Cost Estimating Relationships for Recurring T100 Flyaway Costs

Kyrie M. Rojo
Edward D. White, Ph.D.
Brandon M. Lucas, Ph.D.
Jonathan D. Ritschel, Ph.D.
Shawn M. Valentine

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 variability and can be applied prior to Milestone B (MS B). The second CER explains 88 percent of the variability 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 cross-check in early estimations.

Introduction

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). These programs need a credible and accurate life cycle cost estimate for the acquisition to be successful. In the Department of Defense (DoD), flyaway costs constitute most of the procurement costs in aircraft acquisition: prime mission equipment, systems engineering and program management, test and evaluation, warranties, engineering changes, nonrecurring startup costs, and government-furnished equipment (Department of Defense, 2022). Thus, accurately estimating flyaway costs is a key component in establishing a realistic acquisition program baseline.

Cost estimating relationships (CERs) for airframes or flyaway costs are typically derived using the 100th production unit. When the 100th production unit is not available, that value is derived via a cost improvement curve (e.g. a learning curve utilizing cost data rather than hours). This 100th production unit is therefore referred to as an UC100, the T100 unit cost, or simply T100 (Department of Defense, 1992). A T100 flyaway cost, therefore, looks specifically at the flyaway costs associated with the T100 unit.

This research is the largest aircraft regression study to date for recurring T100 flyaway costs. The study employs and analyzes historical data to create two CERs. These CERs utilize data prior to production and identify key cost drivers. The results from this paper can be used by program managers or estimators early in the aircraft acquisition life cycle as a cross-check to other methods that might estimate the T100 flyaway cost.

Background

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). A CIC addresses the phenomenon that as tasks are repeated, learning occurs making the task more efficient and therefore cost less (Department of Defense, 2022). A CIC measures the reduction in terms of cost, while the more colloquially known learning curve measures the reduction in terms of hours. This analysis employs the CIC construct.

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. 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 adopt. While a CIC 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.

To understand how the T100 flyaway cost is ascertained with actual aircraft production data, we guide the reader through the following process. First, normalize the data to remove the effect of escalation to constant price (CP$) via the Produce Price Index (PPI) 3364, which details price changes in aerospace products and parts (Bureau of Labor Statistics, 2022). Normalizing to CP$ for a CER is a best practice according to the 2021 OSD-CAPE *Inflation and Escalation Best Practices for Cost Analysis*. One then calculates the average unit cost (AUC) by dividing the lot's recurring flyaway costs by the total number of units produced (see Equation 1).

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

Equation (2) shows how the lot midpoint (LMP) for Lot 1 is calculated.

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

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, then divide the total by four (Equation 3).

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

A linear regression is then performed via the natural logs of the AUC and LMP to estimate the flyaway cost for any unit, taking into consideration cost improvement curve and economies of scale. Equation (4) shows this where ln(LMP) (the explanatory variable) is regressed onto ln(AUC) (the response variable).

$$\hat{Y}_X = \hat{\beta}_0 + \hat{\beta}_1 * X \tag{4}$$

Back-transforming from log space, we arrive at the customary cost improvement curve (5)

$$Y_X = A * X^b \tag{5}$$

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 cost improvement curve

Once these calculations are made and the cost improvement curve equation is computed, one evaluates the equation at X = 100 or Y_{100}. This is the flyaway cost of unit 100 or the T100 flyaway cost. This process results in an approximation of the recurring flyaway cost at the theoretical 100th unit while considering the learning effect. This process is what generated the response data we obtained for our study.

Next, we turn to prior published sources to identify possible explanatory variables for the CERs. Unfortunately, we could find no prior studies that predicted recurring T100 flyaway costs (nor any type of flyaway cost for that matter). The most similar study conducted was published in a series of papers by RAND from 1972 to 2001 and investigated cost drivers for different elements of aircraft airframes. To cast a broader net for research related to flyaway costs, we looked for studies focused on production costs; but it resulted in only one report from 1991, which created cost models for production support elements. Altogether, we explored five prior studies. Table 1 lists and summarizes these studies. For our purposes, they serve as a reference to consider which explanatory variables might be predictive of T100 and the development of the CERs within this article.

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 development and production costs of 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, which 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	This report created CERs for production support elements. No single IV was present in all four CERs, and weight is 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.

*Note: AMPR stands for Aeronautical Manufacturers' Planning Report, while AUW is Airframe Unit Weight.

METHODS

Data

We acquired the data analyzed in this article through the Cost Assessment Data Enterprise (CADE), as compiled by the Air Force Life Cycle Management Center (AFLCMC). Contractor, quantity, and cost data, such as the lot costs required to calculate T100 flyaway costs, were collected via the 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. Speed data was provided by the AFLCMC who compiled the data from past studies.

Once all the initial data was captured, the number of aircraft in the dataset was filtered based on availability of specific aircraft data. For an aircraft to have complete data and be included in the finalized 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 excluded several aircraft, most of which are retired.

We developed two CERs. The first CER investigated all identified explanatory variables but excluded EMD (Engineering & Manufacturing Development) costs as a possible explanatory variable. The reason EMD costs were excluded is due to timing. By excluding EMD costs, the practitioner can use the CER prior to MS B. The EMD cost variable was reinstated for the second CER. However, inclusion of this variable for the second CER reduced the number of aircraft available for CER development. Consequently, we created a separate data inclusion criterion to investigate EMD costs as a cost driver. The total number of aircraft available for both the first and second CER is reflected in Table 2. Because they are a different commodity, helicopters are not considered in this article.

Regarding possible explanatory variables in the development of the CERs, these had to meet the following criteria:

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

Inspiration for these variables stemmed from the previous studies shown in Table 1, in addition to logically associated variables with reoccurring flyaway cost or variables that are speculated to perhaps affect these costs. Table 3 lists the potential independent variables considered along with their descriptions. Tables 4 and 5 further delineate some of these explanatory variables.

Table 2. Aircraft Inclusion and Exclusion Criteria.

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**

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 a lot production that was applied to calculate T100 flyaway cost.
AF	Air Force	Dummy variable where 1 = aircraft produced solely for the Air Force and 0 = it was not.
EC	Engine Count	The total number of engines on an aircraft.
Ct	Contractor	Six dummy variables that represent the current contractors who developed and produced the aircraft in this dataset. See Table 5.
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.**		

Table 4. System Type 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

Table 5. 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

For the Stealth dummy (dichotomous) variable, five aircraft were considered to have stealth technology: B-2A, F-117A, F-22A, F-35A, and F-35B. These were coded as a '1', while the other 77 aircraft were coded a '0'. The reasoning was stealth aircraft might have higher reoccurring flyaway cost due to technological complexity.

For the Legacy dichotomous variable, a similar coding logic was employed. The Legacy variable is intended to capture the age and complexity of an aircraft and is defined by whether 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 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 this 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 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 6.

Table 6. 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

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 reflecting production units that occurred around the 100^{th} unit was selected. However, to investigate when in a program's life cycle weight is the most predictive of T100 flyaway costs, four additional variables are analyzed: EW1 and AUW1 which represents data from the first (or only) weight statement for an aircraft, and EW2 and AUW2 which represents the last.

Two other explanatory variables, Air Force (AF) and engine count (EC), are added for possible CER consideration for exploratory purposes. Of the 82 aircraft, 50 or approximately 61% were Air Force aircraft. Therefore, we were interested to see if there might be a difference between AF and non-AF aircraft with respect to reoccurring flyaway cost. With respect to engines, there are five different engine counts an aircraft can possess as observed in our dataset: 1, 2, 4, 6, or 8. The most common engine count is 2, representing exactly half of the dataset (41 out of 82). For the 1, 4, 6, and 8 engine aircraft, we observed counts of 21, 16, 2 and 2 occurrences, respectively.

Statistical Analysis

The descriptive and inferential analysis documented in this article was accomplished with JMP® Pro 15; and a 10% level of significance is used for most statistical tests. We adopt the method of ordinary least squares (OLS) to build the two CERs featured in this article and utilize a stepwise regression approach. Stepwise regression is an automatic process that screens potential independent variables to determine their best combination in predicting the dependent variable (McClave et al., 2017). 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 examined in this stepwise process.

During this stepwise procedure, we utilize a mixed approach with the p-value threshold set to 0.1 for both inclusion and exclusion. To maintain the overall experimentwise error rate, we incorporated the Bonferroni Correction to set individual significance at 0.1/(number of significant explanatory variables). The response variable was recurring T100 flyaway costs. The possible explanatory variables consisted of all the dummy variables and continuous variables, as denoted earlier in this paper; as well any other noted patterns in the descriptive analysis, which preceded the inferential analysis.

To assess model validity, we assessed normality of residuals via the Anderson Darling test and constant variance via the Breusch-Pagan test. Both tests used a 0.05 level of significance. For model diagnostics, we assessed multicollinearity via the Variance Inflation Factor (VIF), outliers via studentized residuals, and overly influential datapoints via Cook's D. Although we recognize that OLS is robust against deviations from normality and constant variance (Kutner et al., 2004), we needed to determine if the finalized stepwise models were statistically sound and valid for practitioner usage.

In addition to testing assumptions and running diagnostics, the model must also be validated. The metrics employed in this article to explain the model's performance are the R^2, adjusted-R^2, and PRESS R^2 statistics. Because 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 disproportionally reflecting model behavior.

Lastly, we performed a sensitivity analysis on the finalized stepwise CERs to investigate what would occur if we took an austere approach of removing any data point that might be an outlier, influential data point or cause residuals to deviate from normality and/or constant variance. The point of this sensitivity analysis was to not make the models 'appear' more significant than they are (as denoted by a very high R^2), but to ascertain if any other explanatory variable would be statistically significant, if we took such a myopic view. Our sensitivity analysis confirmed our finalized two CERs, which we now present.

Table 7. Summary Statistics of Recurring T100 Flyaway Costs.

Summary Statistics of Dependent Variable (in $K and CP$21)	
N	82
Median	$26,914.42
Mean	$51,297.87
Std Dev	$60,533.16
IQR	$44,118.01

RESULTS

Descriptive

Table 7 presents the summary statistics of the T100 flyaway costs for our sample. All dollar amounts are in Constant Price (CP)$21. Given the difference between the mean and median, we expected to see large flyaway costs associated with some aircraft. As shown in Figure 1, some aircraft with a 4-engine count generally have a much higher threshold of recurring T100 flyaway costs than any other engine count, including the four aircraft with six and eight engines. Delving deeper, Figure 2 depicts this is particularly true for heavier, 4-engine aircraft, as the seven heaviest aircraft had four engines. The highlighted datapoints in Figure 2 suggest a subgroup of heavy, 4-engine aircraft might have

Figure 1. Boxplots of Recurring T100 Flyaway Cost vs Engine Count.

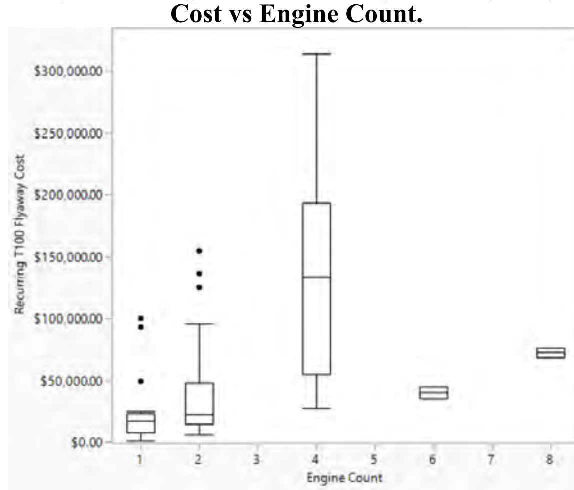
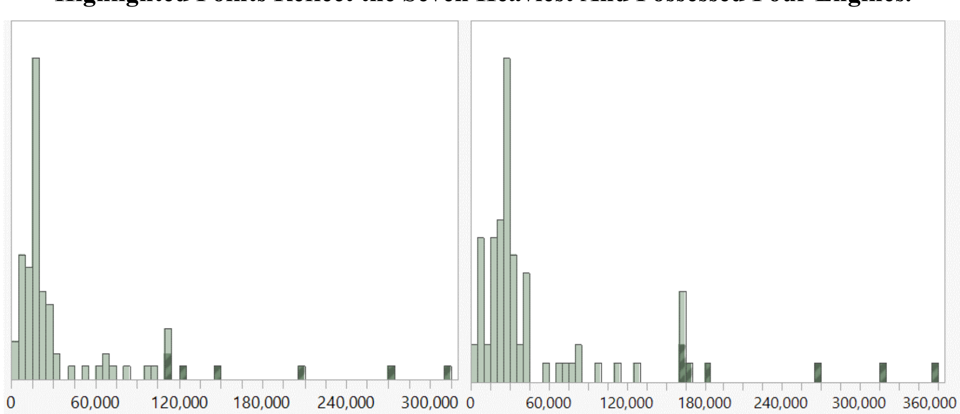


Figure 2. AUW (Left) and EW (Right) Distributions of Aircraft in Study Sample. Highlighted Points Reflect the Seven Heaviest And Possessed Four Engines.



high reoccurring flyaway cost compared to other aircraft in the sample study. Consequently, we created a dummy variable as another explanatory variable for stepwise regression to consider in building the two CERs. Table 8 lists the criteria used for an aircraft to be considered in this cohort, or subgroup. As we shall demonstrate shortly, this cohort became the most significant driver of reoccurring flyaway costs for aircraft. The aircraft in this cohort consisted of the E-3A, E-6A, B-2A, B-1B, C-17A, C-5A, and C-5B.

Table 8. Inclusion Criteria for Cohort.

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

CER Model 1

Tables 9 and 10 present the statistically significant explanatory variables when not including or knowing EMD costs associated with an aircraft. All six variables are significant at the comparisonwise error rate with each *p*-value less than 0.0167 (0.1/6). Although all the various definitions of weight tested individually predictive, stepwise selected EW as the most significant, given the very high VIF scores (in excess of 5000) of the weight explanatory variables when included together. With PRESS R^2, adjusted R^2, and R^2 being relatively close to each other, this result gives an impression of a stable model and suggests CER1 is approximately 85-89% predictive of reoccurring flyaway costs. Equation 6 depicts this model for a practitioner to use, mindful of the ranges applicable to prevent model extrapolation. Those applicable ranges are given in Table 11. Note the coefficients are in $K.

Table 9. CER Model 1.

Variable	Estimate	*t Ratio*	*p-value*
Stealth	93115.58	9.03	<.0001
Cohort	90941.47	6.26	<.0001
Empty Weight	0.336918	5.49	<.0001
ln(Speed in knots)	23984.99	4.08	0.0001
Fighter Aircraft	-25872.6	-3.73	0.0004
Legacy	-18477.4	-3.68	0.0004

Table 10. Metrics for CER Model 1.

Metric	Value
R^2	0.8919
Adjusted R^2	0.8833
PRESS R^2	0.8529

Table 11. Boundaries for Applying CER 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 in knots)	Ln(150 knots) = 5.0106	Ln(1434 knots) = 7.2682

CER Model 2

The process by which we produced the second CER is identical to the first in both initial findings and the robustness check/diagnostics. The initial stepwise regression for the second model was analyzed with all the same explanatory variables from Model 1, plus EMD information. Tables 12 and 13 present our results. Both explanatory

$$\widehat{CER\ Model}\ 1 = -\$115{,}363.70 + \$90{,}941.47 * Cohort + \$93{,}115.58 * Stealth + \$23{,}984.99 * \ln(Speed) - \$25{,}872.60 * Fighter\ Aircraft - \$18{,}477.43 * Legacy + \$0.3369 * Empty\ Weight \quad (6)$$

$$\widehat{CER\ Model\ 2} = \$16{,}686.84 + \$142{,}033.49 * Cohort + \$0.004471 * EMD\ Costs \quad (7)$$

variables are significant at the comparisonwise error rate with each *p*-value less than 0.05 (0.1/2). PRESS R^2, adjusted R^2, and R^2 are relatively close to each other, which again gives the impression of a stable model and suggests the second CER is approximately 86-88% predictive of reoccurring flyaway costs. Equation 7 depicts this model for a practitioner to use, mindful of the ranges applicable to prevent model extrapolation. Those applicable ranges are given in Table 14. Note the coefficients are in $K.

CONCLUSION AND TAKEAWAY

We initially identified 13 explanatory variables (shown previously in Table 3) to be investigated

Table 12. CER Model 2.

Variable	Estimate ($K)	t Ratio	*p-value*
Cohort	142033.5	14.28	<.0001
EMD	0.004471	9.81	<.0001

Table 13. Metrics for CER Model 2.

Metric	Value
R^2	0.8814
Adjusted R^2	0.8771
PRESS R^2	0.8623

Table 14. Boundaries for Applying CER Model 2. Dollars are in $K and CP$21.

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

in the development of two CERs for reoccurring flyaway costs. [Note that Table 3 has two umbrella variables: system type (ST) and contractor (Ct). The individual STs and Cts are not listed in Table 3. Rather, the full set of ST and Ct variables are provided in Tables 4 and 5 respectively]. Combining the full set of categorical variables, ST and Ct, with the initial explanatory variables of Table 3 resulted in 27 variables. Then, to account for the timeline of the different weight statements for empty weight (EW) and airframe unit weight (AUW), four additional weight variables were added: EW1, EW2, AUW1, and AUW2. Ultimately, after visually assessing the descriptive statistics for trends, two final variables were added, the natural log of Speed (ln(S)) and Cohort. Therefore, the total number of explanatory variables considered in developing the two CERs finalized at 33.

Recall that CER 1 does not include the total EMD cost variable. Out of the 32 remaining variables analyzed, six were selected for the final CER 1 model: Cohort, Stealth, ln(Speed in knots), Fighter Aircraft, Legacy, and Empty Weight. All the variables in this model have information available prior to Milestone B, making it applicable well before flyaway costs are incurred. With respect to interpretation of Equation (6), the intercept value of -$115,363.70 is simply a baseline and is uninterpretable for we never observed an instance where all the *x* variables took on the value zero.

The remaining coefficients describe how each explanatory variable effects recurring T100 flyaway costs. If an aircraft is a member of the cohort, it increases reoccurring flyaway costs by $90,941K on average. If an aircraft has stealth technology, it increases costs by $93,115K. For each unit increase in the natural log of an aircraft's speed (in knots), flyaway costs increase by $23,984K. If an aircraft is a fighter system type, it decreases costs by $25,872K on average. If an aircraft is identified as a legacy aircraft (which will not be the case for any future aircraft), then it decreases flyaway costs by $18,477K. Lastly, each pound increase in an aircraft's empty weight increases flyaway costs by $0.3369K (or $336.90). With respect to the explanatory variables' relative weighting and percentage effect on flyaway costs, Table 15 shows those details.

Table 15. Contribution Percentage by Explanatory

Variable	% Effect on CER 1
Cohort	24%
Empty Weight	22%
Stealth	21%
ln(Speed in knots)	12%
Fighter Aircraft	12%
Legacy	9%

All 33 explanatory variables (including total EMD cost) were analyzed for the development of CER Model 2. Of these, only two were selected for the final equation, Cohort and EMD costs. While Cohort can be determined near Milestone B in the acquisition lifecycle, EMD costs can only be incurred near Milestone C, which is still before the production phase when flyaway costs occur. However, this proximity does make the applicability of Model 2 more limited than Model 1. With respect to interpretation of Equation (7), again the intercept is simply a baseline. For the remaining two coefficients, if an aircraft is a member of the cohort, it increases the average reoccurring flyaway cost by $142,033K. Lastly, each dollar increase in EMD costs increases flyaway costs by $0.00471K (or $4.471) – four and a half fold. All dollars reflect CP$21 amounts. With respect to the explanatory variables' relative weighting and percentage effect on flyaway costs, Table 16 shows those details.

A significant discovery in this analysis was the identification of the variable Cohort, which was the only variable included in both CERs. Additionally, as seen in Tables 15 and 16, it has the greatest impact on the response for both models. This subgroup was initially identified in

Table 16. Contribution Percentage by Explanatory

Variable	% Effect on CER 2
Cohort	59%
EMD	41%

several scatter plots as a cluster of seven aircraft and included the E-3A, E-6A, B-2A, B-1B, C-17A, C-5A, and C-5B. While their complete criteria are shown in Tables 11 and 14, they are essentially amongst the heaviest aircraft in the dataset with four engines. Future aircraft that will likely be members of this cohort and whose flyaway cost estimate will benefit from this finding include the B-21.

Another major takeaway from this study is the identification of a proxy for complexity, and how strong a variable EMD is in predicting T100 flyaway costs. Yes, Stealth combined with Legacy were shown to be a significant proxy for complexity, but their effects are greatly diminished if total EMD costs are accessible. In fact, the moment EMD costs are introduced into stepwise regression analysis, five previously significant variables (Empty Weight, Stealth, ln (Speed), Fighter Aircraft, and Legacy) drop out, revealing the predictive power of EMD with respect to reoccurring flyaway costs. So, even if a practitioner chooses neither CER 1 nor CER 2 as a crosscheck for estimating flyaway costs, we advocate capturing complexity in their estimate and incorporating EMD costs, if available.

In summary, this paper fills a gap in the cost estimator toolkit. While previous efforts by RAND and others have developed useful CERs for airframes and other components, no CERs previously existed for recurring flyaway costs. With new aircraft, such as the B-21, T-7, E-7 and Next Generation Air Dominance on the horizon, accurate cost estimates will be of paramount importance. The CERs developed in this paper are a small step in helping achieve more awareness regarding flyaway costs. Thus, we humbly suggest practitioners employ them as a cross-check to their primary methodologies.

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Kyrie M. Rojo , *USAF, is a recent graduate of the Air Force Institute of Technology (AFIT) where she earned a Master's of Science in Cost Analysis. She is currently assigned as a cost analyst for the Aircraft and Weapons Division at the Air Force Cost Analysis Agency. (E-mail address: kyrie.rojo@us.af.mil)*

Dr. ***Brandon M. Lucas*** *is an Assistant Professor of Systems Integration & Cost Analysis in the Department of Systems Engineering and Management at AFIT. He holds a BA in History from the University of Texas at Austin, a MA in International Relations and ME in Teacher Education from the University of Oklahoma, a MS in Cost Analysis from AFIT, and a PhD in Economics from George Mason University. Dr. Lucas' research interests include profit analysis, cost & economic analyses, and incentive structures. (E-mail address: Brandon.Lucas@afit.edu)*

Dr. ***Edward D. White*** *is a Professor of Statistics in the Department of Mathematics and Statistics at AFIT. He received his BS in Mathematics from the University of Tampa, MAS from The Ohio State University, and Ph.D. in Statistics from Texas A&M University. His primary research interests include statistical modeling, simulation, and data analytics. (E-mail address: Edward.White@aft.edu)*

Dr. ***Jonathan D. Ritschel*** *is an Associate Professor of Cost Analysis in the Department of Systems Engineering and Management at AFIT. He received his BBA in Accountancy from the University of Notre Dame, his MS in Cost Analysis from AFIT, and his Ph.D. in Economics from George Mason University. Dr. Ritschel's research interests include public choice, cost analysis, and economic institutional analysis. (E-mail address: Jonathan.Ritschel@aft.edu)*

Mr. ***Shawn M. Valentine*** *is an Operations Research Analyst at AFLCMC/FZCE at Wright Patterson AFB, Ohio. Mr. Valentine graduated from Ohio University with a Bachelor of Science (BS) in Actuarial Science and a Master of Science (MS) in Financial Economics. (Email address: shawn.valentine@us.af.mil)*

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