Predicting the Cost Per Flying Hour for the F-16 Using Programmatic and Operational Data

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ABSTRACT

We analyzed economic, operational, and programmatic data from Air National Guard and active duty F-16C/D fighter wings in search of explanatory variables that influence a wing's cost per flying hour (CPFH). Using data from the Air Force Total Ownership Cost database and from the Air Force Knowledge Systems database, we evaluated the predictive ability of various operational and programmatic variables, such as aircraft age, average sortie duration, base location, utilization rate, percent engine type, percent block, and previous year's CPFH. Although separate models were required for active duty and Air National Guard units, both regression models incorporated utilization rate, base location, percent block, and percent engine type and appeared to accurately predict an F-16 C/D fighter wing's CPFH.

INTRODUCTION

Many military leaders and budget analysts believe that increases in the costs of operating and maintaining aging aircraft have created a budgetary crisis in the United States Air Force. The phrase "death spiral" has been coined to describe the phenomenon where funding is taken away from modernization programs to finance rapidly increasing operations and maintenance (O&M) expenses, which, in turn, takes funding away from modernization programs. In the 2001 Air Force Posture Statement, Air Force Secretary James Roche stated, "Over the past five years, our flying hours have remained relatively constant, but the cost of executing our flying hour program has risen over 45% after inflation. Older aircraft are simply more difficult to maintain as mechanical failures become less predictable, repairs become more complicated, and parts become harder to come by and more expensive" (Roche, 2001).

Part of the Air Force O&M expenses includes the Air Force Flying Hour program. Unfortunately in the past decade, budget estimates have been inaccurate for this program. For example, in both 1997 and 1998, the Air Force ran out of funding for the Flying Hour program and had to request an additional $300M from Congress to make it through each fiscal year (Gebicke, 1999). Such a situation is not desirable. Knowing the possible factors that caused O&M costs to fluctuate may allow for better predictions of the Flying Hour program. This article attempts to quantify the influence operational and program-

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

matic factors have on the Cost Per Flying Hour (CPFH) for perhaps the world's most prolific fighter — the F-16C/D. This knowledge is then utilized to build linear regression models to predict the CPFH for a F-16C/D fighter wing in the United States Air Force.

BACKGROUND

O&M costs are a broad category that cover everything from health care to communications. The portion concerned with operating and maintaining aircraft is called the Flying Hour program. The Air Force Cost Analysis Improvement Group (AFCAIG) develops CPFH factors for each aircraft type, also known as Mission Design Series, and for each Major Command (MAJCOM). Budgets are prepared by multiplying each CPFH factor by the number of hours the MAJCOM is authorized to fly (Gebicke, 1999). Figure 1 depicts the Fiscal Year 2004 (FY04) Flying Hour budget compared to the Air Force's total O&M budget.

The CPFH is composed of three commodity groups: consumable supplies, aviation fuel, and depot level repairables (Rose, 1997). Consumable supplies consist of aircraft parts or supplies that are not economical to repair and are discarded after use. Examples of this type of commodity include screws, washers, wiring, and lights (Rose, 1997). The commodity aviation fuel (AVFUEL) refers to the fuel expended during flight. Lastly, depot level repairables (DLRs) refer to aircraft parts that, when broken or removed for scheduled maintenance, are repaired rather than discarded (Rose, 1997). In 2004, the expenditures in consumable supplies, AVFUEL, and DLRs accounted for 11%, 24%, and 65%, respectively, of the total $6.1 billion dollar Air Force Flying Hour program (SAF/FMC, 2004).

The CPFH factor development process is unique for each specific commodity being estimated. For example, consumable supplies are developed using historical obligations and actual flying hours over the previous eight quarters. They are adjusted to remove non-recurring costs in the baseline period and for known future changes, such as time

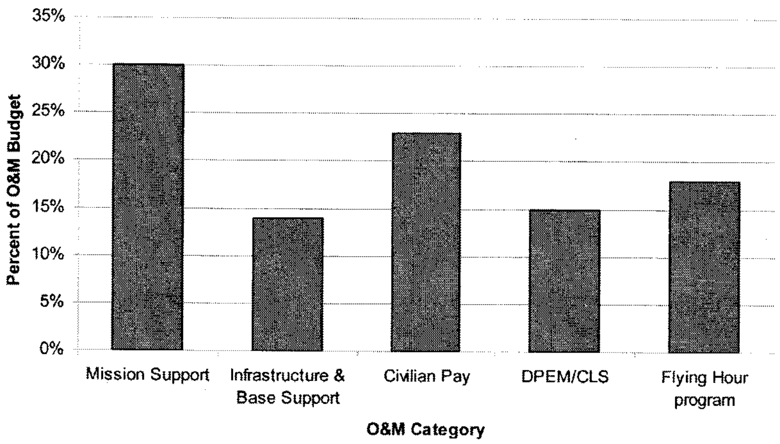

Figure 1. Fiscal year 2004 O&M budget for the US Air Force broken out by category. DPEM stands for depot purchased equipment maintenance and CLS stands for contractor logistics support.

compliance technical orders, phase inspections, modifications, and changes in operations tempo (OPTEMPO). The AVFUEL commodity uses historical gallons of fuel consumed and actual flying hours flown over a five-year moving average. Fuel is adjusted as well to account for reporting errors, anomalies, and future OPTEMPO changes (Lies, 2005). The third commodity group, DLRs, is controlled by the Spares Requirement Review Board (SRRB).

In the past, the spares requirement forecasting process was inefficient (Newsome, 2002). There was no central coordination between consumption estimates, spares pipeline requirements, and readiness spares packages (RSP). Because the flying-hour factor did not cover non-sales based items (e.g., spares pipeline requirements, safety stock, and RSPs), they were not included in the MAJCOM program objective memorandum (POM) submissions. This omission often resulted in unplanned year-of-execution bills to the Air Force (Newsome, 2002). To address this specific issue, along with a host of other financial management issues, the Air Force started the Spares Campaign in December 2001. One of the stated goals of the Spares Campaign was to centralize the spares requirement process, which was accomplished by the creation of the SRRB. This board is solely responsible for forecasting spares requirements. Once developed, the flying spares portion of the SRRB is presented to the CPFH AFCAIG for review and approval of proposed flying spares CPFH factors and requirements (Lies, 2005).

Under this current system, "the SRRB computes spares requirement based upon the best analytical data available and consensus of relevant parties" (Newsome, 2002). The purpose of the SRRB is to integrate the supply chain, historical data, and relevant parties into one process that culminates in budget submission representing both MAJCOMs and Air Force Materiel Command. Consequently, regression models could prove useful in this process and hence motivated the research presented here.

DATABASE

Prior to any modeling building or statistical analysis, this research required a viable database. Because no single database contained all the requisite information, we combined data from the Air Force Total Ownership Cost (AFTOC) database and the Air Force Knowledge System (AFKS) database into a single relational database. The AFTOC database does not create any new data but feeds data in from a variety of sources, mainly the Air Force Core Automated Maintenance System and the Standard Base Supply System. The purpose of the AFTOC database is to capture all the life-cycle costs associated with a particular weapon system (Schmidt and Hitt, 1999). In similar fashion, the AFKS database takes data from 26 different databases and information systems. The data in this database mainly comes from the Reliability and Maintainability Information System (Jackson, 2005).

The joint relational database we created contained operational, economic, and programmatic data for all F-16C/D's assigned to 40 fighter wings across five active duty MAJCOM's and the Air National Guard (ANG). Each data point is one year's worth of those variables for a fighter wing. Total data points consist of 88 for active duty and 175 for ANG wings. Because current accounting systems do not distinguish between dollars spent on F-16C's and F-16D's, all of the F-16C/D's fields are summed together. The modeling database contains data from 1998 to 2004, and all dollars are converted to constant calendar year 2004 (CY04) dollars for uniformity. Data from 2004 is temporary withheld to validate the built regression models (discussed in the next section). After validation, this data is placed back in the database before finalizing the statistical models.

Because the AFTOC and AFKS database contained a common field (hours flown) this analysis investigated whether or not this field matched between these two data sources. This process was done to ascertain to a certain degree the internal consistency of the two databases. On investigation, these databases do not match exactly; however, the variation is extremely minor. Because this variation accounted for only 0.007% of the total variation, we surmise that this difference could well rest in different rounding protocols for the two databases. For all practical purposes, this variation is well within acceptable limits and speaks of internal consistency between AFTOC and AFKS.

One key database assumption for this research is that the block number and engine type of each tail number (associated with an individual aircraft) remained the same across 1998 – 2004. Because neither the AFKS nor the AFTOC database contained this specific historic data, it is necessary to make this assumption and forms a limitation of this research. Another possible limitation of the database, although minor in our opinion, is that we had to exclude data from Mountain Home Air Force Base. The regression diagnostics in the next section flagged most of this data as reacting atypically compared to the rest of the other bases.

Having established a viable database, we then turned to previous studies and similar analyses to compile a list of potential predictors of CPFH. As aircraft age, many different processes take place that influence O&M costs. The Congressional Budget Office in their August 2001 report to Congress titled "The Effects of Aging on the Costs of Operating and Maintaining Military Equipment" listed three main factors: corrosion, fatigue, and obsolete parts (Cappaccio, 2001). Empirical results suggest that each year O&M costs rise on average between 1.7% and 2.5% because of these factors (Crippen, 2001). Taking this information into account, we considered the aging effect by testing whether the previous CPFH is linearly related to the current year's CPFH and by testing whether the average age of aircraft is predictive of a fighter wing's CPFH.

Besides age, other research has considered: mission profile, sortie duration, OPTEMPO, landings per sortie, location, and modifications. Mission profile refers to the objective of the sortie. During training sorties, it is common for pilots to practice high "G" maneuvers. These sorties place extra stress on the aircraft and its components. Using data from 1993 to 1996, Sherbrooke (1997) linked data from the supply database with the core automated maintenance database and determined short training missions where the pilots pulled as many as eight G's had three times as many demands per sortie as long cross-country sorties.

Sherbrooke (1997) also went on to address average sortie duration, utilization rate, and location. As far as average sortie duration, he concluded there is no evidence of a one-to-one relationship between sortie duration and spare part demand. At best, there is only a 7% to 10% increase in demand for every additional hour of flying for most aircraft (Sherbrooke, 1997). With respect to utilization rate, Sherbrooke's analysis concluded that higher utilization rates tend to require less maintenance. Lastly, in terms of location playing a potential role in predicting CPFH, the demand rate for A-10's at Nellis AFB was five times larger than that of other A-10 bases (Sherbrooke, 1997). We mention now and will discuss later that Nellis AFB does becomes a predictive variable for CPFH.

With respect to modifications, this variable refers to the effect of aircraft modernizing on O&M costs. Although desirable to investigate, data for this variable is essentially unattainable. As noted by Pyles (2003),

> "To our knowledge, there have been no previous studies of growth in age-related modification cost. In the past, it may have been irrelevant, because only a few aircraft platforms were retained long enough to require upgrading to meet more-modern operating requirements. As likely, the data for such analyses have been difficult to obtain."

Although we make note of modification being a potential predictor of CPFH, we had no data to test this association and forms a limitation to the analysis.

Now, we list the modeled response of interest and the different possible predictors considered in the analysis. Collected data refers to annual amounts. Additionally, the variables MAJCOM and Base are categorical and, as such, necessitate formulating dummy variables. To isolate the effects of each individual level, a "0" or "1" coding scheme is adopted. Each dummy variable is assigned a "1" if that data point includes that level or a "0" if it does not. The effect of the level that does not have an assigned dummy variable is captured in the intercept (baseline). In this way, the effect of each level is ascertained.

Response: CPFH

Response is the amount of dollars expended by a wing on DLR's divided by the number of hours flown by that fighter wing. Costs are converted to CY04$.

Average Sortie Duration

Average sortie duration is the total number of sorties a wing performed divided by the total number of hours flown.

Average Age

Average age is the average age of all the F-16C/D's in the fighter wing.

Percent Deployed

Percent deployed is the total amount of combat hours a wing has flown divided by the total number of hours flown.

Percent Engine Type

The F-16 has five engines: F0100229, F0100220, F0100200, F0110129, and F0110100. Unfortunately, the data do not distinguish between the engines F0100200 and F0100220 and, therefore, aircraft with either of those engines are counted together.

Percent Block

The United States Air Force currently has seven F-16C/D blocks in service: 25, 30, 32, 40, 42, 50 and 52. Each block represents a technological improvement from the previous block. The approximate percentages for each block (25 through 52) for the ANG from 1998 to 2004 (the span of the study's database) are 24.7%, 52.0%, 2.4%, 2.0%, 14.6%, 0.0%, and 3.9%. For active duty, the percentages are 4.1%, 10.6%, 2.9%, 42.3%, 7.1%, 25.1%, and 7.9%, respectively. For information regarding what improvements were made by block number, please visit the website http://www.faqs.org/docs/air/avf162.html.

MAJCOM

The MAJCOM the fighter wing is assigned to. We analyzed Air Education and Training Command, Air Combat Command, United States Air Force in Europe, Pacific Air Forces, and the ANG. Air Force Materiel Command's data could not be used because their accounting system is different than the other commands and could not be standardized.

Location

This explanatory variable describes the location the wing is assigned to. We initially analyzed 40 base locations but later removed Mountain Home based on anomalies detected.

Utilization Rate

The Air Force defines utilization rate as the number of flight hours per month per aircraft. For the purposes of this research, utilization rate is defined as the number of hours per year per aircraft.

Previous Year CPFH

This explanatory variable is the previous year's DLR obligations divided by the previous year's hours flown.

ANALYSIS AND RESULTS

In this section, we present the regression models developed to predict the CPFH of an F-16C/D fighter wing based on the potential predictors discussed earlier. Before the model building process began, the 2004 data was withheld and used to validate the developed models. Once the models were validated, the 2004 data was reinserted into the database to update parameter estimates. Additionally, all the explanatory variables that were not found to be significant during the initial model building portion were checked again to ensure that nothing was inadvertently left out. Lastly, we used stepwise regression as an independent check of our process, and at no time did this procedure reveal results that contradicted our analytical findings.

On an initial examination of the data, it was obvious that the ANG fighter wings behaved much differently then the active duty fighter wings. Active duty fighter wings fly almost four times as many hours as ANG fighter wings and have a standard deviation that is nearly 10 times as large. These major differences, especially in the variance, necessitate the building of two regression models, one for ANG fighter wings and one for active duty fighter wings.

The first model, Preliminary Active Duty, relates the CPFH of active duty fighter wings to four explanatory variables: utilization rate, Nellis Air Force Base (AFB), Eielsen AFB, and percent block 50. The second model, Preliminary Guard, relates the CPFH of ANG fighter wings to four explanatory variables: utilization rate, Atlantic City ANG, Ellington ANG, and percent block 30. Both initial models are built without the 2004 data as mentioned previously. Tables 1 and 2 display the relevant model results.

These two models have similarities and differences. The obvious differences lie in which operating locations have either a positive or negative impact on the CPFH as well

Table 1. Preliminary regression model for predicting cost per flying hour of active duty F-16C/D fighter wings. Parameter estimates significant at $\alpha = 0.05$.

Variable	Parameter Estimate	P-Value of *t*-Test
Intercept	4106.96	< 0.0001
Nellis Air Force Base	1599.48	< 0.0001
Utilization Rate	–3.67	0.0052
% Block 50	–932.92	< 0.0001
Eielson Air Force Base	–841.00	< 0.0001

Table 2. Preliminary regression model for predicting cost per flying hour of Air National Guard F-16C/D fighter wings. Parameter estimates significant at $\alpha = 0.05$.

Variable	Parameter Estimate	P-Value of *t*-Test
Intercept	4217.44	< 0.0001
Utilization Rate	–5.71	0.0001
% Block 30	–688.95	< 0.0001
Atlantic City ANG	623.36	0.0456
Ellington ANG	858.63	0.0062

as the different blocks. The commonalties rest in the fact that both models are sensitive to utilization rates and that those inversely affect the CPFH. In other words, the more an aircraft is flown, the cheaper it is to maintain, which is in keeping with previous studies. Secondly, the more modern blocks in either the active duty or ANG also decrease the cost of flying, which again makes intuitive sense. Generally, older technology is more expensive to maintain. The blocks differ between the two models because Block 50's in active duty fighter wings are more prevalent in contrast to the more common Block 30's in an ANG fighter wing.

To test the theoretical soundness of the regression models prior to validating, we test for normality and constant variance of the models' residuals via the Shapiro-Wilks and Breusch-Pagan hypothesis tests (Neter at al., 1996). To investigate possible linear redundancies of the explanatory variables as well as influential data points, we turn to the variance inflation factors as well as Cook's distance (Neter et al., 1996). Checking Cook's distance is key to ensure that the analysis has not erroneously concluded absolute or relative predictive capability of a particular explanatory variable based on a few points rather than the average or typical CPFH response.

None of the herein diagnostics revealed any troublesome areas in the theoretical soundness of either model that would cause us concern. Moreover, had there been some issues, the analysis of variance F-test is robust against slight to moderate deviations in both normality and constant variance of model residuals (Neter et al., 1996). With that said though, the standardized or studentized residuals did reveal two major outliers, both associated with Mountain Home Air Force Base (at the time this base was still included in the model building process). Both had abnormally large CPFHs, with the studentized residual values being 4.5 and 5.5, respectively. These values are well beyond three standard deviations and outside the 99.3% coverage zone using the empirical rule. Obviously, these two data are highly suspect. On further investigation, we saw another suspect data point that prevented the explanatory variable, average aircraft age, from being initially predictive. At this point, three of the seven data points from Mountain Home were suspect, which ultimately motivated us to remove this base's information from the modeling database.

To validate the saliency of these two initial regression models, we used the 2004 data that had been initially set aside. Some of the models' explanatory variables are not known prior to the year of execution and, therefore, they have to be forecasted out. For the purposes of this test validation, the previous year's values are used as an estimate. The research uses the test set to validate the models by creating 95% prediction intervals and determining what percentage of the time the individual wing's CFPH for 2004 fell within the predicted range. Table 3 displays the results of this test. One would theoretically expect approximately 95% of the observations to fall in this range. Because the test set was smaller for the ANG model, some slight deviations are expected from this percentage. Given the approximate 96% and 92% empirical results, the validation suggests that both models are viable and statistically sound.

Because both of these initial models pass the standard regression assumptions and are validated using the 2004 test set, the 2004 data is now reinserted back into the database and the parameter estimates are updated. In addition, any explanatory variable that was not initially considered was rechecked. We did this to account for any minor associations that we detected but did not initially input into the preliminary models because of the 0.05 level of significance cutoff for each individual explanatory variable. Tables 4 and 5 reveal the final regression models presented to users to consider when predicting CPFH for F-16 C/D wings.

Initially, Preliminary Guard did not include the previous year CPFH variable because of its borderline p-value of 0.083. With the addition of the 2004 data, the p-value dropped to 0.0137, necessitating its inclusion into the final ANG model. As mentioned earlier, previous researchers quantified the relationship between aircraft age and O&M costs. They found that, on average, O&M costs increase at a rate of 1.7% to 2.5% a year (Crippen, 2001). This lag effect is modeled in the previous year CPFH explanatory variable.

With respect to Preliminary Active Duty, average aircraft age proved to be initially a non-predictive explanatory variable based on its p-value of 0.23. However, after removing the CPFH data from Mountain Home Air Force Base, this p-value dropped substantially to 0.0258. This almost ten-fold increase of statistical significance further bolstered the logic behind the removal of Mountain Home and indicated how dissimilar these seven data points were from the average. These few points masked this predictive variable and its effect on the majority of the other active duty bases.

The relative influence of each explanatory variable for both final models is determined by comparing the magnitude of each parameter estimate. The sign of the estimate determines the direction of the change. Tables 6 and 7 present these comparisons. Both models indicate that utilization rates have the most cost reduction effect on CPFH, although per-

Table 3. Validation results for both preliminary regression models. PI is for prediction interval.

	Active Duty Model	Air National Guard Model
Test Sample Size	27	12
Number of Squadrons within 95% PI	26	11
Percent of Squadrons within 95% PI	96.2%	91.7%

Table 4. Final regression model for predicting cost per flying hour of active duty F-16C/D fighter wings. Parameter estimates significant at $\alpha = 0.05$.

Variable	Parameter Estimate	P-Value of *t*-Test
Intercept	4008.76	< 0.0001
Nellis Air Force Base	1685.67	< 0.0001
Utilization Rate	−6.75	< 0.0001
Percent Block 50	−506.18	0.0002
Average Aircraft Age	69.70	0.0011
Eielson Air Force Base	−409.98	0.0045

Table 5. Final regression model for predicting cost per flying hour of Air National Guard F-16C/D fighter wings. Parameter estimates significant at $\alpha = 0.05$.

Variable	Parameter Estimate	P-Value of *t*-Test
Intercept	3652.36	< 0.0001
Utilization Rate	−5.73	< 0.0001
% Block 30	−476.10	< 0.0001
Previous Year CPFH	0.167	0.0137
Atlantic City ANG	612.44	0.0284
Ellington ANG	590.80	0.0380

Table 6. Relative effect standing of the predictive variables for the final active duty F-16C/D model. The baseline variable is 1. Others are in comparison to this variable.

Variable	Relative Standing
Nellis Air Force Base	3.59
Utilization Rate	−2.43
% Block 50	−1.68
Average Aircraft Age	1.37
Eielson Air Force Base	−1

Table 7. Relative effect standing of the predictive variables for the final Air National Guard F-16C/D model. The baseline variable is 1. Others are in comparison to this variable.

Variable	Relative Standing
Utilization Rate	−2.02
% Block 30	−2.01
Previous Year CPFH	1.25
Atlantic City ANG	1.04
Ellington ANG	1

cent Block 30 is close in its effect for the ANG model. This reduction effect suggests that the more an aircraft is flown, the lower on average the cost to the fly this weapon system. Both models also reveal that more modern engine blocks reduce on average the CPFH. With respect to the effect of time on CPFH, this explanatory variable increases the cost of flying the F-16C/D. In other words, as aircraft age for active duty units or given last year's CPFH for ANG units, the current estimate of CPFH will increase.

Before proceeding to the next section, which goes into greater discussion about the relative effects of the models' variables, we present two hypothetical examples of the regression models in usage. First, assume that an active duty F-16C/D squadron from a base that is neither Nellis AFB nor Eielsen AFB has a utilization rate of 240 hours a year per aircraft, has 20% of its aircraft with Block 50's, and is an average of 15 years old. This assumption implies that on average this squadron would have a CPFH of 4008.76 – 240*6.75 – 506.18*0.2 + 69.70*15 = $3333 in 2004 dollars.

With respect to an example demonstrating the ANG model, assume an F-16C/D squadron that is neither from Atlantic City ANG nor from Ellington ANG, has a utilization rate of 120 hours a year per aircraft, has 20% of its aircraft with Block 30's, and has a previous year's CFPH of $3000 an hour. This assumption implies that on average this squadron would have a CPFH of 3652.36 – 120*5.73 – 476.10*0.2 + 3000*(0.167) = $3370 in 2004 dollars.

DISCUSSION

In this section, we relate in greater detail the various predictive variables in either the active duty or ANG models. We also relate, when possible, back to the studies mentioned earlier to show the interconnection between the findings in this article and that of the historical record. We do this discussion via a series of questions regarding the explanatory variables initially investigated.

Does the CPFH of an F-16 fighter wing increase as aircraft age?

From the data analyzed in this research, there is ample evidence to support the claim that the CPFH increases with the age of the aircraft for active duty fighter wings. There is no direct evidence to support this claim for ANG fighter wings. The rate at which average aircraft age results in higher CPFH is estimated by the corresponding parameter estimate of that explanatory variable. This research estimates that for every additional year of an aircraft's life, the CPFH increases on average $69.7 per hour (CY04$) for active duty F-16C/D fighter wings.

Does the CPFH of an F-16 fighter wing depend on the previous year's CPFH?

Our findings conclude that the CPFH for ANG fighter wings is linearly related to the previous year's CPFH, which is not the case for active duty fighter wings. The estimated slope for this explanatory variable is 0.167, which is interpreted as the rate at which the previous year's CPFH is adding to the current year's CPFH. In our opinion, it is a significant amount.

Does the utilization rate of an F-16 fighter wing influence that wing's CPFH?

Unequivocally, there is a very strong relationship between increased utilization and decreased CPFH. The regression analysis and previous studies support this claim. The age-old heuristic adage, "the more you fly, the less you break", appears to be the case whether an F-16C/D fighter wing is either from the active duty or the ANG.

Do different F-16C/D blocks have a statistically significant influence on the CPFH?

Yes, and this knowledge can be used to increase the predictive power of a model. This variable is highly applicable in both regression models and it can be very accurately forecasted out with respect to increasing the percent of Block 50's in active duty wings or percent of Block 30's in ANG wings.

Does MAJCOM influence the CPFH for F-16 fighter wings?

The only MAJCOM that significantly influences the CPFH is the ANG. This difference between this MAJCOM and the other MAJCOMs is stunning. Explanatory variables, such as percent Block 30 and previous year CPFH, are predictive for ANG fighter wings and not predictive for active duty fighter wings. Also, explanatory variables, such as percent Block 50 and average aircraft age, are predictive for active duty fighter wings and not for ANG fighter wings. This research also identified how the distribution of the CPFH is different for ANG fighter wings when compared to active duty fighter wings. We speculate these differences are caused by the ANG fighter wings utilizing older, less advanced F-16's and flying them far less.

Does base location influence the CPFH for F-16 fighter wings?

We believe there is ample evidence to support the claim that some base locations influence the CPFH. Eielson AFB, Alaska, has a significantly lower CPFH then the rest of the bases. In contrast, the ANG base in Ellington and the ACC base in Nellis had significantly higher CPFH. This research also notes that there were bases in hot climates that did not have a significantly higher CPFH, including Luke AFB in Arizona, Cannon AFB in New Mexico, Kelly ANG in Texas, and Tucson ANG in Arizona. Also, Atlantic City ANG in New Jersey had a significantly higher CPFH even though this location is not considered to have a hot climate.

We also note how much larger Nellis AFB's CPFH is relative to the rest of the explanatory variables. The parameter estimate corresponding to that dummy variable is approximately $1,686. This amount is interpreted as the hourly amount above the rest of the fighter wings in active duty fighter wings that Nellis AFB's estimate needs to be adjusted even after taking into account all of the other explanatory variables. We believe there is something else occurring at Nellis AFB besides the hot climate that is causing this extraordinarily high CPFH. In a previous study, Sherbrooke (1997) estimated that aircraft that fly demanding training sorties had three times as many removals per sortie as long cross-country sorties. Because Nellis AFB is site of Red Flag and other training exercises, it is plausible that the higher CPFH is driven by these differences in mission profile. Also, the fighter wing at Nellis owns the Thunderbirds. This factor, too, may contribute to Nellis AFB's abnormally high CPFH.

What is the relative influence of the models' predictive factors?

This empirical question is answered by comparing the relative standardized effects of each explanatory variable. As shown previously, Tables 6 and 7 display these results for ANG fighter wings and active duty fighter wings, respectively. In both groups of fighter wings, the percent block and utilization are both negative and carry roughly the same amount of influence on the response, CPFH. Similarly, the previous year CPFH for ANG fighter wings and the average aircraft age for active duty fighter wings are both positive and also carry about the same amount of influence on the CPFH.

CONCLUSION

The Flying Hour program is a highly visibly portion of the President's budget that has historically been prone to inaccurate estimates. As noted earlier, inaccurate budget estimates require the Air Force to ask Congress for additional funding. Congress, then, usually takes funding away from modernization programs in order to ensure the solvency of the Flying Hour program (Gebicke, 1999). Fewer dollars to modernize aircraft systems in turn results in aircraft aging even more, which further increases the cost of the Flying Program, resulting in a vicious cycle.

One way to mitigate this effect is to provide better estimates for the Flying Hour program. By utilizing currently known databases and by consulting previous studies, we developed two salient cost models, one for active duty wings and one for ANG wings, to consider and to adopt for better predicting CFPH for the F-16C/D platform. Additionally, these models also provide and highlight potential variables to consider when developing similar regression models for other airframes.

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