Providing a Piece of the Puzzle: Insights into the Aircraft Availability Conundrum

Jonathan D. Ritschel
Air Force Institute of Technology

Tamiko L. Ritschel
Air Force Material Command

Nicole B. York
Air Force Material Command

Follow this and additional works at: https://scholar.afit.edu/facpub

Part of the Management and Operations Commons

Recommended Citation

This Article is brought to you for free and open access by AFIT Scholar. It has been accepted for inclusion in Faculty Publications by an authorized administrator of AFIT Scholar. For more information, please contact richard.mansfield@afit.edu.
Providing a piece of the puzzle: insights into the aircraft availability conundrum

Jonathan D. Ritschel
Department of Systems Engineering and Management, Air Force Institute of Technology, Wright-Patterson AFB, Ohio, USA, and
Tamiko L. Ritschel and Nicole B. York
Department of Studies and Analysis, Headquarters Air Force Material Command, Wright-Patterson AFB, Ohio, USA

Abstract

Purpose – Aircraft availability (AA) is a key metric for assessing operational readiness. The declining trend in AA is a documented concern for senior Air Force leaders. This paper aims to investigate the components of non-available time and subsequently focuses on the largest and fastest growing category: not mission capable maintenance unscheduled (NMCMU). Then, utilization of aircraft platforms is examined to determine the readiness benefits of increasing available hours.

Design/methodology/approach – Stepwise regression is conducted on a data set of 30 aircraft platforms, consisting of 542 observations from 1998 to 2017, to reveal drivers of NMCMU. Next, utilization of aircraft platforms is examined through regression and correlation analysis of aircraft platforms and sorties or hours flown.

Findings – Regression analysis reveals drivers of NMCMU include platform type, average age of aircraft, fleet size, breaks and cannibalization. These factors explain 80.6 per cent of the variance in the data set when predicting NMCMU. Additionally, the utilization results show that when more hours are made available, 5 per cent of each new hour is used for flying. Further analysis at the individual platform level finds a strong or moderate correlation between available hours and sorties flown for 93 per cent of the platforms.

Originality/value – Implications from the regression analysis demonstrate there are remedies to increase AA, but many of these remedies may be costly. The utilization analysis expresses the potential readiness benefits of increasing available hours.

Keywords Regression, Maintenance, Utilization, Aircraft availability

Paper type Research paper

The readiness of the US Air Force (USAF) fleet is receiving increasing attention from military leaders, defense think tanks and the media (Government Accountability Office, 2017; Losey, 2018). While mission capable (MC) rates remain the predominant metric used to assess availability at the unit level, aircraft availability (AA) has become the preferred statistic in the
USAF for fleet assessment of operational readiness (McAneny, 2009; Rainey et al., 2009). As a result, the air force has developed standard targets for availability to reflect the aircraft needed to support operational, training and surge capability (Air Force Instruction 21-103, 2016). The data, however, show AA in the USAF has been in a state of decline over the past 25 years. This trend is drawing the concern of Air Force senior leaders (Brissett, 2017).

While the overarching AA statistic has garnered significant attention, an understanding of the underlying components that result in non-available time is lacking. Thus, the purpose of this article is to examine one of the largest components of aircraft readiness, the not mission capable maintenance (NMCM) segment of downtime. The analysis is designed to identify trigger events and through regression analysis determine the drivers of NMCM. Additionally, key assumptions underlying interpretations of the AA metric are examined. From this, the intuition behind linkages in total active inventory (TAI) and AA is explored. Finally, aircraft utilization is examined to understand the operational impact of increasing available hours.

Background and literature view
Over the past 10 years, the USAF has made a deliberate shift from MC rates to AA rates as the metric of choice in assessing the enterprise (Rainey et al., 2009). The change materialized in response to the desire for an enterprise-wide metric. MC rates are calculated by capturing only the readiness of aircraft that are currently possessed at the unit level (e.g. aircraft awaiting maintenance at a depot are not included in MC calculations). In contrast, the AA statistic accounts for all aircraft in the fleet. In its simplest form, AA is the percentage of time aircraft are available to accomplish mission requirements. It answers the basic question: How many aircraft are ready to fly? The AA rate is calculated using equation (1):

\[
AA \text{ Rate} \% = \frac{MC \text{ Hours}}{TAI \text{ Hours}} \times 100
\]  

AA is considered a key element of air force readiness. As a result, negative changes in AA rates are concerning to senior leaders (Brissett, 2017). Figure 1 shows the AA rate has declined from a high of approximately 75 per cent in the early 1990s to a current low of about 62 per cent.

Figure 1.
AA rates 1991-2017
While Figure 1 demonstrates AA is declining over time, it does not provide insight into the factors driving the phenomenon. To understand this, it is first imperative to delineate the various components of non-available time. As shown in Figure 2, there are five main components of downtime: depot, NMCM, not mission capable supply (NMCS), not mission capable both (NMCB) and unit possessed not reported (UPNR).

Explanations of the five non-available (downtime) categories from Figure 2 are as follows: Depot status is for aircraft possessed by a depot for maintenance or overhaul activities. NMCM status is the percentage of aircraft that are not operationally available because of maintenance being performed at the unit level. This includes the subcategories of scheduled and unscheduled maintenance at the unit level. NMCS status is the percentage of aircraft that are not operationally available for supply reasons such as waiting for spare parts. NMCB status is the percentage of aircraft that are unavailable because of both maintenance and supply reasons. Finally, UPNR status refers to instances where an aircraft is waiting on a decision from another agency regarding how to proceed. In this case, the aircraft is unit possessed but not reported upon until further instructions are received (Fry, 2010).

The contribution of each non-available status to total non-availability from 1991-2017 is depicted in Figure 3. Depot and NMCM are the two largest categories of non-availability and

---

**Figure 2.** Components of non-available time

**Figure 3.** Percentage of total non-availability time by category
together make up an average of 67 per cent of total non-available hours. However, the depot category has seen improvement over the past 17 years, while NMCM has been growing during this same time period. A clear understanding of this growth warrants further exploration and scopes the remainder of this analysis to NMCM. Figure 2 shows there are two primary subcategories of NMCM: not mission capable maintenance scheduled (NMCMS) and not mission capable maintenance unscheduled (NMCMU). NMCMS is the maintenance conducted at the unit level for regularly scheduled maintenance, such as periodic inspections. NMCMU is all the other maintenance activities occurring at the unit level, not associated with scheduled maintenance. On an average, NMCMS comprises 28 per cent of NMCM, with NMCMU comprising the remaining 72 per cent.

Prior to analyzing NMCM, two relevant trends that draw the concern of Air Force leaders are highlighted. First, as shown in Figure 4, the TAI is on a downward glide path. The aircraft inventory has decreased by approximately 31 per cent over the past 25 years. At the same time, the age of the air force fleet is also increasing. The average age has increased by approximately 61 per cent, from 17 years in 1991 to 27.4 years in 2017. These trends are not a surprise as much has been written about the aging fleet (National Research Council, 1997; Pyles, 2003; Ulshoffer et al., 2005; Thompson, 2018) and the declining inventory (Government Accountability Office, 2016; Heritage Foundation, 2016). Discussion centered on these trends, along with the decreasing AA rate, tend to elicit bleak forecasts of the Air Force’s ability to meet future readiness requirements (Government Accountability Office, 2016; Everstine, 2017).

The fact that AA is decreasing (see Figure 1) at the same time TAI is decreasing (see Figure 4) appears, on the surface, to be a conundrum. Why isn’t AA stable? Recall from equation (1) that TAI hours is the denominator in the AA rate equation. The inherent problem is an erroneous inference that a drop in TAI will result in a proportional drop in non-available hours, thereby holding AA relatively steady over time. The logic seems to follow that with fewer aircraft to maintain, there will be fewer breaks, less scheduled maintenance and less overall downtime. In other words, a common assumption is non-available hours are linked to the number of aircraft being maintained (or in inventory),

![Figure 4. TAI and average aircraft age 1991-2017](image-url)
instead of perhaps stronger linkages to fluctuations in manpower, flying hours, aircraft age or other factors. A logical solution is to see if these assumptions hold up under data analysis. Figure 5 shows non-available hours are demonstrating a rather meager decline and certainly not keeping proportional pace with the reductions in TAI hours. When comparing non-available hours in context with available and TAI hours, the picture indicates available hours mirror the declining TAI hours (see Figure 5). Given these facts, the math follows that AA percentage will naturally decline over time.

The relative stability in non-available hours over time is perhaps not intuitive on the surface, but there are many factors that likely contribute to this stability, some of which are:

- Scheduled aircraft maintenance in the USAF is primarily completed on an hours-flown basis.
- Trigger events for unscheduled maintenance (aborts, breaks, pilot reported discrepancies, etc.) typically happen when planes fly.
- The way in which excess capacity is used in maintenance functions potentially mitigates fluctuations (e.g. depots).

Though this is far from a complete list of possible factors, it does illustrate many factors are not tied directly to TAI, which is the underlying assumption many make when assuming AA will remain steady while TAI is decreasing.

The insights illuminated thus far point to non-available time as the key piece to understanding the dynamics of AA. The relatively stable nature of non-available hours is driving the AA rate downward as TAI decreases. Thus, the remainder of this paper examines potential explanatory variables for the NMCM segment of non-available time.

**Methods**

The primary data source for regression analysis is the USAF’s maintenance data repository – Logistics, Installations and Mission Support-Enterprise View (LIMS-EV). To ensure robustness of platforms selected for inclusion, the platform must have 10 years of availability data and a
fleet size of at least ten aircraft in multiple years of the data. Additionally, the platform must have corresponding utilization and maintenance data in LIMS-EV. The final data set contains 30 aircraft platforms (542 observations) from 1998 to 2017. Table I shows the final set of included platforms and the exclusion screens for non-selected platforms.

Recall that NMCM comprises both scheduled and unscheduled components. Scheduled maintenance, by definition, is known or predictable maintenance requirements, often based on time or hours flown on an aircraft (Air Force Technical Order 00-20-1, 2016). This makes the non-availability hours associated with the scheduled maintenance portion intuitive. As a result, the regression is designed to investigate only the unscheduled component. Thus, the dependent variable is NMCMU hours per aircraft. Independent, predictor variables come from LIMS-EV. These include average age of the aircraft, fleet size, hours flown per aircraft and a multitude of utilization and maintenance variables discussed in the next section. Independent variables are standardized on a per-aircraft basis by platform to control for the variance in the number of aircraft in the inventory.

Prior to any model building, the regression data set is separated into two groups: the model building data set and validation data set. For multiple regression, a random sampling of the data uses approximately 80 per cent for the model building portion and 20 per cent for the validation set. Variables may or may not be included in the model, depending on individual significance and contingent on passing regression diagnostics. The mixed stepwise function in JMP Pro Version 12 is used to determine which predictor variables are initially included in the model. A significance level of 0.05 is the threshold to enter or exit the model. The assumption of normality is assessed using the Shapiro–Wilk test and a plot of the studentized residuals, while the assumption of constant variance is assessed with the Breusch–Pagan test and a residual by predicted plot. Both tests are conducted at the 0.05 level of significance.

Furthermore, multicollinearity, influential data points and outliers are investigated to prevent additional bias. Variance inflation factors (VIF) highlight linear relationships between two explanatory variables, and a VIF higher than 10 indicates multicollinearity. Cook’s distance detects influential data points that could be skewing the model, and any value greater than 0.5 is investigated thoroughly. Any studentized residual that is greater than three standard deviations from the mean is considered an outlier and must also be investigated further. The final assessment is the Holm–Bonferroni correction, which aims to control the family-wise error rate and reduce Type I error (false positives).

Once all diagnostics are passed, the model building set is validated against the validation set using multiple criteria: mean absolute percentage error (MAPE), median absolute percentage error (MdAPE) and adjusted \( R^2 \). When the model is deemed internally valid, then

<table>
<thead>
<tr>
<th>Exclusion screen</th>
<th>Platforms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than 10 years of data</td>
<td>EF-111, F-35, F-111, FB-111, OV-10, RF-4</td>
</tr>
<tr>
<td>Lack of break data</td>
<td>C-5, C-12, C-21, KC-10, WC-130</td>
</tr>
<tr>
<td>Included</td>
<td>A-10, AC-130, B-1, B-2, B-32, C-17, C-20, C-130, E-3, E-8, EC-130, F-15, F-15E, F-16, F-22, KC-135, MH-53, MQ-1, MQ-9, RC-135, T-1, T-6, T-37, T-38, UH-1</td>
</tr>
</tbody>
</table>

Table I.
all data points are combined to update the final model using the variables selected from the model building process.

Non-availability regression results
The regression is designed to provide insight into the drivers of NMCMU. Independent variables in the model were selected based on the literature review and corresponding data in LIMS-EV. Initial multivariate plots of all predictor variables, in addition to VIF scores, provided insight into multicollinearity issues and removal of variables from the model. The final set of independent variables for inclusion in the model is shown in Table II.

The initial regression diagnostics indicated several severe outliers in the data set. Specifically, the B-2 platform data is six standard deviations from the mean. The B-2 is the Air Force’s only stealth bomber. The radar-absorbent materials and coatings of the large aircraft among other unique structural stealth capabilities require significantly more maintenance per hour flown than other bomber aircraft. For these reasons, the B-2 was removed from the data set.

With the data set finalized, stepwise regression was run on the model building set. Several independent variables were found insignificant and removed from the model during the stepwise regression process: hours flown per aircraft, mean time between maintenance, repeats/recur per aircraft and year. Additionally, statistical significance below the comparison-

<table>
<thead>
<tr>
<th>Name</th>
<th>Type of variable</th>
<th>Description</th>
<th>Measuring</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Platform</td>
<td>Binary</td>
<td>There are 30 individual aircraft platforms, as delineated in Table I. The base case is the A-10</td>
<td>Technology, complexity, etc.</td>
<td>LIMS-EV</td>
</tr>
<tr>
<td>Aircraft age</td>
<td>Continuous</td>
<td>Average age of all aircraft in the corresponding platform</td>
<td>Effects of age</td>
<td>LIMS-EV</td>
</tr>
<tr>
<td>Hours flown per aircraft</td>
<td>Continuous</td>
<td>Average hours flown per aircraft</td>
<td>Usage</td>
<td>LIMS-EV</td>
</tr>
<tr>
<td>Breaks per aircraft</td>
<td>Continuous</td>
<td>Average breaks incurred per aircraft</td>
<td>Reliability</td>
<td>LIMS-EV</td>
</tr>
<tr>
<td>Sorties per aircraft</td>
<td>Continuous</td>
<td>Average sorties flown per aircraft</td>
<td>Usage</td>
<td>LIMS-EV</td>
</tr>
<tr>
<td>Aborts per aircraft</td>
<td>Continuous</td>
<td>Average missions aborted on the ground or in the air per aircraft</td>
<td>Reliability</td>
<td>LIMS-EV</td>
</tr>
<tr>
<td>Cannibalization</td>
<td>Continuous</td>
<td>Average removals of a serviceable part from an aircraft or engine to replace an unserviceable part on another aircraft or engine</td>
<td>Maintenance practice</td>
<td>LIMS-EV</td>
</tr>
<tr>
<td>Repeat/recur per aircraft</td>
<td>Continuous</td>
<td>Average times a repeat discrepancy occurs on the same system or subsystem on the first through fourth sorties attempt after originally reported</td>
<td>Maintenance quality, test equipment, etc.</td>
<td>LIMS-EV</td>
</tr>
<tr>
<td>Mean Time Between maintenance (hours)</td>
<td>Continuous</td>
<td>Represents the average time between all maintenance actions, both corrective and preventive in hours</td>
<td>Reliability</td>
<td>LIMS-EV</td>
</tr>
<tr>
<td>Year</td>
<td>Binary</td>
<td>Includes years 1998-2017</td>
<td>Fluctuations in requirements Scale effects</td>
<td>LIMS-EV</td>
</tr>
<tr>
<td>Fleet size</td>
<td>Continuous</td>
<td>Number of aircraft in the inventory by platform type</td>
<td>Pilot assessment</td>
<td>LIMS-EV</td>
</tr>
<tr>
<td>Pilot reported discrepancy (PRD) per aircraft</td>
<td>Continuous</td>
<td>Average number of times a pilot reported a discrepancy per aircraft</td>
<td>Pilot assessment</td>
<td>LIMS-EV</td>
</tr>
</tbody>
</table>

Table II. Independent variables in the regression analysis
wise error Holm–Bonferroni correction rate of 0.05/9 = 0.005 resulted in the removal of the
sorties variable. Next, the 80 per cent model building set is validated against the 20 per cent
validation set. Comparison of MAPE (10.10 per cent training vs 11.06 per cent validation) and
MdAPE (14.96 per cent training vs 15.32 per cent validation) between the models are within 1.5
per cent of each other. The similarity of these results indicates the model is valid.

After model validation, all the data points are combined into a final model. Using the
variables selected from the model building process in the full data set, parameter estimates
are updated. Table III shows the final model regression results.

The $R^2$ of the model is 0.806, indicating that 80.6 per cent of the variance is explained by the
model. Checking for multicollinearity, the largest VIF score is 8.31, which falls below the
threshold of 10. All other variables have VIF scores of five or less. This indicates there is little
multicollinearity in the model. Similarly, the presence of influential data points is very minor.
The largest Cook’s distance value is 0.04, which is well below the 0.50 threshold. One of the
underlying assumptions of regression models is normality of the residuals. The Shapiro–Wilk
test resulted in a statistical failure of this assumption. However, a plot of the studentized
residuals shows that the residuals follow the bell-shape curve of a normal distribution. The
deviation from the normal curve is that more values are centered on zero than a normal
distribution. This can be considered a soft fail of the test as values centered on zero are
acceptable, whereas large spikes on the histogram tails are unacceptable (Cohen et al., 2003).

The independent variables from Table III provide several interesting insights. First,
platform type matters when it comes to non-available hours. This indicates that future
investigations into NMCMU should focus on platforms, rather than the enterprise level. Second,
age is important. As the positive coefficient on this variable indicates, downtime increases as
the average age of the platform increases. This result resonates with the repeated concerns of
senior USAF leaders on the perils of an aging fleet. Third, cannibalization can have some
positive impacts on downtime. The practice of cannibalization of a few aircraft is positively
correlated with increased availability time. This is not to say there are no negatives to
cannibalization. Negative impacts related to inventory, increased maintenance man hours and
decreased morale from cannibalization are well documented in the literature (General
Accounting Office, 2001; Salman et al., 2007). The regression simply shows that the benefit of
cannibalizing parts in the absence of spares can result in reduced maintenance turnaround
time. Fourth, fleet size matters. As the size of the fleet increases, the associated downtime per
aircraft decreases. Perhaps this is because of some scale efficiencies being realized. It is
important to note, however, the fleet size’s relative contribution to the model (as determined
through the standard beta) is the least of all the variables. Additionally, the sign of the
coefficient corroborates the previous discussion on the presumed conundrum of falling TAI
and the associated drop in AA. While the negative coefficient sign means that increasing fleet
size will result in less downtime, the converse is also true. The reality is that the USAF is

<table>
<thead>
<tr>
<th>Predictor variable</th>
<th>Estimate</th>
<th>p-value</th>
<th>Standardized beta</th>
<th>Variance inflation factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>607.72</td>
<td>&lt; 0.0001</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Aircraft age</td>
<td>6.73</td>
<td>&lt; 0.0001</td>
<td>0.30</td>
<td>3.21</td>
</tr>
<tr>
<td>Breaks</td>
<td>10.17</td>
<td>&lt; 0.0001</td>
<td>0.44</td>
<td>3.35</td>
</tr>
<tr>
<td>Platform</td>
<td>Various</td>
<td>&lt; 0.0001</td>
<td>Various</td>
<td>Various</td>
</tr>
<tr>
<td>Cannibalization</td>
<td>–10.54</td>
<td>&lt; 0.0001</td>
<td>–0.29</td>
<td>2.84</td>
</tr>
<tr>
<td>PRD</td>
<td>–0.79</td>
<td>&lt; 0.0001</td>
<td>–0.30</td>
<td>5.38</td>
</tr>
<tr>
<td>Fleet size</td>
<td>–0.27</td>
<td>&lt; 0.0001</td>
<td>–0.23</td>
<td>8.31</td>
</tr>
</tbody>
</table>

Table III. Regression results
experiencing decreasing fleet sizes. This decrease in fleet size actually correlates with an increase in non-available time, which negatively impacts the AA rate. Thus, the regression lends support to the previous discussion on the mathematical mechanics of the AA equation with respect to the underlying assumption that decreasing TAI will lead to a proportional decrease in non-available hours.

**Utilization**

Implications from the regression analysis show that there are remedies to increasing AA. However, the cost and feasibility of these remedies must be considered. For example, the age of the fleet is a significant factor in downtime. To reverse this through the retirement of older aircraft and procurement of new aircraft is extremely expensive. Similarly, fleet size was found to be a driver of non-availability. But it is difficult to retroactively change fleet size decisions. As these two examples illustrate, there needs to be the potential for significant benefits prior to making these types of costly and difficult decisions in the acquisition cycle. Therefore, we examine utilization of available hours. The purpose is to help answer the following question: do we fly more hours or sorties when given more available hours? The answer to this can help decision-makers trade off the costs of more availability with the associated benefits.

We analyze utilization through two approaches. First, an ordinary least squares regression model on the total data set is developed. Hours flown is the dependent variable in the model. Controlling for platform type, available hours is found to be a very significant variable with a p-value of < 0.0001. This indicates that as available fleet hours increase, the fleets fly more. The coefficient on the available hours variable is 0.05. The interpretation is that for every additional hour made available, 5 per cent of that hour is used for flying. How does that compare to current utilization? Interestingly, current fleet-wide average utilization of available hours is about 7 per cent. Thus, the regression coefficient substantiates what is seen in the field today. It is important to note, however, that the regression results show correlation, not causation. It is plausible that the reverse is true: pressures to fly or results in maintainers making more aircraft hours available. Regardless of the direction of causation, the essential takeaway is that available hours and hours flown are correlated.

Some may argue that the Air Force should not expend resources to improve AA if only 5 per cent of additional hours will be used for flying. Robust analysis of the reasons behind this low percentage of utilization is beyond the scope of this paper and is left for future research. However, we do provide some considerations for future researchers when addressing the issue. The AA metric presumes the Air Force needs aircraft available 24 h/day. In truth, much of what the air force does is fly training sorties during the day and has aircraft sit idle, but available, on the flight line the remaining hours of the day. Therefore, the 5 per cent utilization figure potentially undersells the impact that improvements to AA have on the Air Force mission.

The second approach to analyzing utilization is through analysis at the individual mission design (MD) level. There are two parts to this investigation. Correlations between available hours and sorties is examined as are correlations between available hours and hours flown. Results are shown in Table IV.

Using a threshold of greater than 0.75, strong correlations are found for 18 of 30 platforms between available hours and sorties flown. Ten additional platforms have moderate correlation (defined as 0.50-0.74). One platform has minor correlation (defined as 0.26-0.49). Only one platform is found to have weak correlation (defined as less than 0.25) between available hours and sorties flown. Similarly, 22 of 30 platforms have strong correlations between available hours and hours flown, while only one has a weak correlation.
The overarching finding, therefore, is that availability appears to be a limiting factor for utilization of USAF fleets. This is not to say that it is the only limiting factor. Crew availability and funding are just two examples of other resources posing possible limiting constraints. The validity of those factors is not explored and is beyond the scope of this paper. The results here simply show that increasing available hours is correlated with additional hours and sorties flown.

**Conclusion**

AA has decreased from 75 per cent in the 1990s to a current low of only 62 per cent. The downward trend has drawn the concern of USAF senior leaders. This paper’s investigation of the phenomenon reveals several interesting insights. First, the intuition behind decreasing TAI and assumed proportional decreases in non-available hours is not borne out. The data shows non-available hours remaining nearly constant. Owing to the mechanics of the calculation of the AA statistic, this mathematically necessitates that AA decreases along with TAI. In other words, AA has become so intricately linked to USAF planning and operating that there is a tendency to overlook the metric’s shortcomings. Second, we find NMCM is the largest component of downtime. NMCM is also the fastest growing category of downtime, with unscheduled maintenance comprising the largest segment of NMCM. Drivers for NMCMU include age, platform type and fleet size, among others. Many of these predictors are expensive to
retroactively change, necessitating an examination of utilization to determine the return to increasing available hours. Third, the data show available hours may be a limiting factor to utilization of the USAF fleet. Individual platform analysis by sorties and by hours flown shows strong correlation with utilization in the majority of platforms. This suggests that there is potential for real readiness benefits to increasing available hours. Quantifying those benefits to provide a comparison to the costs of increasing availability is the next logical step for future research.

As with any research, there are limitations associated with the findings. Perhaps the largest limitation is the exclusion of manpower as an explanatory variable in our regression model. Some maintenance manpower data at the enterprise level were available for analysis; however, we were unable to obtain manpower data specific to individual platforms. While previous researchers were able to conduct a case study examining the relationship between manpower and MC rates on the F-16 (Chimka and Nachtmann, 2007), this type of approach was not feasible here. Additionally, the available manpower data we did obtain in this research were only germane to the organically (not contractor logistically supported) maintained platforms. While we did explore regression analysis with this limited manpower data, it did not have enough variation to be significant in the models. Future research should explore the role of manpower if data can be obtained at the platform level for organically maintained aircraft and the associated manpower related to contractor maintained aircraft.

References
Fry, F.G. (2010), “Optimizing aircraft availability: where to spend your next O&M dollar (AFIT/GCA/ENV/10-M03)”, Master of Science thesis, Air Force Institute of Technology, Department of Systems Engineering and Management, Wright-Patterson AFB, OH.


About the authors

Jonathan D. Ritschel, PhD, is an Assistant Professor of cost analysis, Department of Systems Engineering and Management at the Air Force Institute of Technology. He received his BBA in Accountancy from the University of Notre Dame, MS in Cost Analysis from AFIT and PhD in Economics from George Mason University. Dr Ritschel’s research interests include managerial decisions, public choice and Department of Defense cost estimating, and some of his works have been published in the Journal of Cost Analysis and Parametrics, Journal of Public Procurement, Econ Papers and Defense Acquisition Research Journal. Jonathan D. Ritschel is the corresponding author and can be contacted at: ritschel1@msn.com

Tamiko L. Ritschel is an Operations Research Analyst at Headquarters Air Force Material Command. She has extensive expertise in organizational development and logistics, including previous research projects for the DoD. She received a BS degree in mathematics from the University of Notre Dame, an MS degree in operations research from the Air Force Institute of Technology and an MBA degree from Wright State University. Ritschel’s research interests include organizational development, logistics, decision analysis and simulation and modeling, and some of her works have been published in the Air Force Journal of Logistics, Air and Space Power Journal and Journal of Transportation Management.

Nicole B. York is an Operations Research Analyst with Headquarters Air Force Material Command. She has a BS degree in engineering management and business economics from Miami University and an MS degree in operations research from the Air Force Institute of Technology. Her research interests include game theory, organizational management, operations and supply chain optimization and data visualization.