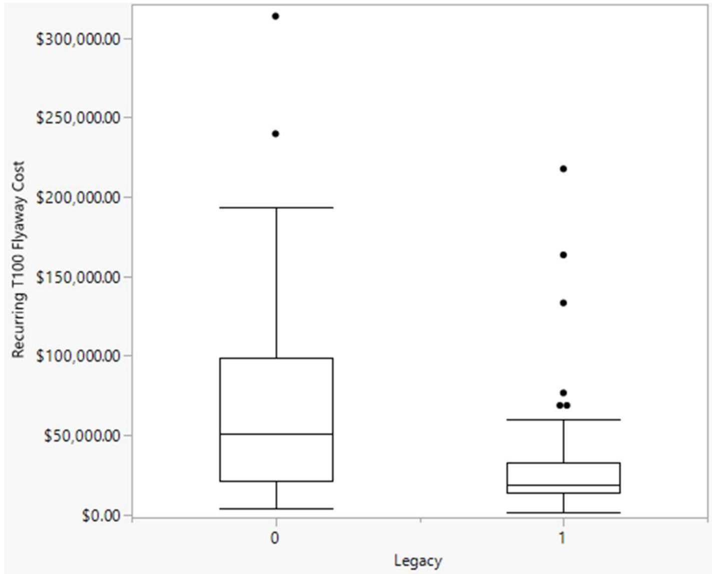


Figure 18. Boxplots of Recurring T100 Flyaway Cost vs Legacy Aircraft

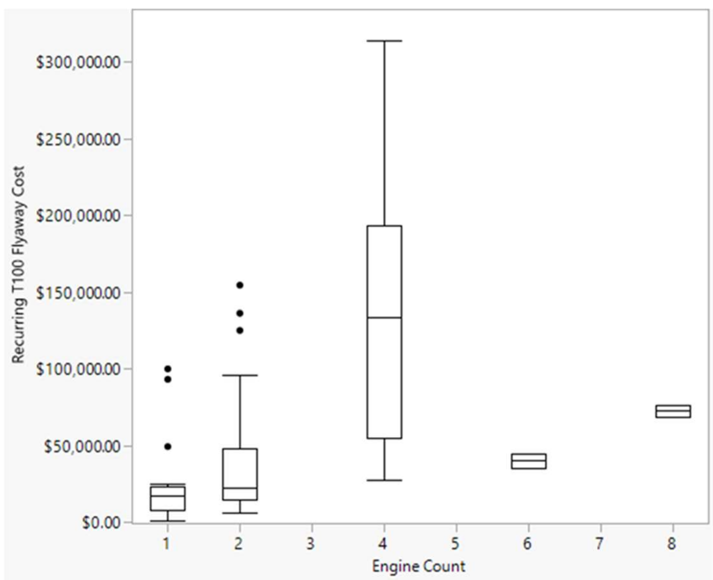


Figure 19. Boxplots of Recurring T100 Flyaway Cost vs Engine Count

Figure 20 is a scatterplot of the EMD cost data, which is the only variable that will not be included in the regression for the first CER model (it is included for the second CER). The potential cohort circled in Figure 20 are the same seven variables circled in the scatterplot for speed in Figure 12, and seem to follow a different pattern than the rest of the data. Notice that there is some flaring of the data, but there appears to be a positive relationship between EMD costs and recurring T100 flyaway costs.

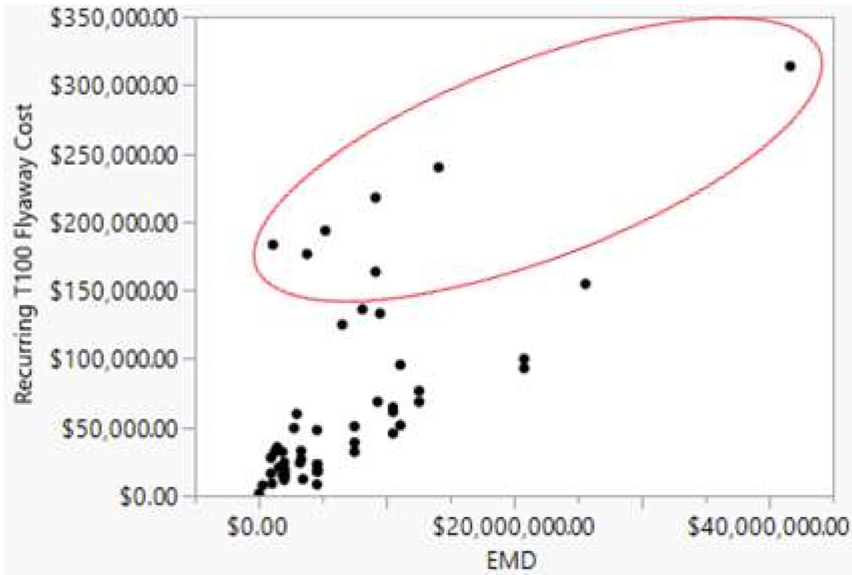


Figure 20. Scatterplot of Recurring T100 Flyaway Cost vs EMD Costs with Potential Cohort Circled

Statistical Analysis

Each variable and trends identified in the previous section, was individually regressed on the response variable, recurring T100 flyaway costs. The results are presented in three tables. Table 10 are the results of all of the continuous and dummy variables, and Tables 11 and 12 are the results of the categorical variables that were transformed into dummy variables, System Type and Contractor. It is worth noting that these results do not affect any further analysis conducted. Regardless of their individual significance, each variable will still be included in the stepwise regression during the next section.

However, it is valuable to discover how certain variables compare to one another, such as the three different empty weight variables, which all have a similar effect on the response. Thus, it is fair to say that the timeline for when a weight statement is submitted does not have a major impact to the results of the model. It is also interesting to learn how much variation in the response is explained by each variable, which is accomplished by assessing their R^2. For instance, weight and EMD costs account for nearly half of the variation in recurring T100 flyaway costs alone, while speed and the natural log of speed account for almost none.

Table 10. Results of Individual Regression Analysis

Variable	Coefficient	R^2	*p*-Value
Qt	-57.89	0.092	0.0056*
AF	19,763.46	0.026	0.1504
S	-10.86	0.004	0.5531
ln(S)	-862.32	0.000	0.9447
Stealth	112,916.58	0.202	<0.0001*
EW	0.6723	0.564	<0.0001*
EW1	0.6668	0.563	<0.0001*
EW2	0.6625	0.563	<0.0001*
AUW	0.8035	0.534	<0.0001*
AUW1	0.7920	0.545	<0.0001*
AUW2	0.7864	0.532	<0.0001*
AD1	204,485.03	0.085	0.0077*
AD2	-204,485	0.085	0.0077*
Engine Count	17,691.41	0.182	<0.0001*
Legacy	-40,428.42	0.111	0.0022*
EMD Costs	0.0064	0.450	<0.0001*
*Statistically significant at the 5% level			

Table 11. Results of Regression Analysis for System Type Dummy Variables

Variable	System Type	Coefficient	R^2	*p*-Value
ST1	Attack	-30,501.01	0.030	0.1206
ST2	Bomber	41,314.12	0.055	0.0343*
ST3	Electronic Attack	-43,668.47	0.006	0.4768
ST4	Fighter	-27,872.52	0.052	0.0401*
ST5	Fighter/Attack	7,299.51	0.001	0.8157
ST6	Patrol	33,615.36	0.007	0.4413
ST7	Reconnaissance	140,499.47	0.130	0.0009*
ST8	Trainer	-39,231.10	0.015	0.2732
ST9	Transport/Tanker	32,189.84	0.036	0.0888
ST10	UAV/Drone	-32,555.06	0.010	0.3638
*Statistically significant at the 5% level				

Table 12. Results of Regression Analysis for Contractor Dummy Variables

Variable	Contractor	Coefficient	R^2	*p*-Value
Ct1	Boeing	52,151.65	0.066	0.0197*
Ct2	General Atomics Aeronautical Systems, Inc	-47,251.02	0.015	0.2783
Ct3	General Dynamics	-20,264.11	0.005	0.5171
Ct4	Leonardo Aviation (1948)	-35,376.23	0.004	0.5646
Ct5	Lockheed Martin	37,465.74	0.026	0.1455
Ct6	Northrop Grumman	-1,918.347	0.000	0.9751
*Statistically significant at the 5% level				

Cohort Analysis

While assessing Figure 12, a trend of seven aircraft was identified as a potential cohort: E-3A, E-6A, B-2A, B-1B, C-17A, C-5A, and C-5B. A dummy variable was created labeled “Cohort” where 1 indicates a member of the cohort, which was then regressed on the dependent variable. Results of this regression is displayed in Table 13;

with a *p*-value less than 0.0001, the null hypothesis of non-significance is rejected concluding that the cohort is predictive of recurring T100 flyaway costs.

Table 13. Results of Regression Analysis for Cohort Dummy Variable

Variable	Coefficient	R-Squared	*p*-Value
Cohort	176,285.7	0.670	<0.0001*
*Statistically significant at the 5% level			

Since the cohort was found to be predictive, the seven aircraft were scrutinized to establish what common elements they shared. Afterwards, it was determined that each aircraft had four engines and were among the top nine heaviest aircraft in the dataset. Figure 21 shows the distribution of the airframe unit weight and empty weight of the dataset with the cohort highlighted to demonstrate how heavy the cohort's aircraft are. The inclusion criteria were established to specify what makes the cohort unique. Therefore, the cutoff weight is rounded down from the exact weights of the seven aircraft, but in a way that still only applies to the cohort. The complete inclusion criteria for the variable Cohort are defined in Table 14.

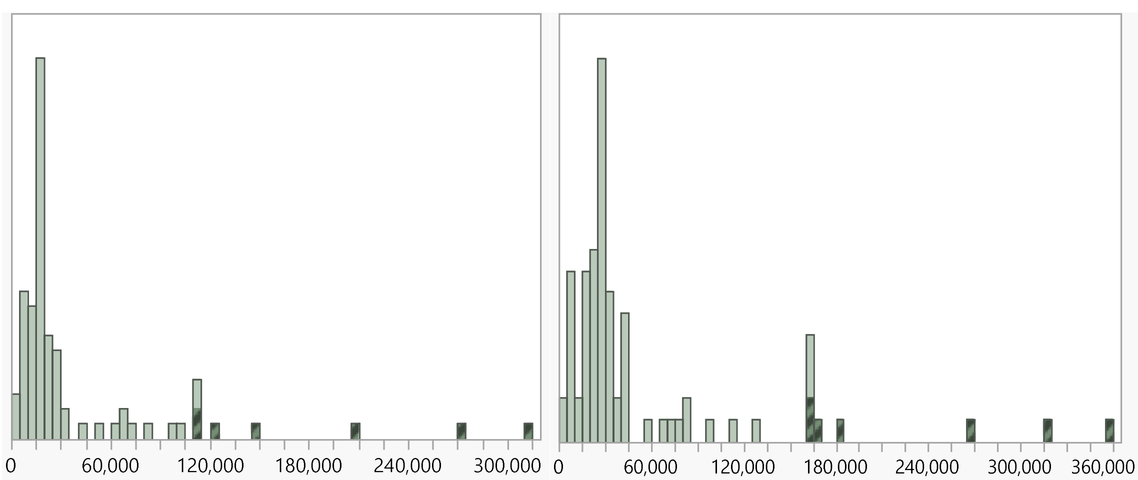


Figure 21. AUW (Left) and EW (Right) Distributions of the Aircraft with Cohort Highlighted

Table 14. Inclusion Criteria for Cohort

Criteria	Aircraft Remaining
1. AUW > 111,000	Cohort plus B-52A and B-52D
2. EW >162,000	Cohort plus B-52A and B-52D
3. Engine Count = 4	Cohort

CER Model 1

The initial stepwise regression for the first model produced 12 variables that are shown in Table 15 along with their individual *p*-values, and the complete results of the step history are in Appendix A. Table 15 also reveals the 12 variables ranked highest to lowest based on their *t* ratios and *p*-values, with Stealth being the most significant predictor of recurring T100 flyaway costs, followed by Cohort. Additionally, the VIF scores are presented in Table 15 displaying the extremely high multicollinearity that is anticipated amongst the several weight variables that have overlapping effects.

Table 15. Preliminary Model 1 - Estimate and Effect Summary

Term	Estimate	t Ratio	*p*-value	VIF
Stealth	90955.88	10.55	<.0001	1.193
Cohort	92490.03	7.31	<.0001	3.507
ln(S)	24250.2	4.75	<.0001	2.150
AUW2	-4.04048	-4.31	<.0001	768.947
ST4	-23454.2	-4.01	0.0002	2.305
EW1	-8.04382	-3.95	0.0002	5325.995
Legacy	-16566.7	-3.89	0.0002	1.251
AUW1	3.318769	3.57	0.0006	761.187
ST6	37043.93	2.78	0.0070	1.185
EW2	4.495043	2.21	0.0306	5396.027
EW	4.457746	1.93	0.0573	6737.445
Ct6	31041.62	1.75	0.0845	1.062

As a reminder, ST4 and ST6 are the aircraft with fighter and patrol system types, respectively, and Ct6 is the contractor Northrop Grumman. Additionally, ln(S), is the natural log of maximum speed in knots, which was individually not statistically significant (*p*-value = 0.9447 shown in Table 10).

Table 16 contains the metrics for the Preliminary Model 1; with an R^2 of 0.9320 and an adjusted R^2 of 0.9202, the model accounts for most of the variation amongst the recurring T100 flyaway costs. However, the PRESS R^2 is 0.8243, which is a substantial decrease from the adjusted R^2 indicating an inflation of the model's performance.

Table 16. Preliminary Model 1 – Metrics

Preliminary Model 1 Metrics	
R^2	0.9320
Adjusted R^2	0.9202
PRESS R^2	0.8243

Figure 22 is an overlay plot of the Cook's D influence for the Preliminary Model 1 with points greater than 0.5 highlighted. The five highlighted points are the B-58A, P-3C, P-8A, C-5B, and C-17A. With the highlighted points removed, the 12 variables from the Preliminary Model 1 were ran through stepwise regression again, which trimmed the model to only six explanatory variables: Stealth, Cohort, EW, ln(S), ST4, and Legacy. This indicates that the five highlighted points from Figure 22 were overinfluencing the variables that were trimmed from the Preliminary Model 1.

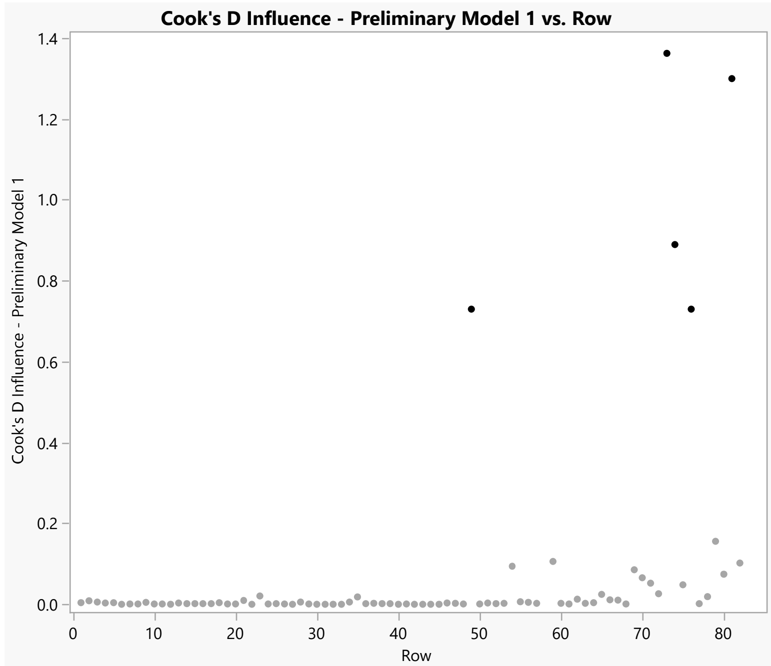


Figure 22. Preliminary Model 1 – Overlay Plot of Cook's D Influence with Points > 0.5 Highlighted

Trimmed Model 1

The five datapoints that were removed were then included back into the trimmed model and fitted through standard least squares regression, creating a model referred to as the Trimmed Model 1. The Trimmed Model 1 is displayed in Figure 23, its estimate and effect summary in Table 17, and its metrics in Table 18. Table 17 shows Stealth is still the most significant variable in the model, and all six variables are significant at the comparisonwise error rate with each *p*-value less than 0.0167 (0.10/6). Additionally, with EW being the only weight variable in the model, the VIF scores are now all below four, verifying there is little multicollinearity amongst the variables. The R^2 and adjusted R^2 are still reasonably high, but they did decrease, which can be attributed to the overfitting of variables in Preliminary Model 1. With an increase in the PRESS R^2 getting closer to the adjusted R^2, the Trimmed Model 1 gives an impression of a stable model.

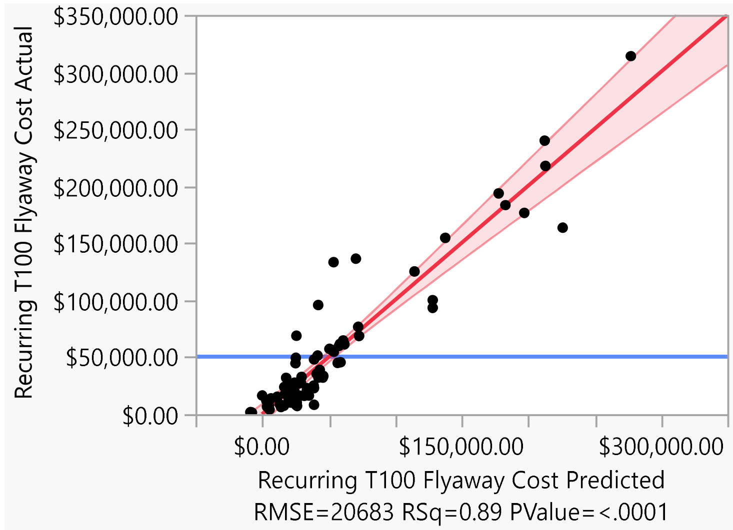


Figure 23. Trimmed Model 1 – Actual by Predicted Values

Table 17. Trimmed Model 1 – Estimate and Effect Summary

Term	Estimate	*t* Ratio	*p*-value	VIF
Stealth	93115.58	9.03	<.0001	1.1673
Cohort	90941.47	6.26	<.0001	3.1572
EW	0.336918	5.49	<.0001	3.2629
ln(S)	23984.99	4.08	0.0001	1.9543
ST4	-25872.6	-3.73	0.0004	2.2201
Legacy	-18477.4	-3.68	0.0004	1.1892

Table 18. Metrics for Trimmed Model 1 vs Preliminary Model 1

Metric	Trimmed Model 1	Preliminary Model 1
R^2	0.8919	0.9320
Adjusted R^2	0.8833	0.9202
PRESS R^2	0.8529	0.8243

Trimmed Model 1 Diagnostics and Assumptions

With each explanatory variable now verified as statistically significant in predicting recurring T100 flyaway costs and all VIF scores less than four, diagnostics must be assessed to identify any outliers or overinfluencing datapoints. Figure 24 is a histogram of the studentized residuals with three datapoints flagged as outliers: B-58A, P-8A, and C-5B. Figure 25 is an overlay plot of Cook's D influence with only one datapoint flagged as overinfluencing, the C-5B which was also identified as an outlier. All three datapoints were verified and determined to be free of error, therefore an inquiry into why they are outliers is assessed. The C-5B is exceptionally heavy (which has already been observed in the cohort analysis) and is the heaviest aircraft in the dataset. The B-58A is exceptionally fast, being the only bomber aircraft in the dataset with speeds on par with the fighter aircraft. Then the P-8A is simply an anomaly in the dataset, being the 11th heaviest aircraft in the dataset and the 9th most expensive, but it is a slow two-engine patrol aircraft. Therefore, there is no valid reason to remove all three datapoints from the model.

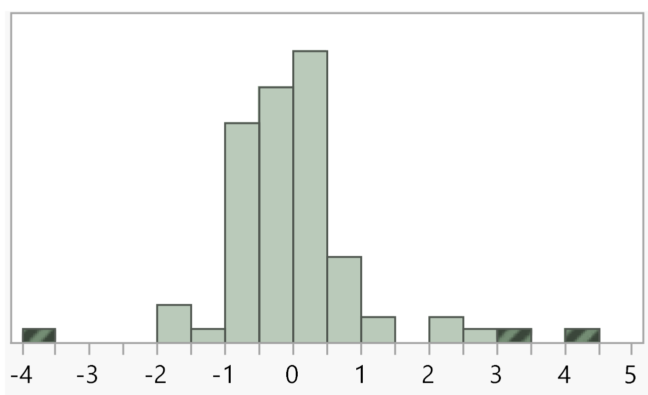


Figure 24. Trimmed Model 1 - Histogram of Studentized Residuals with Outliers Highlighted

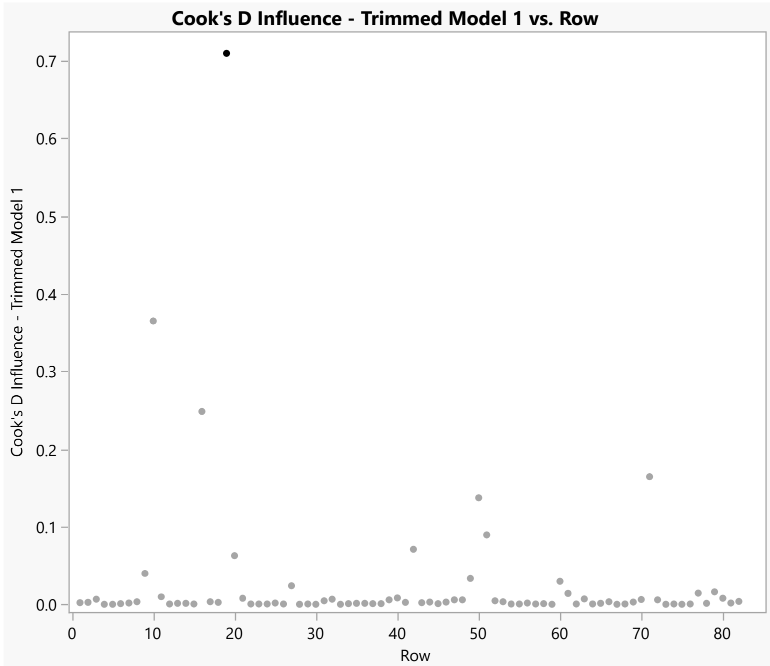
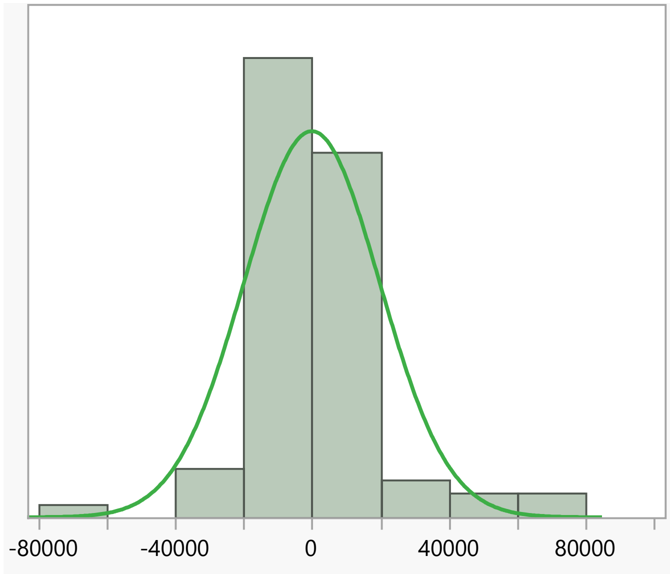


Figure 25. Trimmed Model 1 – Overlay Plot of Cook's D Influence with Points > 0.5 Highlighted

Next, in order to utilize the *p*-values for the *t* tests, the condition of normality must be tested. Figure 26 shows the histogram of the residuals with a normal fitted line that appears narrower than a typical bell-shaped curve. This is confirmed with the accompanying results of the Anderson-Darling test that has a *p*-value <.0001, rejecting the null hypothesis and concluding the residuals are not normally distributed. It is important to note that normality is also required to utilize the Breusch-Pagan test for assessing constant variance, but the residuals in Figure 26 are still relatively symmetrical, and although they are more peaked than a standard normal they are not skewed which would be the real issue of concern.



Anderson-Darling Test	
A2	Prob > A2
2.705	<.0001

Figure 26. Trimmed Model 1 - Histogram of Residuals with Accompanying Anderson-Darling Test

To test for constant variance, first the variance of the residuals is shown in Figure 27, displaying what appears to be a flaring out effect. This is confirmed with the results of the Breusch-Pagan test in Table 19 that has a *p*-value <.0001, rejecting the null hypothesis and concluding that the residuals do not have constant variance.

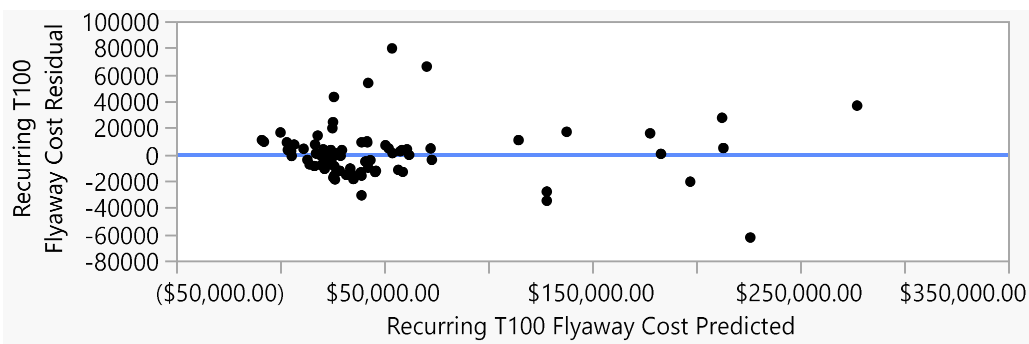


Figure 27. Trimmed Model 1 – Residuals by Predicted Values

Table 19. Trimmed Model 1 – Results of Breusch-Pagan Test

Breusch-Pagan Test					
Model Degrees of Freedom	Sample Size	Sum of Squares Error	Sum of Squares Model	Test Statistic	*p*-Value
6	82	3.208E+10	1.0936E+19	35.7173	<.0001

Not passing the assumption of constant variance means that the Trimmed Model 1 is not the "best", and therefore is not BLUE (best linear unbiased estimate). Essentially, the parameter estimates that are derived from this model will not have a minimum variance, and therefore the standard errors, which are used to calculate the *p*-values to determine if the variables are significant predictors of the response, may be slightly off (but not to an extent to dissuade what variables are predictive). Furthermore, if the condition of normality is not met, those same *p*-values assessed in the significance of the explanatory variables, may be incorrect because they require the data is normally distributed. However, if it is shown that an alternative version of the Trimmed Model 1 passes these two assumptions while maintaining its integrity (i.e., same significant variables), then the Trimmed Model 1 is considered stable.

To create an alternative to the Trimmed Model 1, the three aforementioned outliers were removed from the model to investigate how it performs without them. Then, the model was assessed for outliers and overinfluencing datapoints again, until there were no longer any present. Ultimately, in addition to the three outliers/overinfluencing datapoints previously identified, three more were flagged, the F-14D, B-2A, and F-111A. These six datapoints were removed from the Trimmed Model 1, to create a new model referred to as the Alternative Model 1. The purpose of the new model is to determine if the Trimmed

Model 1 is stable, by assessing whether or not the removal of outliers and overinfluencing points produces a similar model.

Alternative Model 1

Figure 28 displays the actual by predicted values for Alternative Model 1, which is the Trimmed Model 1 minus the P-8A, B-58A, C-5B, F-14D, B-2A, and F-111A. Table 20 compares the estimate and effect summary from the Trimmed Model 1 to the Alternative Model 1, and the results are remarkably similar between the two models, even with the outliers and influential datapoints removed. Both models have the same effect order based on standardized betas, with Cohort having the strongest effect on both models followed by EW. For the Alternative Model 1, each explanatory variable is still statistically significant at the comparison wise error rate, with all six variables having *p*-values <.0001.

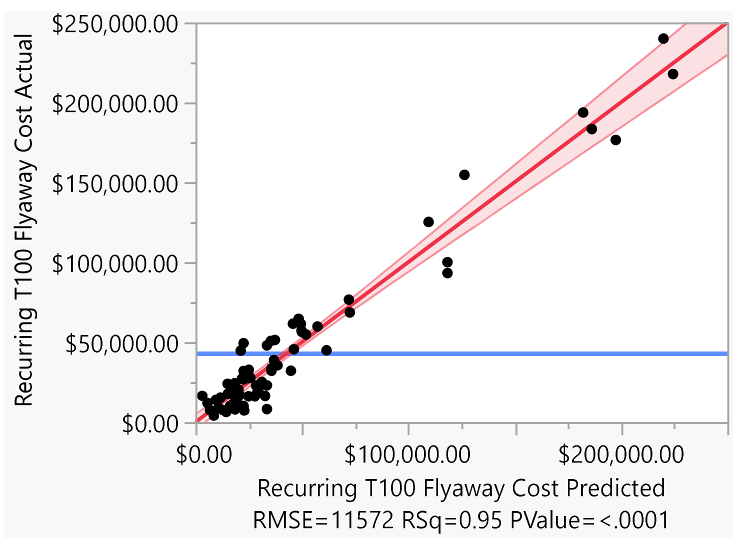


Figure 28. Alternative Model 1 – Actual by Predicted Values

Table 20. Estimate and Effect Summary for Alternative Model 1 vs Trimmed Model 1

Term	Model	Estimate	*p*-value	Std Beta	VIF
Cohort	Alternative	97222.6	<.0001	0.4766	2.8509
	Trimmed	90941.5	<.0001	0.4224	3.1572
EW	Alternative	0.36627	<.0001	0.4239	2.9415
	Trimmed	0.33692	<.0001	0.3764	3.2629
Stealth	Alternative	87113.8	<.0001	0.3847	1.2167
	Trimmed	93115.6	<.0001	0.3703	1.1673
ln(S)	Alternative	15464	<.0001	0.1678	1.9968
	Trimmed	23985	0.0001	0.2163	1.9543
ST4	Alternative	-17063	<.0001	-0.1658	2.3176
	Trimmed	-25873	0.0004	-0.2109	2.2201
Legacy	Alternative	-15613	<.0001	-0.1530	1.2262
	Trimmed	-18477	0.0004	-0.1524	1.1892

The metrics for the Alternative Model 1 compared to the Trimmed Model 1 are shown in Table 21. The R^2, adjusted R^2, and PRESS R^2 all increased and are considerably similar in value to one another. This is expected since the datapoints that had the worst fit (outliers and influential points) for the trimmed model 1 were excluded, which artificially decreased the errors for the Alternative Model 1.

Table 21. Metrics for Alternative Model 1 vs Trimmed Model 1

Metric	Alternative Model 1	Trimmed Model 1
R^2	0.9525	0.8919
Adjusted R^2	0.9483	0.8833
PRESS R^2	0.9352	0.8529

Alternative Model 1 Diagnostics and Assumptions

Figure 29 is a histogram of the studentized residuals verifying that there are no outliers in Alternative Model 1, which was already known since this model was created by removing outliers. Additionally, there are no overinfluencing datapoints in the Cook's D overlay plot in Figure 30, which again is by design.

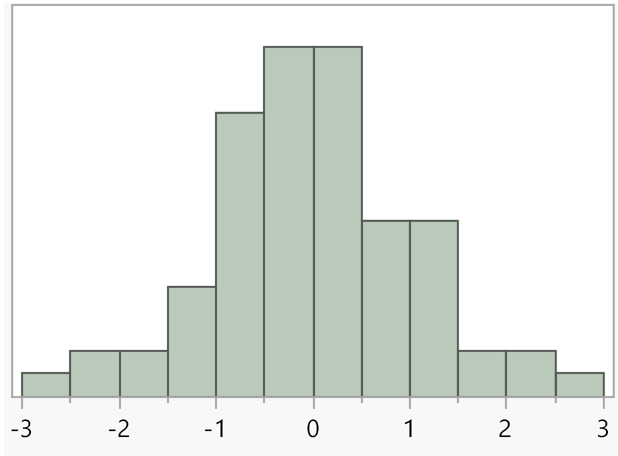


Figure 29. Alternative Model 1 - Histogram of Studentized Residuals

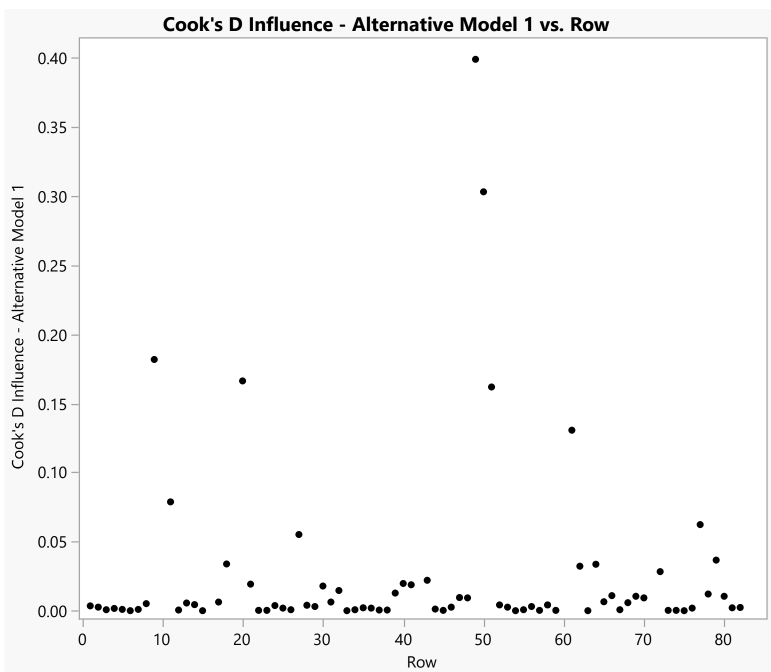
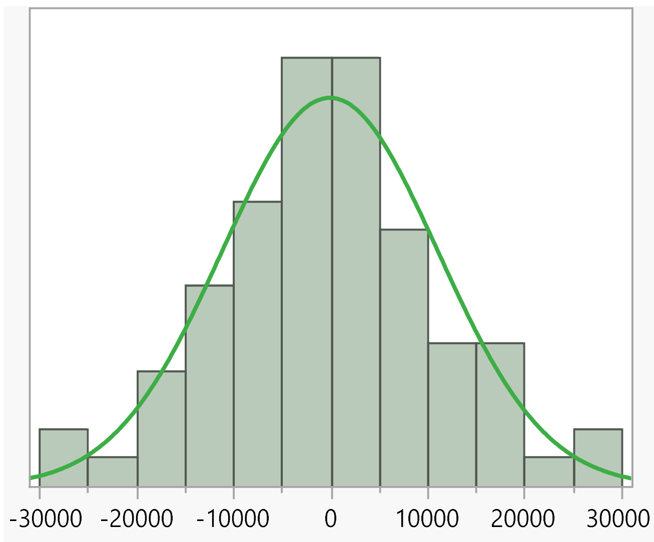


Figure 30. Alternative Model 1 – Overlay Plot of Cook's D Influence

Now that it is has been revealed that the results of the Alternative Model 1 are comparable to the results of the Trimmed Model 1, and diagnostics found no outliers or overinfluential points, the conditions of normality and constant variance must still be tested. Figure 31 is a histogram of the residuals with a fitted line that is almost perfectly symmetrical and has a classic bell-shaped curve. This is confirmed with the results of the accompanying Anderson-Darling test that has a *p*-value = 0.744, which implies that we fail to reject the null hypothesis and conclude the residuals are normally distributed.



Anderson-Darling Test	
A2	Prob > A2
0.256	0.744

Figure 31. Alternative Model 1 - Histogram of Residuals with Accompanying Anderson-Darling Test

In Figure 32, the graph of the residuals versus predicted values is shown. The flaring out is no longer present, but the points on the right are more spread out than on the left. The result of the Breusch-Pagan test in Table 22 has a *p*-value <.0001, rejecting the hypothesis that the residuals have constant variance. However, this failure is considered a good failure and is due to how dense the cluttering of points is on the left side of Figure 32, and not due to a fanning outward shape that would be considered a bad failure. In other words, it is a robust deviation of constant variance and is acceptable.

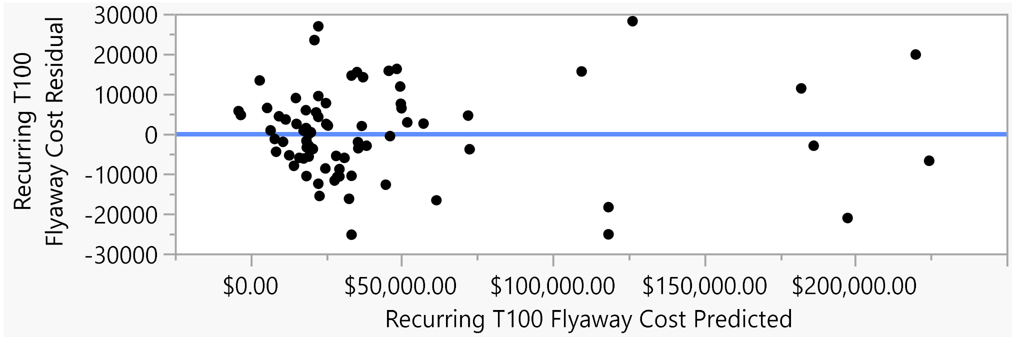


Figure 32. Alternative Model 1 – Residuals by Predicted Values

Table 22. Alternative Model 1 – Results of Breusch-Pagan Test

Breusch-Pagan Test					
Model Degrees of Freedom	Sample Size	Sum of Squares Error	Sum of Squares Model	Test Statistic	*p*-Value
6	76	9.240E+09	9.1476E+17	30.9428	<.0001

Final Model 1

The Trimmed Model 1 has strong results with six statistically significant explanatory variables that produce a high R^2, adjusted R^2, and PRESS R^2. It shows no signs of multicollinearity, but it does fail normality, constant variance, and contains a few outliers and influential datapoints. However, once these points were removed, the Alternative Model 1 did not alter the results of the Trimmed Model 1, and even passed the assumption of normality and had a robust deviation of constant variance. This suggests that the Trimmed Model 1 is a stable model and the final Model 1. The Alternative Model 1 has higher metrics than the Trimmed Model 1, but its sole purpose was to demonstrate that the Trimmed Model 1 is indeed a strong model and that it behaves the same way with all of its issues removed. The following regression model is the cost estimating relationship for Model 1:

$$\widehat{CER\ Model}\ 1 = -\$115{,}363.70 + \$90{,}941.47 * Cohort + \$93{,}115.58 * Stealth + \$23{,}984.99 * \ln(Speed) - \$25{,}872.60 * Fighter\ Aircraft - \$18{,}477.43 * Legacy + \$0.3369 * Empty\ Weight$$

To interpret CER Model 1, the subsequent explanation is how each independent variable effects recurring T100 flyaway costs. First, the intercept -$115,36.70 is simply a baseline, and cannot be interpreted for we never observed an instance where all of the *x* variables took on the value zero. If an aircraft is a member of the cohort, it increases the response variable by $90,041.47K. If an aircraft has stealth technology, it increases the response variable by $93,115.58K. Each unit increase in the natural log of an aircraft's speed (in knots), increases the response variable by $23,984.99K. If an aircraft has a fighter system type, it decreases the response variable by $25,872.60K. If an aircraft is identified as a legacy aircraft (which will not be the case for any future aircraft), then it decreases the response variable by $18,477.43K. Lastly, each pound increase in an aircraft's empty weight, increases the response variable by $0.3369K (or $336.90).

To demonstrate the effect that each explanatory variable has on the response, the absolute values of the standardized betas are presented in Table 23. The Pareto chart in Figure 33 provides a visual representation of this data, where Cohort has the largest effect on recurring T100 flyaway costs, followed closely behind by EW and Stealth.

Table 23. Model 2 – Absolute Values of Standardized Betas Ranked Largest to Smallest

Variable	Absolute Value of Standardized Betas
Cohort	0.4224
EW	0.3764
Stealth	0.3703
ln(S)	0.2163
ST4	0.2109
Legacy	0.1524

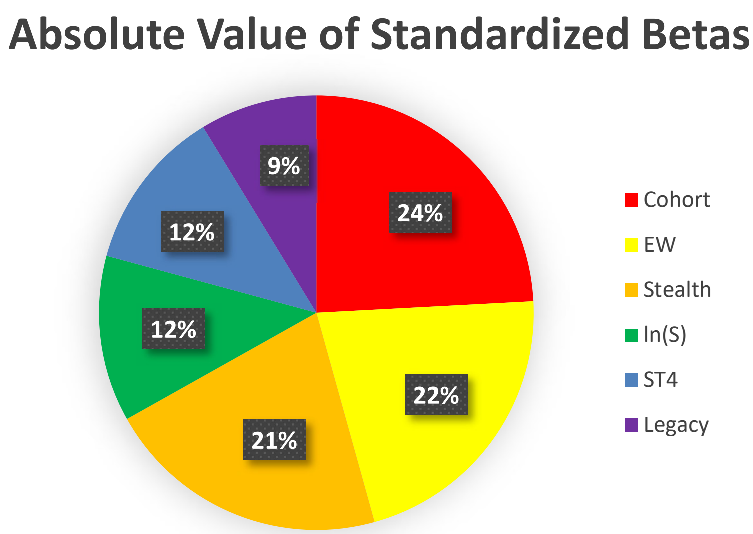


Figure 33. Model 1 – Pie Chart Displaying Pareto Analysis Effect of Model Inputs

When utilizing Model 1 to estimate the cost of an aircraft's recurring T100 flyaway costs, it is paramount to only enter data that is within the limits of the dataset used to create the model. To ensure that Model 1 is not extrapolated beyond the limits of the variables, the boundaries for applying Model 1 are stated in Table 24. An example for how to apply Model 1 and create a 95% confident interval is demonstrated in the next section.

Table 24. Boundaries for Applying Model 1

Variable	Minimum	Maximum
Cohort – Airframe Unit Weight	111,899 lbs	310,484 lbs
Cohort – Empty Weight	162,228 lbs	356,797 lbs
Cohort – Engine Count	4	4
Empty Weight	2,183 lbs	356,797 lbs
Ln(Speed)	Ln(150 knots) = 5.0106	Ln(1434 knots) = 7.2682

Example Applying Model 1 to Program A

To show how to apply Model 1, data for Program A is used as an example. Table 25 contains the data that will be entered into Model 1, which are the bold numbers in the equation that follows.

Table 25. Program A Data for Applying Model 1

Variable	Program A Data
Cohort	0
Stealth	1
ln(S)	Ln(1,434.79) = 7.2688
ST4	1
Legacy	0
EW	45,475.98

$$Program\ A\ \widehat{Recurring\ T}100\ Flyaway\ Cost = -\$115{,}363.70 + \$90{,}941.47 * \mathbf{0} + \$93{,}115.58 * \mathbf{1} + \$23{,}984.99 * \mathbf{7.2688} - \$25{,}872.60 * \mathbf{1} - \$18{,}477.43 * \mathbf{0} + \$0.3369 * \mathbf{45{,}475.98} = \$\mathbf{141{,}542.23K}$$

When applying Program A data to Model 1, the predicted cost is $141,542.23K, and compared to the actual cost ($158,672.33K) has a percent error of about 10.8%. The 95% and 99% confidence interval (shown in Table 26) were created by utilizing the Fit Model function in JMP Pro. A summary of the Program A example is given in Table 26.

Table 26. Results of Program A Estimate by Applying Model 1

Program A Estimate Summary (in $K)	
Predicted Recurring T100 Flyaway Costs	$141,542.23
95% Confidence Interval	[$121,747.97, $161,335.99]
99% Confidence Interval	[$115,280.66, $167,803.31]
Actual Recurring T100 Flyaway Costs	$158,672.33

CER Model 2

The initial stepwise regression for the second model was analyzed with all of the same variables from Model 1, plus EMD, and produced only four variables that are shown in Table 27. The four variables in Table 27 are ranked highest to lowest based on their *t* ratios, which shows that Cohort (the same inclusion criteria as with the first CER development) has the strongest effect on the response, followed by EMD. As a reminder, ST6 represent the aircraft that have a patrol system type and Qt are the quantified units of each aircraft. However, with a *p*-value of 0.0708, Qt does not pass the Bonferroni correction of 0.025 (0.10/4). The complete results of the step history are located in Appendix A.

Table 27. Preliminary Model 2 - Estimate and Effect Summary

Term	Estimate	*t* Ratio	*p*-value	VIF
Cohort	139589.5	14.89	<.0001	1.1596
EMD	0.004392	10.42	<.0001	1.1174
ST6	44210.21	2.81	0.0070	1.0257
Qt	-15.684	-1.84	0.0708	1.1256

Table 28 contains the metrics for the Preliminary Model 2, and with an R^2 of 0.9044 and an adjusted R^2 of 0.8973, the model, similar to the Preliminary Model 1, accounts for a substantial amount of the variation amongst recurring T100 flyaway costs. Additionally, the drop from the adjusted R^2 of 0.8973 to the PRESS R^2 of 0.8534 indicates some inflating of the model. Figure 34 is an overlay plot of the Cook's D influence for the Preliminary Model 2, with points greater than 0.5 highlighted. The three highlighted points are the B-2A, P-3C, and P-8A. With the highlighted points removed, the four variables from the Preliminary Model 2 were analyzed through stepwise regression again, which trimmed the model to only two explanatory variables: Cohort and EMD.

Table 28. Preliminary Model 2 – Metrics

Preliminary Model 2 Metrics	
R^2	0.9044
Adjusted R^2	0.8973
PRESS R^2	0.8534

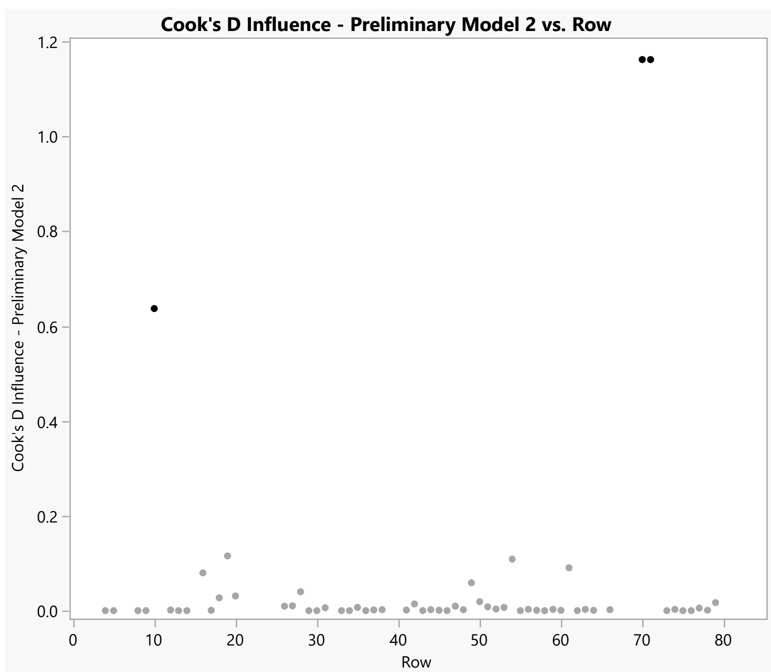


Figure 34. Preliminary Model 2 – Overlay Plot of Cook's D Influence with Points > 0.5 Highlighted

Trimmed Model 2

The three datapoints that were removed were then included back into the trimmed model and fitted through standard least squares regression. This new model is referred to as the Trimmed Model 2 and is displayed in Figure 35. The estimate and effect summary for the Trimmed Model 2 is in Table 29 and reveals that Cohort still has the largest effect on the response. However, both explanatory variables, Cohort and EMD, have p-values < 0.0001 and therefore pass the Bonferroni correction of 0.05 (0.10/2). Additionally, since there are only two explanatory variables in the model, they have the same VIF score which is slightly above one, indicating nearly zero multicollinearity. Lastly, Table 30 contains the metrics for the Trimmed Model 2 and with the R^2 (0.8814), adjusted R^2 (0.8771), and PRESS R^2 (0.8623) being very close together, it expresses a stable model.

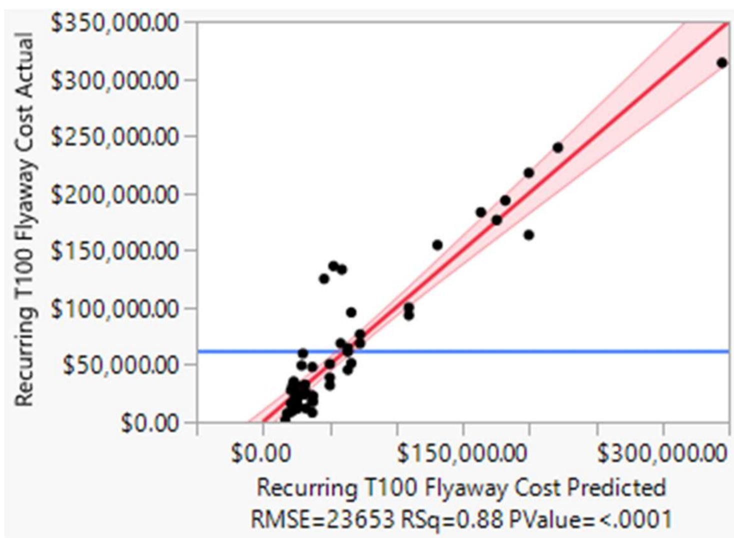


Figure 35. Trimmed Model 2 – Actual by Predicted Values

Table 29. Trimmed Model 2 – Estimate and Effect Summary

Term	Estimate	t Ratio	*p*-value	VIF
Cohort	142033.5	14.28	<.0001	1.0916
EMD	0.004471	9.81	<.0001	1.0916

Table 30. Metrics for Trimmed Model 2 vs Preliminary Model 2

Metric	Trimmed Model 2	Preliminary Model 2
R^2	0.8814	0.9044
Adjusted R^2	0.8771	0.8973
PRESS R^2	0.8623	0.8534

Trimmed Model 2 Diagnostics and Assumptions

The first diagnostic assessed for the Trimmed Model 2 is the studentized residuals to identify any outliers. Figure 36 displays a histogram of the studentized residuals with three points highlighted that are greater than three: the F-117A, P-8A, and B-58A. These three aircraft were verified to be correctly entered into the dataset, and therefore are true outliers. For the next diagnostic, Figure 37 is an overlay plot of Cook's D influence for the Trimmed Model 2 with only one datapoint flagged as overinfluencing, the B-2A.

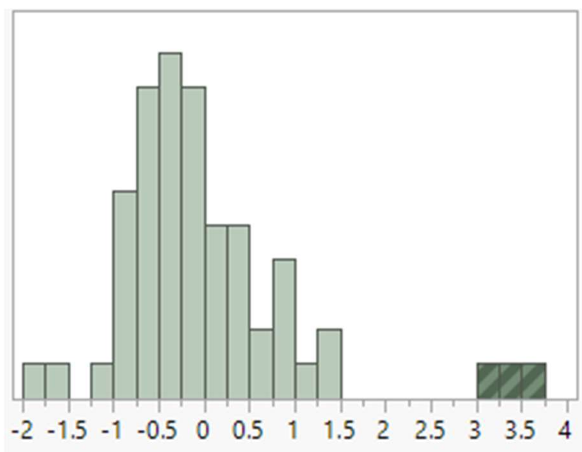


Figure 36. Trimmed Model 2 – Histogram of Studentized Residuals with Outliers Highlighted

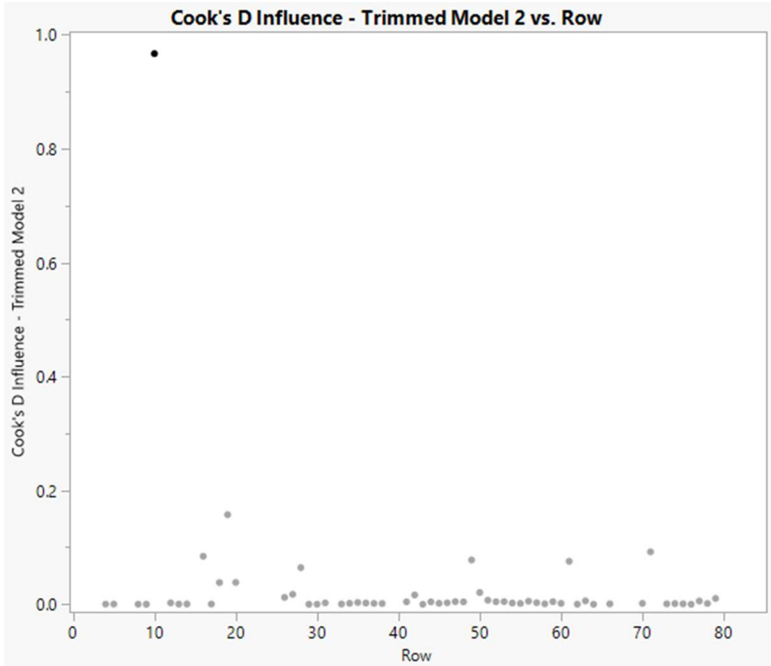
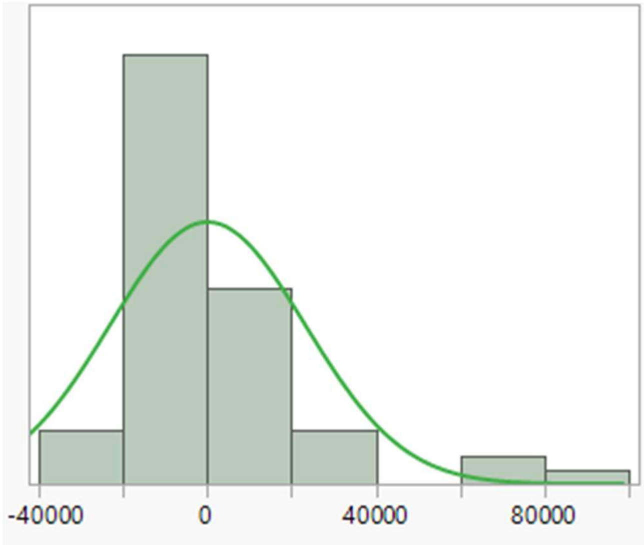


Figure 37. Trimmed Model 2 – Overlay Plot of Cook's D Influence with Points > 0.5 Highlighted

After the diagnostics are assessed, the conditions of normality and constant variance are tested. To test for normality, Figure 38 shows a histogram of the residuals with a normal fitted line that is skewed right, potentially due to the outliers identified in the diagnostics assessment. With the *p*-value of the Anderson-Darling test <.0001, the null hypothesis is rejected concluding the residuals are not normally distributed.



Anderson-Darling Test	
A2	Prob > A2
3.014	<.0001

Figure 38. Trimmed Model 2 – Histogram of Residuals with Accompanying Anderson-Darling Test

To test for constant variance, Figure 39 displays the variance of the residuals, which shows no flaring and a relatively uniform height of the residuals. The results of the Breusch-Pagan test in Table 31 have p-value of 0.1827, which fails to reject the null hypothesis and concludes that the Trimmed Model 2 has constant variance. However, the failure of the normality assumption makes the results of the Breusch-Pagan test perhaps questionable. Therefore, to demonstrate robustness of constant variance, both assumptions are tested again on an alternative model.

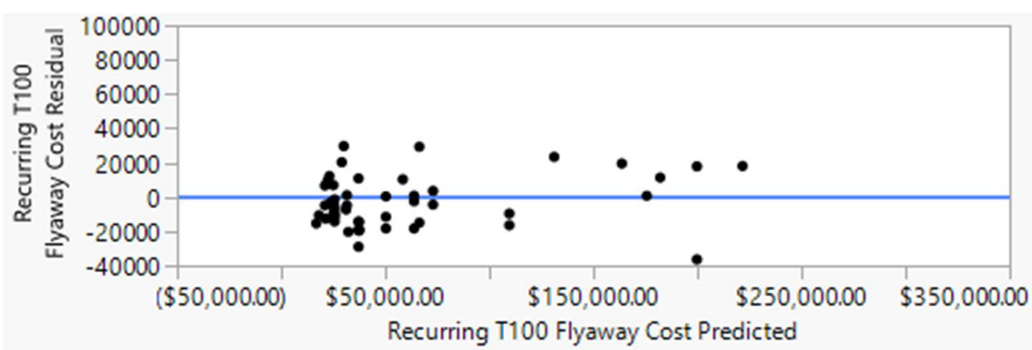


Figure 39. Trimmed Model 2 – Residuals by Predicted Values

Table 31. Trimmed Model 2 – Results of Breusch-Pagan Test

Breusch-Pagan Test					
Model Degrees of Freedom	Sample Size	Sum of Squares Error	Sum of Squares Model	Test Statistic	*p*-Value
2	59	3.133E+10	1.9175E+18	3.4001	0.1827

The importance for passing these assumptions was previously discussed for the prior model, and for the same reasons, an alternative to the Trimmed Model 2 will be created for comparison. To accomplish this, the outliers and overinfluencing datapoints are removed from the model, ran through standard least squares regression again, and assessed for outliers and influential datapoints until there are no longer any present. Through this process, there was only one additional datapoint that was flagged, the C-5B. The removal of the five datapoints (the B-2A, B-58A, C-5B, F-117A, and P-8A) created a new model, referred to as the Alternative Model 2. Exactly like Model 1, this step is performed to determine if the result of the model is significantly altered without the misfit datapoints, or if it is indeed a stable model.

Alternative Model 2

Figure 40 is a model of the actual by predicted values for Alternative Model 2, which is the Trimmed Model 2 minus the B-2A, B-58A, C-5B, F-117A, and P-8A. Table 32 compares the estimate and effect summary from the Trimmed Model 2 and Alternative Model 2, suggesting comparable outcomes in both models. Table 33 displays the same trends that occurred in model 1, where the exclusion of datapoints with the worst fits artificially inflate the metrics. Once again, this is expected.

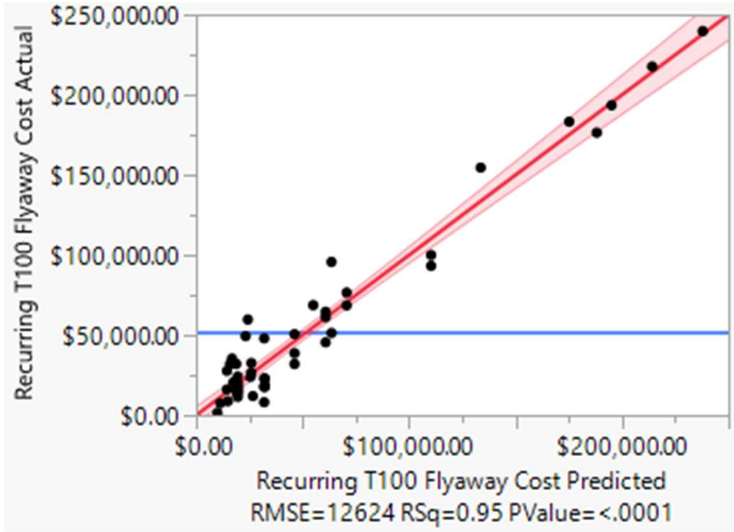


Figure 40. Alternative Model 2 – Actual by Predicted Values

Table 32. Estimate and Effect Summary for Alternative Model 2 vs Trimmed Model 2

Term	Model	Estimate	*p*-value	Std Beta	VIF
Cohort	Alternative	159965.8	<.0001	0.8250	1.0034
	Trimmed	142033.5	<.0001	0.6864	1.0916
EMD	Alternative	0.004836	<.0001	0.4753	1.0034
	Trimmed	0.004471	<.0001	0.4718	1.0916

Table 33. Metrics for Alternative Model 2 vs Trimmed Model 2

Metric	Alternative Model 2	Trimmed Model 2
R^2	0.9524	0.8814
Adjusted R^2	0.9505	0.8771
PRESS R^2	0.9460	0.8623

Alternative Model 2 Diagnostics and Assumptions

A histogram of the studentized residuals in Figure 41 shows that no datapoints are further than three standard deviations from zero, signifying no outliers. Figure 42 is an overlay plot of Cook's D for the Alternative Model 2, and although there is a point slightly less than 0.45, no points are greater than 0.50, which was the established benchmark for an overinfluencing data point. The results of the diagnostics were already predetermined because the Alternative Model 2 was created by removing the points highlighted by the diagnostic tests. This simply proves that the process was correctly done, which is essential in proving that the Trimmed Model 2 is stable.

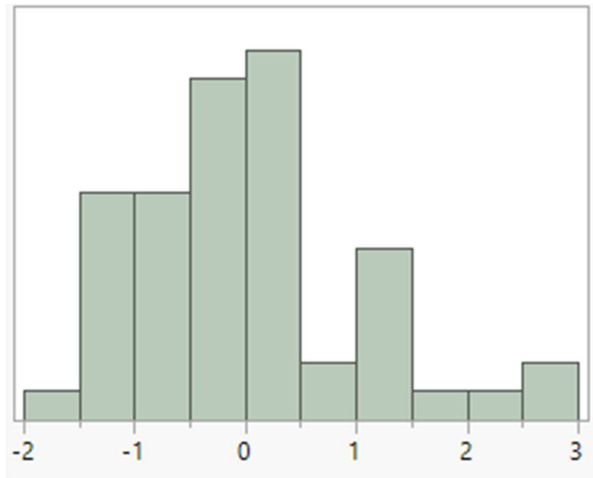


Figure 41. Alternative Model 2 - Histogram of Studentized Residuals

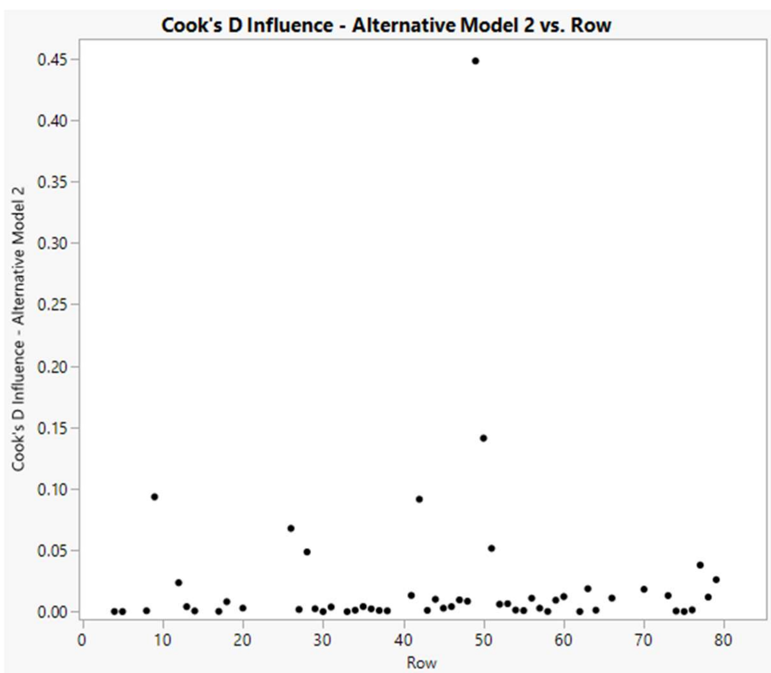
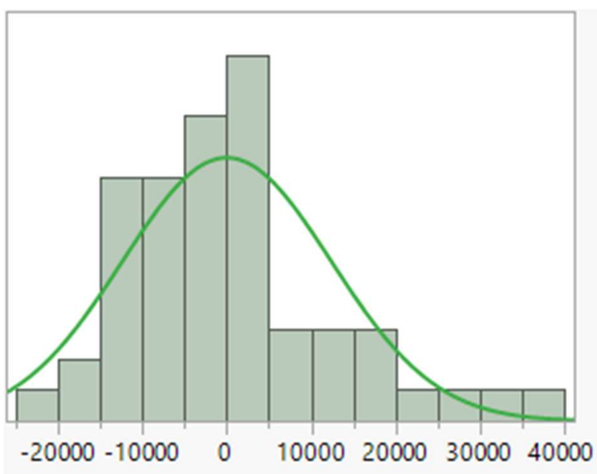


Figure 42. Alternative Model 2 – Overlay Plot of Cook's D Influence

The results that were not predetermined and must still be tested are the conditions of normality and constant variance. Figure 43 is a histogram of the residuals with a normal fitted line that is still somewhat skewed right, even though it is not as predominant as the Trimmed Model 2. This is confirmed with the results of the Anderson-Darling test that has a *p*-value of 0.022, which still rejects the hypothesis (at a 0.05 level of significance) that the residuals are normally distributed. However, the close resemblance of the fitted line in Figure 43 to a standard bell curve demonstrates a good failure of normality, and not one that would invalidate the results of the model's *p*-values nor the following Breusch-Pagan test. Figure 44 are the residuals by predicted values, and there is still an appearance of constant variance. This is verified with the results of the Breusch-Pagan test in Table 34 that has a *p*-value of 0.2401, failing to reject the null hypothesis and concluding that the Alternative Model 2 does indeed have constant variance.



Anderson-Darling Test	
A2	Prob > A2
0.822	0.022

Figure 43. Alternative Model 2 - Histogram of Residuals with Accompanying Anderson-Darling Test

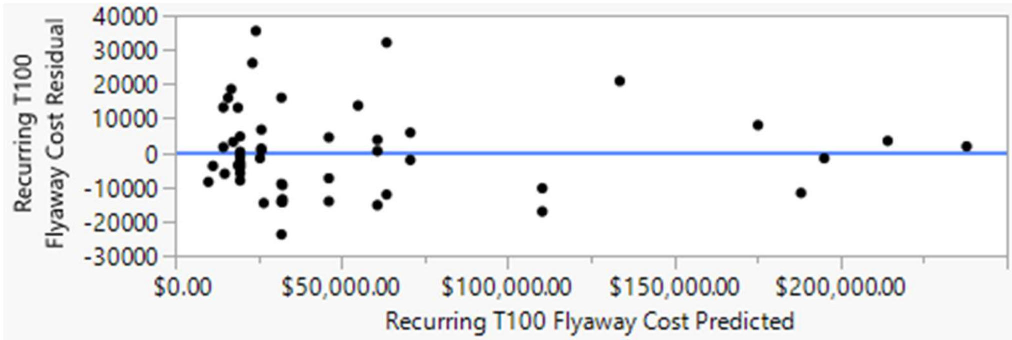


Figure 44. Alternative Model 2 – Residuals by Predicted Values

Table 34. Alternative Model 2 – Results of Breusch-Pagan Test

Breusch-Pagan Test					
Model Degrees of Freedom	Sample Size	Sum of Squares Error	Sum of Squares Model	Test Statistic	*p*-Value
2	54	8.127E+09	1.2927E+17	2.8535	0.2401

Final Model 2

The results of the Alternative Model 2 show that the outliers and overinfluential datapoints present in the Trimmed Model 2, do not have an altering effect on the model. Due to this, the Trimmed Model 2 is determined to be stable, and is the final Model 2. The following regression model is the cost estimating relationship for Model 2:

$$\widehat{CER\ Model}\ 2 = \$16{,}686.84 + \$142{,}033.49 * Cohort + \$0.004471 * EMD\ Costs$$

As with Model 1, to interpret CER Model 2 the subsequent explanation is how each independent variable effects recurring T100 flyaway costs. Once again, the intercept \$16,686.84 is a baseline and cannot be interpreted. If an aircraft is a member of the cohort, it increases the response variable by \$142,033.49K. Lastly, each dollar increase in EMD costs increases the response variable by \$0.00471K (or \$4.471).

To demonstrate the effect that each explanatory variable has on the response, the absolute values of the standardized betas are presented in Table 35. The Pareto chart in Figure 45 provides a visual representation of this data, where Cohort has the largest effect on recurring T100 flyaway costs. However, supplying 41% of the effect on the response, EMD possesses a strong impact as well.

Table 35. Model 2 – Absolute Values of Standardized Betas Ranked Largest to Smallest

Variable	Absolute Value of Standardized Betas
Cohort	0.6864
EMD	0.4718

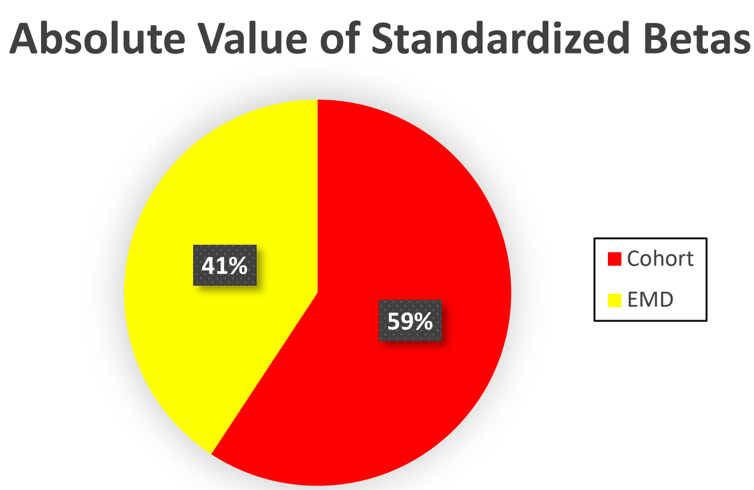


Figure 45. Model 2 – Pie Chart Displaying Pareto Analysis Effect of Model Inputs

As with Model 1, it is important to only apply Model 2 within the boundaries of the data utilized to develop it, which are contained in Table 36. An example for how to apply Model 2 and generate a 95% and 99% confident interval are shown in the next section.

Table 36. Boundaries for Applying Model 2

Variable	Minimum	Maximum
Cohort – Airframe Unit Weight	111,899 lbs	310,484 lbs
Cohort – Empty Weight	162,228 lbs	356,797 lbs
Cohort – Engine Count	4	4
EMD Costs	$36,793.92	$41,667,947.73

Example Applying Model 2 to Program A

To show how to apply Model 2, data for the Program A is used as an example again. Table 37 contains the data that will be entered into Model 2, which are the bold numbers in the equation that follows.

Table 37. Program A Data for Applying Model 2

Variable	Program A Data
Cohort	0
EMD Costs	$26,754,134.53

$$Program\ A\ \widehat{Recurring\ T}100\ Flyaway\ Cost$$

$$= \$16{,}686.84 + \$142{,}033.49 * \mathbf{0} + \$0.004471 * \$\mathbf{26{,}754{,}134.53}$$

$$= \$\mathbf{136{,}304.58K}$$

When applying Program A data to Model 2, the predicted cost is $136,304.58K, and compared to the actual cost ($158,672.33K) has a percent error of about 14.1%. This is not as close of an estimate as Model 1 (10.8% error), but it is still reasonably close. A summary of the Program A example is given in Table 38, along with a 95% and 99% confidence interval that was created in JMP Pro as with Model 1.

Table 38. Results of Program A Estimate by Applying Model 2

Program A Estimate Summary (in $K)	
Predicted Recurring T100 Flyaway Costs	$136,304.58
95% Confidence Interval	[$116,243.85, $156,383.73]
99% Confidence Interval	[$109,598.70, $163,028.88]
Actual Recurring T100 Flyaway Costs	$158,672.33

Summary

Chapter IV presented all of the analysis and results for developing the two CER models that estimate recurring T100 flyaway costs. It first assessed the descriptive statistics for each variable in order to identify any trends. Next, it statistically tested those trends which created a new variable, Cohort, as well as analyzed what effect each individual variable had on the response. Subsequently, a method of stepwise regression and variable trimming was performed to create each model, that was then put through a rigorous process of assumptions and diagnostic testing to prove each model’s stability. Lastly, each model’s uncertainty was characterized and guidelines for applying it were established. The next and final chapter, Chapter V, addresses the research questions, relevance of our findings, and provides conclusions for this thesis.

V. Conclusions and Recommendations

Chapter Overview

This chapter reintroduces the two CER models that were created and highlights the major takeaways. Then it responds to the four research questions originally proposed and compares the results to prior research. Finally, it provides recommendations for future research and concludes this thesis.

Conclusions of Research

After investigating 33 variables and 82 aircraft, two CERs were developed that we believe can be utilized to estimate future recurring T100 flyaway costs. The first model that was produced is presented again in Equation 1 with a snapshot of its performance in Table 39. All six variables in this model have information that is available prior to Milestone B, making it applicable early in the acquisition lifecycle well before flyaway costs are incurred. The second model is shown in Equation 2 with a snapshot of its performance in Table 40. Only two explanatory variables were selected for this model, Cohort and EMD costs, and while Cohort can be determined near Milestone B in the acquisition lifecycle, EMD costs can only be incurred near Milestone C. This is still before the production phase when flyaway costs occur, but this does make the applicability of Model 2 more limited than Model 1.

Equation 1. CER Model 1

$$\widehat{Recurring\ T100\ Flyaway\ Costs}$$
$$= -\$115{,}363.70 + \$90{,}941.47 * Cohort + \$93{,}115.58 * Stealth$$
$$+ \$23{,}984.99 * \ln(Speed) - \$25{,}872.60 * Fighter\ Aircraft$$
$$- \$18{,}477.43 * Legacy + \$0.3369 * Empty\ Weight$$

Table 39. Summary of CER Model 1

CER Model 1	
R^2	0.8919
Adjusted R^2	0.8833
PRESS R^2	0.8529
Sample Size	82
Variables Investigated	32

Equation 2. CER Model 2

$$\widehat{Recurring\ T100\ Flyaway\ Costs}$$
$$= \$16{,}686.84 + \$142{,}033.49 * Cohort + \$0.004471 * EMD\ Costs$$

Table 40. Summary of CER Model 2

CER Model 2	
R^2	0.8814
Adjusted R^2	0.8771
PRESS R^2	0.8623
Sample Size	59
Variables Investigated	33

A significant discovery in this thesis was the identification of the variable Cohort, which was the only variable included in both models. Additionally, as seen via the Pareto analyses, it has the greatest impact on the response for both models. Cohort was identified in several scatter plots as a group of seven aircraft that moved together as demonstrated in Figure 46. The seven aircraft in the dataset that are members of the cohort are E-3A, E-6A, B-2A, B-1B, C-17A, C-5A, and C-5B. Their complete criteria are shown again in Table 41, and they are essentially amongst the heaviest aircraft in the dataset with four engines (also shown in Figure 46). Future aircraft that will likely be members of this cohort and whose flyaway cost estimate will benefit from this finding include the B-21.

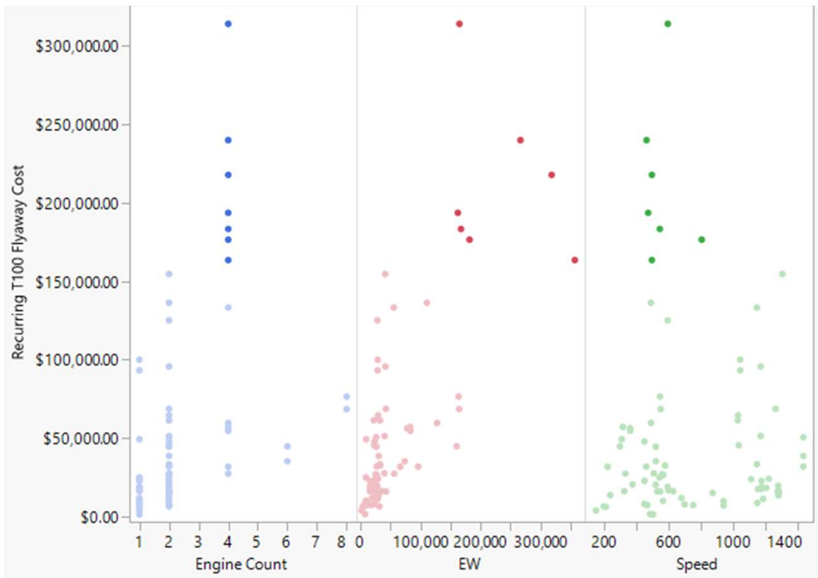


Figure 46. Scatterplot of Recurring T100 Flyaway Cost vs Engine Count, EW, and Speed with Cohort Highlighted

Table 41. Inclusion Criteria for Cohort

Criteria
1. AUW > 111,000
2. EW >162,000
3. Engine Count = 4

Another major takeaway from this thesis is the identification of a proxy for complexity, and how strong of a variable EMD is in predicting T100 flyaway costs. Yes, Stealth combined with Legacy were shown to be a significant proxy for complexity, but it's practically useless if EMD costs are accessible. The fact that the moment EMD costs are introduced into stepwise regression analysis, five previously significant variables (EW, Stealth, ln(S), ST4, and Legacy) drop off, reveals the power of EMD. So, even if a practitioner does not utilize Model 1 nor Model 2 for a future cost assessment, we would implore them to at least attempt to capture complexity in their estimate and incorporate EMD costs if available.

Research Questions Revisited

Research Question 1

What type of effect, if at all, does an aircraft's system type have on recurring T100 flyaway costs?

After individually testing the effect that each system type has on the response, three out of the ten system types were significant predictors of T100 flyaway costs at a 5% level of significance: bomber, fighter, and reconnaissance aircraft. However, after performing the stepwise regression analysis and trimming for Model 1, fighter aircraft was the only system type predictive of flyaway costs. For Model 2, there were no system types included.

Answer: An aircraft's system type does not have an effect on recurring T100 flyaway costs, with the exception of fighter aircraft in certain circumstances (such as when EMD costs are not evaluated). For Model 1, if an aircraft has a fighter system type, it decreases recurring T100 flyaway costs by $25,872.60K.

Research Question 2

What is an adequate proxy for complexity in estimating recurring T100 flyway costs?

To recall there were three variables assessed to address this question: Stealth, Legacy, and EMD. This part of the analysis provided some interesting results, mainly that complexity does play an important role in predicting flyaway costs, but the appropriate way to represent it depends on when it will be applied. As mentioned, Model 2 cannot be used to estimate recurring T100 flyaway costs until EMD costs are incurred, and therefore EMD is not an adequate proxy for complexity prior to the EMD phase.

Nevertheless, that does not mean that Stealth and Legacy are better proxies for complexity than EMD. From the results of the two models, it is already shown that all three variables can be proxies for complexity. However, Legacy (which has a negative effect on the response variable) and Stealth (which has a positive effect on the response variable) are only significant when assessed without EMD, because as soon as EMD is brought into the regression analysis Legacy and Stealth both drop out of the model. For Model 2, each dollar increase in EMD costs increases recurring T100 flyaway costs by \$0.00471K (or \$4.471).

Answer: The best proxy for complexity that has been tested in this thesis is EMD, but in the absence of EMD costs the combination of Legacy and Stealth are adequate.

Research Question 3

Which calculation of weight (empty weight, airframe unit weight, or aircraft density) best predicts recurring T100 flyaway costs?

There were differing results amongst prior research between what version of weight is the best predictor for aircraft airframes, and it varied from empty weight (EW) to airframe unit weight (AUW). Therefore, this thesis included both weights as potential variables in addition to aircraft density (AD), which is a calculation that uses EW and AUW as proxies for an aircraft's volume. As seen in the final equation for Model 1, empty weight was more predictive than AUW and AD. Despite this, none of the three variables discussed in this section were included in Model 2. This is likely due to EMD costs already accounting for weight and the discovery of the variable Cohort. The inclusion criteria for Cohort suggests that while the weight of an aircraft is a predictor of recurring T100 flyaway costs, an even stronger predictor is if the aircraft is exceptionally heavy and has four engines.

Answer: Out of the three variables tested, empty weight is the strongest predictor for recurring T100 flyaway costs. For Model 1, each pound increase in empty weight increases recurring T100 flyaway costs by $0.3369K (or $336.90).

Research Question 4

How does an aircraft's contractor influence recurring T100 flyaway costs?

Similar to Research Question 1, after individually testing the effect that each of the six contractors have on the response, Boeing was the only significant predictor of recurring T100 flyaway costs at a 5% level of significance. However, there were no contractor variables included in either of the final two models.

Answer: None of the contractors assessed in this thesis have a meaningful influence on recurring T100 flyaway cost.

Comparison to Previous Studies

Several variables were investigated in this thesis due to their inclusion in prior equations, and the results of this thesis are consistent with the findings of previous research. Weight and maximum speed were the two variables consistently identified as positive cost drivers for aircraft airframes or production support elements, and Model 1 confirms that this is still valid with both variables increasing flyaway costs. However, a discovery in this thesis is that EMD costs are a more significant cost driver than speed and weight combined, due to the fact that weight and speed are already captured by EMD costs.

Another similar finding with a prior study is the significant influence that fighter aircraft have on production related costs. Hess and Romanoff (1987) attempted to create a set of CERs for attack, fighter, and bomber/transport airframe costs, but were only able to identify an acceptable model for fighter aircraft. Once again aligning with previous research, Model 1 confirms that fighter aircraft are the only system type that is a significant predictor of flyaway costs.

Recommendations for Future Research

There were certain variables that were not considered in this thesis due to the effect they may have on the size of the dataset. The material and material mix of an aircraft may be predictive of an aircraft's airframe cost, but the level of detail required for such variable was not obtainable for most aircraft. However, since we chose a larger dataset over a larger collection of potential explanatory variables, another researcher could explore the alternative route and sacrifice sample size for data. This could include other overlooked variables such as manufacturing techniques and labor hours.

On a broader scale not involving T100 flyaway costs, it would be intriguing to assess how predictive EMD costs are in estimating other phases of the acquisition lifecycle, specifically operations and support (O&S). An alternative to this could be investigating just how close of a proxy EMD costs are for complexity of an aircraft. This could involve subject matter expert (SME) input to define a complexity rating scale and then compare it to EMD costs. As mentioned in the Key Findings, we truly believe there could be more usage for EMD cost as a predictor for cost estimates, and that complexity does not need to be as elusive as we think.

Summary

This chapter concludes this thesis by summarizing the results, answering the research questions, and providing suggestions for future research. This thesis investigated two large datasets to create two models that estimate recurring T100 flyaway costs. In the end, which model is better? That depends on where in the acquisition lifecycle a program is when a flyaway cost estimate is created. With the second model including all of the variables, its results are stronger than the first model's. However, the second model can only be applied once EMD costs are known, which makes the first model more appropriate in the earlier phases of an aircraft's lifecycle.

Appendix A – Aircraft Analyzed in Dataset

Mission Design Series (MDS)	Aircraft Name	Number of Aircraft Produced	Analyzed in Model 2
A-10A	Thunderbolt II	503	Yes
A-3A/B	Skywarrior	193	
A-4A	Skyhawk	158	
A-5A/RA-5C	Vigilante	109	
A-6A	Intruder	416	Yes
A-6E	Intruder	205	Yes
A-7A/B	Corsair II	388	
A-7D	Corsair II	459	
B-1B	Lancer	100	Yes
B-2A	Spirit	21	Yes
B-36A	Peacemaker	328	
B-47A	Stratojet	100	Yes
B-52A	Stratofortress	275	Yes
B-52D	Stratofortress	427	Yes
B-57A	Canberra	277	
B-58A	Hustler	103	Yes
B-66B	Destroyer	131	Yes
C-123B	Provider	280	
C-130A	Hercules	159	
C-130J	Super Hercules	100	
C-131A	Samaritan	26	
C-141A	Starlifter	284	Yes
C-17A	Globemaster III	112	Yes
C-27J	Spartan	23	
C-5A	Galaxy	74	Yes
C-5B	Galaxy	50	Yes
E-3A	Sentry	31	Yes
E-6A	Mercury	14	Yes
EA-18G	Growler	98	Yes
EA-6B	Prowler	84	Yes
ES-3A	Viking	15	Yes
F/A-18A	Hornet	524	Yes
F/A-18C	Hornet	604	Yes
F/A-18E/F	Super Hornet	563	Yes
F-100A	Super Sabre	1933	Yes
F-101A	Voodoo	807	Yes

F-102A	Delta Dagger	1000	Yes
F-104A	Starfighter	503	Yes
F-105A	Thunderchief	818	Yes
F-106A	Delta Dart	340	Yes
F-111A	Aardvark	141	Yes
F-117A	Nighthawk	59	Yes
F-14A	Tomcat	658	Yes
F-14D	Tomcat	42	Yes
F-15A	Eagle	425	Yes
F-15C	Eagle	575	Yes
F-15E	Strike Eagle	269	Yes
F-16A/B	Fighting Falcon	1188	Yes
F-16C	Fighting Falcon	20	Yes
F-16C/D	Fighting Falcon	474	Yes
F-22A	Raptor	178	Yes
F-35A	Lightning II	67	Yes
F-35B	Lightning II	41	Yes
F-4B	Phantom II	556	Yes
F-4C	Phantom II	634	Yes
F-4D	Phantom II	16	Yes
F4D-1	Skyray	419	
F-4E	Phantom II	924	Yes
F-4F	Phantom II	175	Yes
F-4J	Phantom II	102	Yes
F-5E	Tiger II	614	
F-5F	Tiger II	32	
F-80A	Shooting Star	259	Yes
F-80C	Shooting Star	100	Yes
HC-130J	Combat King II	11	
KC-135A	Stratotanker	577	Yes
MC-130J	Combat Talon II	14	
MQ-1C	Gray Eagle	124	
MQ-9A	Reaper	136	
P-3C	Orion	155	Yes
P-8A	Poseidon	68	Yes
RB-57D	Canberra	20	
RB-66B	Destroyer	73	Yes
RF-4B	Phantom II	46	Yes
RF-4C	Phantom II	365	Yes
RF-4E	Phantom II	106	Yes

RQ-4A	Global Hawk	47	Yes
S-3A	Viking	268	Yes
S-3B	Viking	59	Yes
T-38A	Talon	488	
T-39A	Sabreliner	191	
T-45TS	Goshawk	125	

Appendix B – Stepwise Regression JMP Output

Stepwise Regression Results for Model 1

Step History

Step	Parameter	Action	"Sig Prob"	Seq SS	RSquare	Cp	p	AICc	BIC
1	Cohort	Entered	0.0000	1.99e+11	0.6704	227.94	2	1952.8	1959.72
2	Stealth	Entered	0.0000	3.97e+10	0.8040	105.94	3	1912.4	1921.51
3	EW	Entered	0.0000	1.16e+10	0.8432	71.564	4	1896.38	1907.62
4	Legacy	Entered	0.0006	6.591e+9	0.8654	52.956	5	1886.19	1899.51
5	AUW2	Entered	0.0016	4.92e+9	0.8819	39.57	6	1877.81	1893.14
6	EW1	Entered	0.0135	2.757e+9	0.8912	32.95	7	1873.55	1890.83
7	AUW1	Entered	0.0121	2.648e+9	0.9001	26.671	8	1869.06	1888.22
8	ST5	Entered	0.0339	1.784e+9	0.9062	23.092	9	1866.57	1887.54
9	ST6	Entered	0.0618	1.326e+9	0.9106	20.945	10	1865.24	1887.94
10	EW2	Entered	0.0718	1.192e+9	0.9146	19.219	11	1864.22	1888.58
11	ln(S)	Entered	0.0715	1.156e+9	0.9185	17.603	12	1863.22	1889.16
12	ST4	Entered	0.0020	3.159e+9	0.9292	9.7248	13	1854.66	1882.08
13	ST5	Removed	0.6799	52287666	0.9290	7.8883	12	1851.94	1877.88
14	Ct6	Entered	0.0845	8.959e+8	0.9320	7.087	13	1851.3	1878.72

Stepwise Regression Results for Model 2

Step History

Step	Parameter	Action	"Sig Prob"	Seq SS	RSquare	Cp	p	AICc	BIC
1	Cohort	Entered	0.0000	1.79e+11	0.6775	299.81	2	1418.21	1424.01
2	EMD	Entered	0.0000	5.39e+10	0.8814	77.497	3	1361.5	1369.07
3	ST6	Entered	0.0037	4.48e+9	0.8983	60.836	4	1354.79	1364.05
4	Qt	Entered	0.0708	1.59e+9	0.9044	56.215	5	1353.67	1364.52

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REPORT DOCUMENTATION PAGE			*Form Approved* *OMB No. 074-0188*

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1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From – To)*
23-03-2023	Master's Thesis	October 2021-March 2023

TITLE AND SUBTITLE CREATING A COST ESTIMATING RELATIONSHIP FOR RECURRING T100 FLYAWAY COSTS	**5a. CONTRACT NUMBER** **5b. GRANT NUMBER** **5c. PROGRAM ELEMENT NUMBER**
AUTHOR(S) Rojo, Kyrie M.	**5d. PROJECT NUMBER** **5e. TASK NUMBER** **5f. WORK UNIT NUMBER**
7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S) Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/EN) 2950 Hobson Way, Building 640 WPAFB OH 45433-7765	**8. PERFORMING ORGANIZATION REPORT NUMBER** AFIT-ENV-MS-23-M-228
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Air Force Life Cycle Management Cost Staff Shawn Valentine, Civ, USAF 1865 Fourth Street, Building 14, Area B Wright-Patterson AFB, OH 45433-7765 937-656-5504 ATTN: Shawn Valentine (shawn.valentine@us.af.mil)	**10. SPONSOR/MONITOR'S ACRONYM(S)** AFLCMC/FZCE **11. SPONSOR/MONITOR'S REPORT NUMBER(S)**

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

13. SUPPLEMENTARY NOTES
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14. ABSTRACT
This research investigates a dataset of over 80 Air Force and Navy aircraft and applies regression techniques to create two cost estimating relationships (CERs) for predicting recurring T100 flyaway costs, depending on where in the acquisition lifecycle the estimate takes place. The first CER explains 89 percent of the variation in the dataset and can be applied prior to Milestone B (MS B). The second CER explains 88 percent of the variation in the dataset and can be applied between MS B and MS C. Significant cost drivers identified include stealth, cohort, empty weight, the natural log of speed, legacy aircraft, fighter aircraft, and Engineering and Manufacturing Development costs. This research is the largest aircraft regression study to date for recurring T100 flyaway costs and can be used by cost analysts as a reliable cross-check in early estimates.

15. SUBJECT TERMS
T100, Flyaway Costs, Cost Estimating Relationship, Model Building

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			Dr. Edward D. White III, AFIT/ENC
U	U	U	UU	116	**19b. TELEPHONE NUMBER** *(Include area code)* (937) 255-3636, ext. 4540. e-mail: Edward.White@afit.edu

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Prescribed by ANSI Std. Z39-18