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A Condition Based Maintenance Approach to Forecasting B-1 Aircraft Parts

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A CONDITION BASED MAINTENANCE APPROACH TO FORECASTING B-1 AIRCRAFT PARTS

THESIS

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Abstract

United States Air Force (USAF) aircraft parts forecasting techniques have remained archaic despite new advancements in data analysis. This approach resulted in a 57% accuracy rate in fiscal year 2016 for USAF managed items. Those errors combine for $5.5 billion worth of inventory that could have been spent on other critical spare parts. This research effort explores advancements in condition based maintenance (CBM) and its application in the realm of forecasting. It then evaluates the applicability of CBM forecast methods within current USAF data structures. This study found large gaps in data availability that would be necessary in a robust CBM system. The Physics-Based Model was used to demonstrate a CBM like forecasting approach on B-1 spare parts, and forecast error results were compared to USAF status quo techniques. Results showed the Physics-Based Model underperformed USAF methods overall, however it outperformed USAF methods when forecasting parts with a smooth or lumpy demand pattern. Finally, it was determined that the Physics-Based Model could reduce forecasting error by 2.46% or $12.6 million worth of parts in those categories alone for the B-1 aircraft.

For God, Family, and Country

Acknowledgments

I would like to express my sincere appreciation to my advisors. To Dr. Alan Johnson for his sage advice, breadth of knowledge, and many connections which were foundational in helping me put together the elements of this work. To Dr. Michael Kretser, whose forecasting expertise and maintenance acumen was especially influential in helping me navigate which research paths to explore.

Additionally, I would like to thank several other professors who have spent quality time educating me. Dr. Jason Freels taught me the fundamentals of analyzing reliability statistical data, and Dr. Daniel Steeneck revolutionized my view on condition based maintenance forecasting techniques.

A mentor of mine often said, "Logistics is a team sport." Through this experience, I have learned that research is too. For that, I am also indebted to many people from multiple organizations who helped me on this journey. To the researchers at the Logistics Management Institute who connected me with the original Physics-Based Model and who willingly shared many other of their research efforts (Dr. Brad Silver, Dr. David Peterson, Steve Long, Ward "Skip" Tyler). To Dr. Marvin Arostegui who gladly helped me obtain the D200 forecast data necessary for this research. Joshua Moore (420 SCMS) was critical in helping me understand how the Air Force forecasting process works. Chief Joseph Sternod was pivotal in helping me categorize B-1 parts as well as understand how we can collect better data for future efforts. Finally, to John Rusnak and Bill Donaldson from HAF/A4P and Mr. Don Lucht at AFMC/A4P for sponsoring this research.

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I. Introduction

Background

As technology advances, it should follow that forecasting techniques will advance as well. However, aircraft parts forecasting practices for the United States Air Force (USAF) have remained archaic, resulting in a 57% accuracy rate in fiscal year 2016 for USAF managed items. The error from this approach inhibited $5.5 billion worth of inventory from being repurposed toward other USAF priorities. This research effort explores advancements in condition based maintenance (CBM) research, and specifically its application in the realm of forecasting. Then it will evaluate the applicability of those forecast methods within current USAF data structures. The Physics-Based Model will be used to demonstrate a CBM-like forecasting approach, and error results will be compared to USAF baseline procedures.

CBM is not a new concept for the USAF. In 2002, the Deputy Under Secretary of Defense for Logistics and Material Readiness directed the military to develop and implement Condition Based Maintenance Plus (CBM+). This directive defined CBM as "a set of maintenance processes and capabilities derived from real-time assessment of weapon system condition obtained from embedded sensors and/or external test and measurements using portable equipment" (Smith, 2003). The annotation of "CBM+" that is unique to the military services is signaling the integration of technologies and processes, with the aim of improving system effectiveness (Under Secretary of Defense for Acquisition Technology and Logistics, 2012). CBM+ could be further explained as CBM that is enhanced by reliability analysis and prognostic capabilities. However, it should be noted that other sources include this aspect as an inherent aspect of CBM, as will be discussed later (Jardine, Lin, & Banjevic, 2006).

Furthermore, the CBM+ initiative was an integral part of the Expeditionary Logistics for the 21st Century (eLog21) campaign. This movement sought to implement the systems and processes in place that would enable Agile Combat Support, one of the six core competencies of the USAF (Navarra, Lawton, McCusker, & Hearrell, 2007). The main goal behind moving toward CBM+ was to improve maintenance agility and responsiveness, to increase operational availability, and to reduce lifecycle total ownership costs (Navarra et al., 2007). In order to do this, it was recognized that Information Technology (IT) systems and processes would need to be redesigned around this new concept. A future state model of the IT system that a CBM+ program would necessitate is shown in Figure 1.

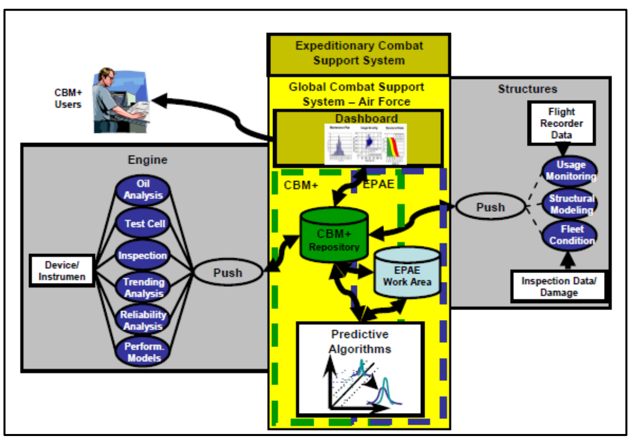


Figure 1: CBM+ Future State (Navarra et al., 2007)

The Expeditionary Combat Support System was the program undertaking this immense responsibility. However, when that program was discontinued in 2012, CBM+ in the USAF essentially died as well.

USAF methodology for maintenance and supply support is based on engineering and decades of refined practice. Traditional USAF maintenance practices are founded on technical order instructions, which specify when and how to perform maintenance actions. This methodology fits under preventative maintenance practices (L. Swanson, 2001). Generally speaking, maintenance actions are completed on fixed time or use intervals, precluding hard part failures. This method is imprecise and frequently results in disposing parts long before reaching the end of their useful life (Ellis, 2008). The USAF's demand forecasting techniques have evolved over the years, however still primarily rely on historic demand (Bachman, 2007).

The USAF uses a variety of forecasting techniques, however the primary method used is an eight quarter moving average. This method is used in over 80% of occurrences. Details of this as well as other USAF techniques will be elaborated on in Chapter II. While these practices have been adequate for the USAF, the Chief of Staff, General Goldfein stressed in a recent newsletter that "Air and Space superiority are not American birthrights" (Goldfein, 2017). He went on to describe that the USAF is at a pivotal moment where its superiority gap over other nation's air forces is diminishing, and in some cases has already closed. *Readiness* is a term frequently used to describe the USAF's state of preparedness to engage in warfare. Often readiness is measured by the rate of aircraft availability. The only component of aircraft availability that pertains to spare parts is the Total Non-Mission Capable for Supply (TNMCS). A snapshot taken of

December 2016's supply performance shows that 18 of 39 (46%) weapon systems did not meet their TNMCS standard for the month (Appendix A: Weapon Systems Dash Board). This metric tells us that the USAF supply chain does not deliver the supply support it is programmed to provide. It is the hope that by studying new demand forecasting techniques that the USAF can improve its supply performance and thereby reduce the amount of aircraft not meeting their respective TNMCS standards.

The need for better processes is clear to see within the USAF. As CBM is still a relatively new maintenance philosophy, the pressing challenge is to unlock the benefit from behind what conditional data can provide. According to Greitzer et al. (1999), CBM is still in a research and development phase, because many challenges exist before having refined prognostics techniques and logistics models that fully leverage the new technology of censor data. This research is aimed at making the USAF aware of CBM methods, and recommending which techniques to consider for implementation.

Problem Statement

The USAF relies on scheduled maintenance practices which do not maximize the useful life of parts. The USAF primarily uses an eight quarter moving average of historical aircraft parts demand to predict future demand. These imprecise methods often result in buying and stocking the wrong parts, resulting in failing to meet established supply support goals, and costing the USAF billions in misappropriated funds. Further, as IT system capabilities expand, it is critical for the USAF to have an awareness of established maintenance and forecasting methods that could be leveraged with new technology. CBM is a promising practice that deserves to be evaluated for advancing processes the USAF critically relies on.

Investigative Questions

Given the above problem, this research will seek to highlight common CBM forecasting methods that are well established and evaluate its suitability with current USAF data collection and prognostic methods. One such method will be evaluated in detail and its accuracy will be compared to the USAF's forecast techniques to measure the effectiveness of this new method. In order to address the objectives of this thesis, four investigative questions (IQs) were posed:

IQ1. What established prognostic CBM methods produce a demand forecast?
IQ2. What data does the USAF currently collect that fits under CBM?
IQ3. What CBM forecast methods can be used by the USAF with current IT systems?
IQ4. How well does a CBM forecast compare to the USAF's current forecast method?

Research Focus

This study evaluates prognostic CBM practices by identifying relationships between flying event data and parts failures to increase forecast accuracy. There were two research sponsors, AF/A4P (Deputy Director of Resource Integration and Logistics Chief Information Officer) and AFMC/A4D (Depot Operations Division). This research will center on finding relationships between how the B-1 aircraft is used and aircraft parts demand. The analyst will apply known CBM prognostic methods that build forecasts on predictor variables. The scope of this research will be limited to assessing USAF managed aircraft parts demand at base-level. The formal term the USAF uses to identify this class of demand is Operational and Intermediate Maintenance. Assessing demand at the base-level allows for a more refined look at correlation between flying operations and the demand signal. It was necessary to exclude depot level demand, as the demand signal becomes much more complex with the addition of aircraft overhauls that are scheduled years in advance, regardless of current flying activities. Finally, this analysis will not include Defense Logistics Agency managed parts. The Defense Logistics Agency uses entirely separate forecasting methods from the USAF, and therefore no evaluation of their forecast accuracy will be made in this research.

Methodology

The Physics-Based Model (PBM) is a reliable CBM-like method that can be used to forecast total aircraft removals per year (Wallace, Houser, & Lee, 2000). In this research the PBM will be evaluated for its effectiveness to forecast parts demand at the national item identification number (NIIN) level per quarter. Comparisons will be made based on NIIN category such as mechanical, electronic, hydraulic, etc. Another comparison will be tested to provide evidence for the PBMs accuracy by demand pattern. The demand forecast accuracy of each group will be compared between the PBM forecast and the USAF's baseline eight quarter and four quarter moving average methods.

Assumptions and Limitations

There are three main assumptions of this research. The first is that any data obtained from USAF databases is correct and is an accurate reflection of failure events and flying operations. Some of the data used in this study is entered by hand into a system of record such as mission type, and therefore is susceptible to human error. The second assumption is that the NIINs evaluated within each group fail in a homogeneous manor that is representative of the population of NIINs in each category. It would be unrealistic and unbeneficial from a management perspective to evaluate each individual NIIN. Therefore, a method has been chosen that will evaluate the PBM's applicability to forecasting similar items. The final assumption in this research relies on using the actual flying profile (ratio between combat sorties and training sorties) in a forecast period as if it were a known value, and not an additional forecast parameter. This logic will be explained further in the Methods chapter.

Significance of Research

This research challenges the status quo parts forecasting method that the USAF uses, and postulates that CBM offers new comprehensive techniques that the USAF can and should take advantage of. Moreover, this work aims at stepping towards what some call the 'holy grail' of inventory management, which is a system that no longer predicts demand, but rather tracks degradation processes and can use high velocity transportation to deliver parts to the customer exactly at the moment of failure. Without CBM forecasting, that dream would remain a mythology. It is realistic to presume that the USAF can implement the results of this research immediately, and begin leveraging its accuracy. Additionally, this research should stand as a foundation for future researchers to leverage, as it identifies the gaps in practice between USAF data collection and CBM forecasting and inventory management techniques.

What to Expect

This thesis is laid out in the following order: Chapter II, the literature review, will illustrate forecasting methods the USAF currently uses as well as established CBM forecasting methods. Chapter III will focus on the methodology conducted in this research. Chapter IV will present the results and statistical analysis of the data collected, and will elaborate on how they answer the research questions. Finally, Chapter V will bring attention to the main points and conclude with recommendations.

II. Literature Review

Chapter Overview

The purpose of this chapter is to provide a CBM definition and to review the history of CBM both in the military and in the civilian sector. Additionally, there will be a thorough discussion of aircraft parts forecasting techniques to provide a foundational background to the application of this research. Finally, a literature review of other pertinent topics will be presented to paint a picture of contiguous research areas that affect how the USAF performs parts forecasting.

USAF Forecasting

The central guidance for the USAF's demand forecasting machine is Air Force Materiel Command Manual 23-1, *Requirements for Secondary Items*. This text delineates every responsibility and calculation for forecasting USAF managed parts. *Secondary items* is the term used for parts installed in a higher assembly such as an aircraft, a vehicle, a piece of equipment, or another recoverable secondary item (Air Force Materiel Command, 2011). Further, this manual explains the behind the scenes processing completed by the IT system used to manage the forecasting process for both consumable and reparable assets, designated D200A. It is important to specify that this process is completely separate from the process used for Defense Logistics Agency managed items and frequently different from forecasting demand for parts governed by performance based logistics contracts.

From a top level perspective, the USAF forecast process should be thought of as a compilation of many separate requirement forecasts across multiple timelines simultaneously. For brevity, this overview will focus on requirements directly related to this research effort. Forecasts are made at a subgroup master NIIN level, and will be referenced simply as NIIN from here on in this report. A subgroup master is a primary identification used for any set of substitute items. This allows the system to compute a forecast for a group of substitute items. There are 16 separate computations for each NIIN that determine its total requirement. These are broken into three categories. First, the focus of this research, is Organizational and Intermediate Maintenance (OIM). This can be thought of as base-level demand and maintenance. Its specific categories are:

- Total OIM Demand Rate
- OIM Base Repair Rate
- OIM Depot Demand Rate
- Base Not Repaired This Station Percent
- Base Processed Percent
- Base Condemnation Percent

The next two categories of demand are the Management of Items Subject to Repair (MISTR) and Depot Level Maintenance which do not pertain to this study. The computations above are completed for several time horizons, ranging from 9.5 years to one quarter in order to provide forecasts for immediate operational needs and baseline fiscal year budgeting. However, this research effort will only use an annual forecast horizon (aggregating four quarters of forecasts). A new iteration of total requirements is completed on a quarterly cycle.

D200A uses *factors* as a percentage demand rate tie between past demand drivers and future demand drivers. Typically flight hours is the usage driver, however according to the AFSC/LGPS office that performs forecasting analysis, the number of sorties is sometimes used. The determining aspect is based on what driver is more correlated with failure patterns. Separate factors are established for each failure, replacement, and condemnation requirement. D200A allows forecasters to use five methods for computing requirements. The first character of the three digit factor indicator code designates the particular forecast method used for OIM factor computation, and is categorized as follows:

- A - 8 Quarter Average
- C - 4 Quarter Average
- K - Exponential Smoothing
- B, D, F, H, J, L - Estimates (human input; if estimate not present the system will default to another method according to code value)
- E, G, I - Predictive Logistics (12 quarter regression estimate; available for Total OIM Demand Rate only; system defaults to 8/4 quarter average or exponential smoothing for other estimates)
- M - Estimate only (human input)
- Q - Best Fit (computer selects best fit of A, C, or K)

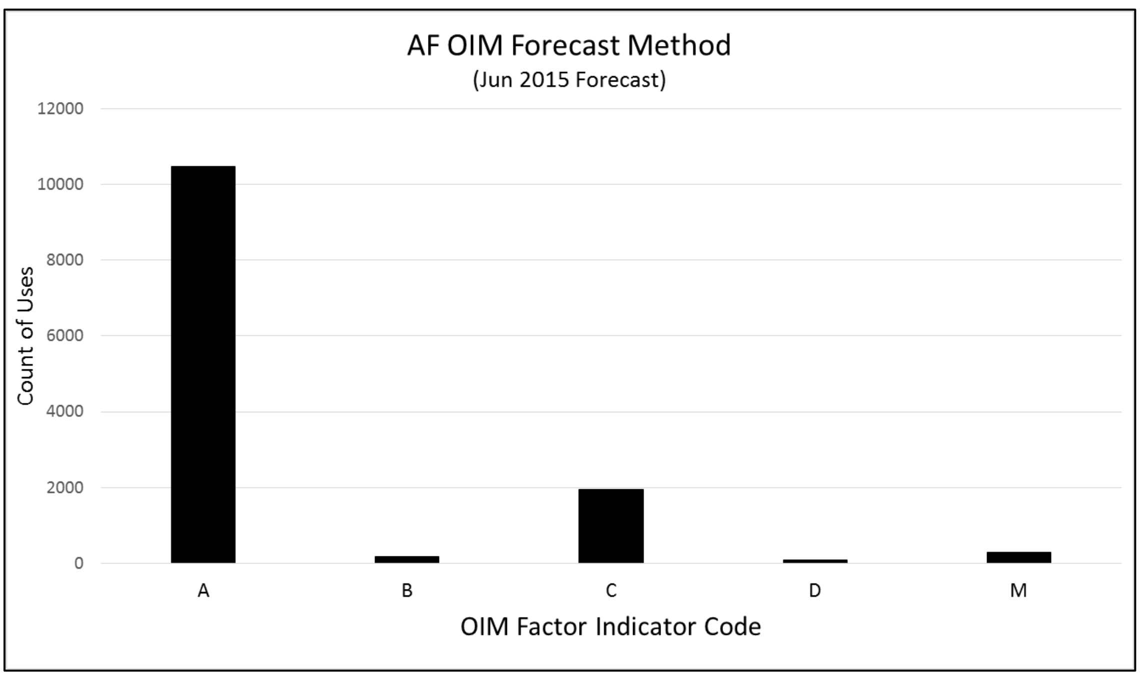


Figure 2: USAF OIM Forecast Method

Looking at Figure 2, it is easy to see that the USAF primarily uses an eight quarter and a four quarter moving average that is proportional to the number of flying hours flown. These are nearly 80% and 15% respectively, of the total base-level forecast methods used. There are many instances where this method, often called the *proportional model*, works very well. The main explanation is because of the fact that the calculation incorporates a robust amount of data. To elaborate, consider a lumpy demand cycle. The eight quarter average has the ability to slowly trend upwards or downwards depending on the tendency. As each data point is weighted equally, no one point is overly influential, making the computation more resilient to sporadic change. Additionally, several studies agree that as long as the aircraft continues to fly relatively similar operations, the proportional flying hour method with an eight quarter moving average are typically adequate forecasting methods (Slay & Sherbrooke, 1998; Wallace et al., 2000).

USAF Forecast Accuracy

There is a long history of U.S. Government Accountability Office (GAO) investigations into DoD spare parts practices. The first was in a 1984 report, when the GAO estimated that the USAF overstated $31.1 million in needs for aircraft being phased down or phased out, while simultaneously under estimating $28.8 million need for new aircraft needs (U.S. General Accounting Office, 1984). Furthermore, the GAO felt the issues were a result of miscalculations driven from the very same flying hour proportional model used today. After an estimated $30 billion in excess parts was discovered, inventory management was consequently added to the High Risk List (U.S. General Accounting Office, 1990). In 2013, another GAO study was completed and estimated spare parts excess inventories at $9.2 billion (U.S. Government Accountability

Office, 2013). While marginal steps were taken to eliminate waste, there was still more work to be done. The 2013 report stated that with regard to inventory management, there were nine key areas needing improvement, one of which was demand forecasting. It was specifically noted that the DoD was in the early stages of implementing numerous actions to improve demand forecasting. Finally, as recently as 2015, inventory management was cited again as still lacking "demonstrated progress" in order to be removed from the GAO High Risk List (U.S. Government Accountability Office, 2015).

Lowas, an independent researcher, performed a very rigorous analysis of the USAF's forecasting methods. First, to get an overall sense of accuracy, he utilized the USAF's web based Forecast Analysis Comparison Tool Plus (FACT+). He limited his analysis to airframe (structural) components, noting that previous studies showed this category of parts to have the highest forecast accuracy. Here he found that the aggregate forecast accuracy for airframe NIINs was approximately 50% over the 2010-2011 period (Lowas III, 2015). He then further refined his purview by filtering out NIINs with intermittent and sporadic demand, as well as NIINs with small sample sizes. This left him only with items that displayed smooth demand. Table 1 shows the forecast accuracy of the most common forecasting methods used by the USAF (excluding Hotl's). Even with isolating what should be definitively the most predictable parts, the USAF's best result is narrowly better than a 30% forecast error with an eight quarter moving average. Additionally, when analyzing lumpy demand patterns, errors rose well over 40%. Lowas' final judgment was that "it is apparent that current common forecasting methods are inadequate for aircraft spare parts forecasting" (Lowas III, 2015).

Table 1: Smooth Structural NIINs and Associated Forecasting Accuracies *(Lowas III, 2015)*

Demand Variability			Model Types and Resulting Forecast Error						
CV	ADI	Max Gap	4QMA	8QMA	SES(0.1)	SES(0.8)	Holt's	Part type	Aircraft
0.44	1.00	1	35.4%	34.5%	34.5%	37.8%	34.1%	Fuel Tank	C-130
0.48	1.00	1	32.7%	33.1%	33.9%	38.3%	32.9%	Fuel Tank	C-130
0.47	1.00	1	36.3%	36.5%	36.5%	40.5%	35.8%	Fuel Tank	C-130
0.47	1.00	1	35.0%	32.1%	33.5%	40.9%	36.6%	Fuel Tank	C-130
0.37	1.00	1	28.5%	29.8%	29.4%	30.0%	27.9%	Cowling	C-5
0.40	1.00	1	32.1%	30.7%	30.3%	36.3%	28.5%	Windshield	KC-135
0.30	1.00	1	23.0%	22.1%	21.6%	29.5%	21.3%	Windshield	KC-135
0.45	1.01	2	25.3%	24.0%	26.4%	29.2%	22.3%	Radome	
0.37	1.00	1	27.4%	27.4%	27.5%	29.7%	26.4%	Exhaust	A-10
0.48	1.00	1	32.3%	37.2%	38.9%	32.2%	29.8%	Fuel Tank	A-10
0.38	1.00	1	25.0%	23.8%	25.8%	26.9%	24.7%	Door	C-5
0.42	1.00	1	28.0%	27.3%	28.3%	29.4%	27.0%	Door	C-5
Ave. Method Error			30.1%	29.9%	30.5%	33.4%	28.9%		

Demand Forecast Accuracy

There are multiple ways to measure forecast error or accuracy. Demand Forecast Accuracy, the method the USAF uses, is calculated as (FACT+ User Manual, 2016):

$$DFA = 1 - \frac{\sum_{i=1}^{n} |Actual\ Demand - Forecast\ Demand|}{\sum_{i=1}^{n} Actual\ Demand} \quad (1)$$

where n is the number of periods aggregated in the forecast horizon. Note that this calculation is really a calculation of one minus the forecast error, which results in an accuracy measurement. In instances where actual demand is zero, to avoid an undefined result the FACT+ tool defines these results as -999% or non-applicable (FACT+ User Manual, 2016). This practice has large issues, particularly on parts with intermittent or lumpy demand patters which frequently have periods with no demand.

A more commonly accepted forecast error measurement is mean absolute percent error. This calculation has the benefit of being scale independent, and therefore can compare error across multiple series of forecasts (Hyndman, 2006). The main difference between demand forecast accuracy and mean absolute percent error is that the latter divides both the numerator and denominator by *n*, and leaves the expression in terms of error, instead of subtracting from one.

Hyndman (2006) shows how mean absolute percent error, and subsequently demand forecast accuracy, frequently result in biased distributions when actual demand is close to zero. Again, actual demand values that are close to zero are common for intermittent and lumpy demand items. Additionally, this calculation puts a heavier penalty on positive errors than on negative errors, which adds to the biased result (Hyndman, 2006). Because of this, analysts should be strongly cautioned from using these measurements as valid forecast error tools in which accuracy measurements will be evaluated on. In light of this knowledge, Hyndman (2006) recommends a new calculation called mean absolute scaled error. This calculation has been shown to be non-biased and more applicable for intermittent demand patterns. For these reasons, mean absolute scaled error will be the error measurement used in this study. A detailed description of this calculation is denoted in the Chapter III.

Replacement Parts Forecasting

This next section will discuss common parts forecasting methods used in spare parts forecasting. Tibben-lembke and Amato (2001) reference a number of surveys that have shown that the most common replacement parts forecasting methods are weighted moving averages, straight-line projections, and exponential smoothing. This corroborates common understanding that simpler methods are often implemented because of ease of use. A hierarchy diagram lists the most common forecast methods in Figure 3.

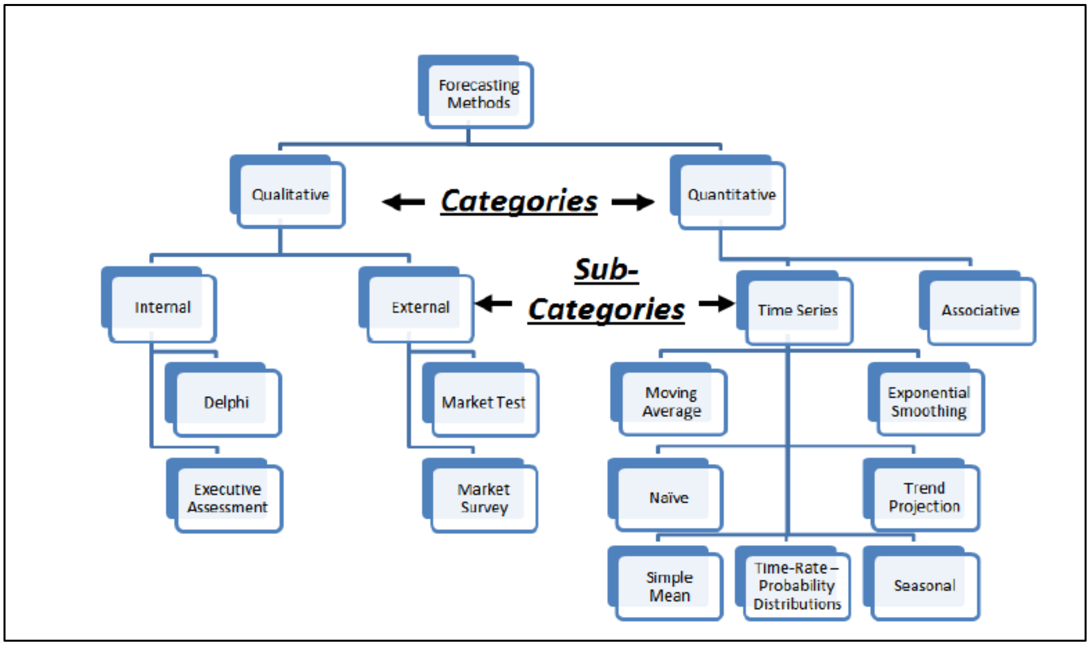


Figure 3: Hierarchy of Forecasting Methods (Lowas III, 2015)

Tibben-lembke and Amato go on to elaborate on the value information can add to forecasting methods. They estimate failure using an exponential distribution. The benefit of the exponential distribution over the Weibull is that it only has one distribution parameter that can be estimated easily as mean time between failures. Their analysis showed this method to be more precise than exponential smoothing and weighted moving average (Tibben-lembke & Amato, 2001). A connection here should be made to a similar premise to this thesis research, in that additional information is being used to form a new forecast method with explanatory variables in lieu of a purely historic forecasting technique.

In reliability theory, the Weibull distribution is commonly used to model the failure of spare parts (Lowas & Ciarallo, 2016). Lumpy or sporadic demand are very common issues among aircraft parts forecasting, making it very difficult to be accurate. However, the root cause of this pattern had never fully been vetted (Lowas & Ciarallo, 2016). Boylan (2005) provided a rule of thumb for sporadic demand parts as having at least 20% of time periods with zero demand. Lowas and Ciarallo (2016) explored the use of the Weibull distribution in order to find fleet-wide variables that may cause lumpy demand patterns. They used a Monte Carlo simulation to measure fleet-wide demand characteristics by comparing ranges of fleet sizes, buy period lengths, time to failure lengths, as well as varying Weibull distribution parameters. Results of the Monte Carlo simulation show that the variable that increased lumpy demand the most was aircraft fleet size. The second largest variable accounting for lumpiness was the buy period. The observation was that a longer buy period increased demand variability (Lowas & Ciarallo, 2016).

Several other researchers have addressed the issue of sporadic demand for the USAF. In 2007, Bachman formulated a *Peak* inventory policy that reduced wholesale wait-time and backorders by establishing a new reorder point based on exponential smoothing of an item's peak demand pattern. In 2013, he established a new inventory policy that assessed item cost, procurement and repair lead times, and overall demand patterns to build a cost versus aircraft availability tradeoff curve (Bachman, 2013). This method is used today throughout the USAF, and is known as Readiness Based Sparing. Gehret (2015) looked at a stockage policy based on how likely a specific location is to have a demand, given the population's demand and that location's time since its last demand. The takeaway from the above three studies is that in lieu of a strong demand signal, inventory policies are the method used to provide a high level of supportability in-place of demand forecasting techniques. The benefit of CBM is that it does not rely solely on a demand signal. Instead, it offers the ability to use conditional data as will be discussed later in this chapter.

Alternative USAF Forecasting Models

Work done by Oliver (2001) used linear regression to correlate F-16 mission capability rates with numerous explanatory variables. Oliver's work had a very broad aperture of variables considered. A few examples were maintenance manning, maintenance skill levels, maintenance retention, aircraft break rates, aircraft fix rates, flying operations tempos, and spare parts issues among many other variables including spare parts funding. His results showed that a predictive mission capability model included the number of sorties, flying hours, average aircraft inventory, total maintenance personnel assigned, and controlling for interactions between total maintenance personnel and average aircraft inventory. The significance of this research pinpointed controllable inputs that decision makers could use to improve MC rates. In 2013, Theiss performed a similar investigation by evaluating which variables would characterize C-17 mission reliability. His analysis concluded that mission type, operating organization type, departure theater, aircraft age, as well as other variables are significant. Such research like these will serve as fodder for explanatory variables used in this research. Even though not all of these variables will be used in this work, the premise of using event data to explain parts failure is of a similar line of reasoning.

To this point, the appropriateness of the proportional flying hour failure model has only been subtlety questioned. However, there are several studies which directly uncover the fallacies with its use. Before looking at other research efforts, let us first discuss what a similar proportional cost model assumes. Van Dyk (2008) defines the model as a proportional relationship between costs and flying hours such that:

1. When no hours are flown costs are zero.
2. A 1% increase in flying hours will increase costs by 1%.

The spare parts proportional model definition is presumably the same for demand forecasting; as total costs are merely a function of the number of parts demanded.

One organization who has performed several research efforts on the proportional model is the Logistics Management Institute (LMI). A 1995 study performed by LMI on war time demands showed that a pure flying hour approach would overstate demands, while a pure sortie-based approach would understate demands as shown in Figure 4 (Slay, 1995).

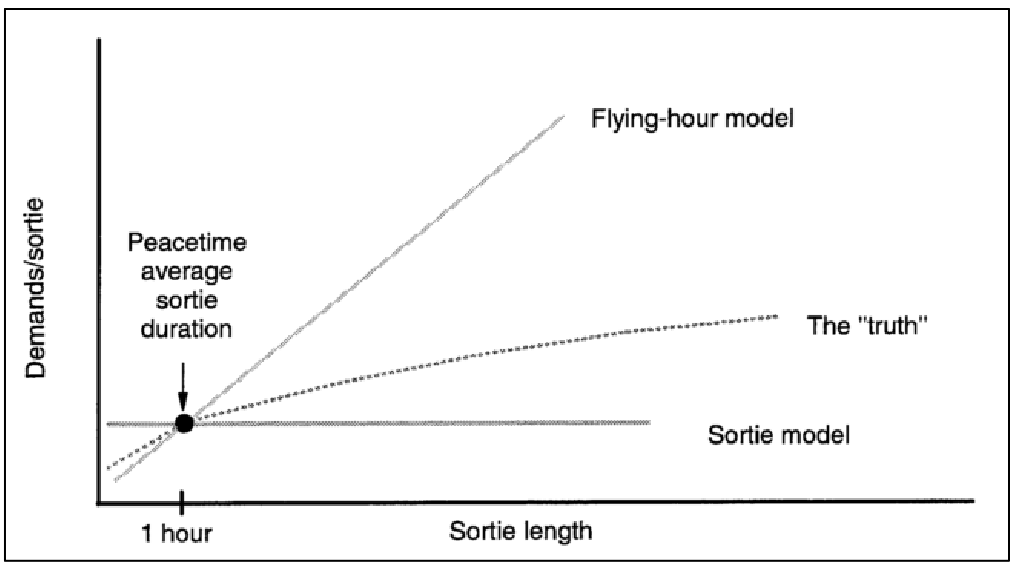


Figure 4: Proportional Flying Hour Model Vs. Sortie Model (Slay, 1995)

A more rigorous study was then completed by LMI two years later showing that after analyzing 250,000 sorties, a 2-hour fighter sortie caused only 10% more parts to break than a 1-hour sortie did (Slay & Sherbrooke, 1998). This refutes the second principle of

Van Dyke's (2008) definition because a 2-hour sortie should have produced a 100% increase in broken parts over a 1-hour sortie under the proportional model. This concept led the analysts to look at the problem through another lens; one that shifted toward incorporating what stressors were placed on the aircraft. For example, they analyzed F-15 parts demand based on what mission type the aircraft flew. Table 2 from LMI's analysis shows that cross-country missions produce fewer demands than training missions. In light of this analysis LMI recommended a "decelerated" forecast model which is a 10% demand rate per sortie hour after accounting for a baseline intercept of per sortie demand (Slay & Sherbrooke, 1998).

Table 2: Mission Type Impact on Langley F-15C/D Parts Demand (Slay & Sherbrooke, 1997)

Mission type	Number of sorties	Average length (hours)	Average demands/sortie
Aerial combat training	7,247	1.32	0.39
Cross-country	498	1.47	0.15
Deployment	973	1.64	0.27
Other	201	1.23	0.56
Overall total/average	8,919	1.36	0.37

Another pivotal LMI study that will serve as the foundation methodology in this research effort was called, "A Physics-Based Alternative to Cost-Per-Flying-Hour Model." In this research Wallace et al. (2000) argued that the proportional model was significantly less adequate when used to predict demand from combat sorties. Note that in their research they used the number of part removals from an aircraft as a surrogate for actual spare parts demand due to accessibility of data. A C-5 Operation Desert Storm analysis corroborated much of what the previous LMI studies had shown. As Figure 5 from that study illustrates, prior to Operation Desert Storm the proportional forecast model worked adequately. Under the proportional model, when flying operations increased under Operation Desert Storm, then removals should subsequently increase as well. However, the actual number of removals stayed relatively the same regardless of the increase in flying hours per month.

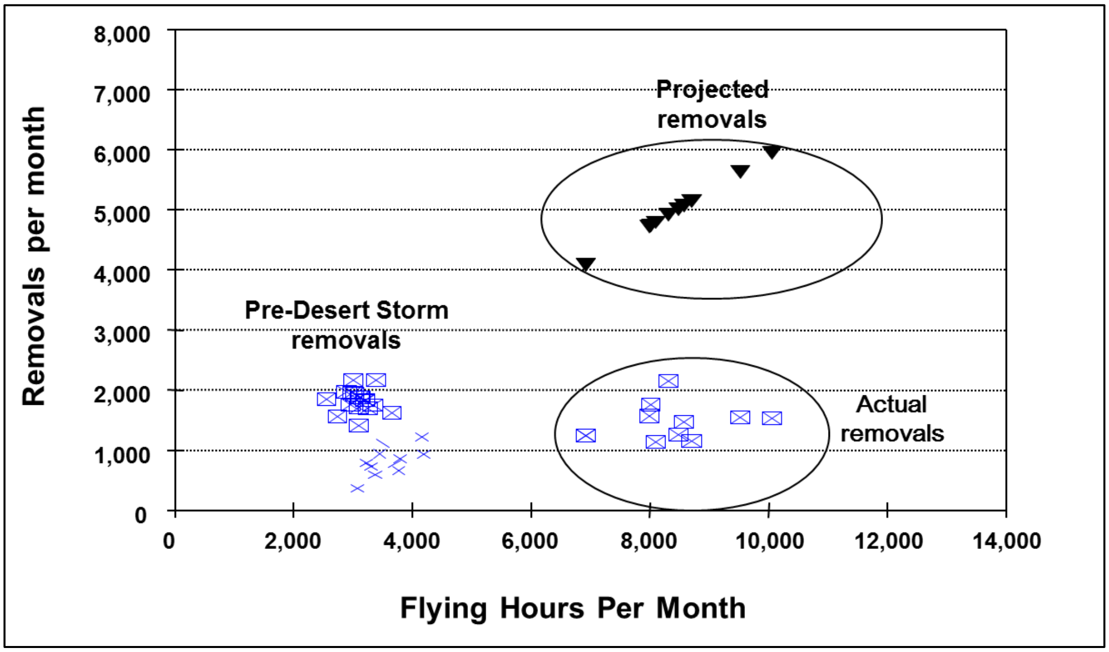


Figure 5: Operation Desert Storm C-5 Analysis (Wallace et al., 2000)

On the back of this research and previous studies, this LMI team decided to segregate forecast parameters based on combat sorties and training sorties. From this they established the Physics-Based Model (PBM), which incorporates predictor variables that were driven by the physical behavior of the aircraft such as the number of landings, the number of sorties, and the number of hours on the ground in addition to flying hours (Wallace et al., 2000). In order to test their model's accuracy relative to the proportional model, they compared four separate time series data sets for the C-5, the C-17, the KC-

135, and the F-16. The PBM had a lower forecast error in each of the 16 cases analyzed (Wallace et al., 2000).

CBM Philosophy

A simple description of a Condition Based Maintenance (CBM) system was postulated by Jardine, et al. (2006), stating that every CBM system has three steps. First, is data acquisition. This step is centered on obtaining data on the health of the system. Second, is data processing; which is analyzing the signals from step one. The final step is maintenance decision-making, which revolves around making policies that drive maintenance actions based on the analysis from step two.

CBM is a maintenance strategy that bases decisions on information collected through condition monitoring (Ellis, 2008). Prajapati, Bechtel, and Ganesan (2012) postulate that CBM is a subset of reliability centered maintenance, which is made up of a mix between CBM and scheduled (preventative) maintenance. The primary goal of CBM aims at avoiding unnecessary maintenance tasks until there is significant evidence of need (Jardine et al., 2006). Maintenance actions based on this premise can lead to remaining useful life improvements, resulting in lower maintenance costs (Tracht, Goch, Schuh, Sorg, & Westerkamp, 2013). This notion contrasts that of scheduled maintenance which relies on fixing or replacing a part based on a designated time (or use) interval regardless of the actual condition of the part.

Diagnostics/Prognostics

Diagnostics is defined as the process of finding a fault after or during the process of the fault occurring in the system (Prajapati et al., 2012). This analysis is performing fault detection, isolation or identification with posterior event data (Jardine et al., 2006). The following section will elaborate on the aspects of this type of analysis. Prognostics in the realm of machine data analysis is defined as the process of predicting the future failure of any system, by analyzing current and previous history of operating conditions (Prajapati et al., 2012). This application is different from diagnostic in that it explicitly performs prior event analysis so it can predict or forecast a failure event (Jardine et al., 2006).

Event Data

Event data are descriptors of the physical history of a particular machine. Examples could include installation, breakdown, overhaul, preventative maintenance action, oil change, number of uses, etc. (Jardine et al., 2006). These data are typically entered into a database by hand, making them prone to errors.

Condition Monitoring Data

Condition monitoring data are typically collected through sensors. Depending on equipment being monitored, the sensors may be measuring vibrations, acoustics, oil analysis results, temperature, pressure, moisture, humidity, weather or environmental factors, etc. (Jardine et al., 2006). These types of data, sometimes called covariates, can identify deterioration, resulting in time to failure (TTF) models. Common descriptive data analysis tools such as clustering or multivariate analysis can be used to assess which variables will be useful to detect part failures. Murray, et al. compare multiple fault detection algorithms including support vector machines, rank-sum, and recommend their own naïve Bayesian classifier called the multiple-instance naïve Bayes (mi-NB) algorithm. Their study specifically assessed the varying method’s ability to detect fault from a multiple-instance learning environment (many simultaneous condition indicators). This is useful in cases involving multiple sensors on one part; each with their own limits set to trigger a fault indicator (Murray, Hughes, & Kreutz-Delgado, 2005). Results of their study show that support vector machines achieved the highest accuracy, however computationally took longer than other methods. Their proposed method, mi-NB, serves as a good model that balances both accuracy and speed (Murray et al., 2005).

CBM+ in DoD

As mentioned earlier, CBM first came into the DoD's lexicon in 2002. The DoD established the term Condition Based Maintenance Plus (CBM+), which refers to integrating technologies for the purpose of enhanced prognostic capabilities. The USAF's journey establishing a CBM+ program began in 2003, where the Air Force Logistics Management Agency completed a concept analysis, and provided recommendations for implementing CBM+ (T. Smith, 2003). In 2007, the USAF had a central office orchestrating the future state picture of reliability prognostics that lasted for nearly a decade. This organization was charged with orchestrating a common system infrastructure and accompanying services for integrating all combat support IT systems (Navarra et al., 2007). More specifically, they set their sights on improving maintenance agility and responsiveness in order to increase operational availability, and to reduce lifecycle total ownership costs.

In order to assemble this IT infrastructure, the USAF contracted with a database management company named Teradata who built a proprietary high-performance distributed computing architecture, complete with data bus that enables integrated throughput between multiple computing nodes (Navarra et al., 2007). The result is now referred to as the Logistics, Installation, and Mission Support–Enterprise View (LIMS-EV), and is made up for multiple suites to access data universes. The backbone of this system is the Global Combat Support System-Data Services which stands as the central data warehouse for most of the USAF's logistics IT systems. In addition to the IT infrastructure, the USAF's CBM+ office established the Enterprise Predictive Analysis Environment. The thought was that this node would act as a central hub for building prognostic algorithms that could leverage data sets across all logistics IT systems from the LIMS-EV package. Figure 1 (in chapter 1) shows a system diagram of how the Global Combat Support System-Data Services and the Enterprise Predictive Analysis Environment components fit into the CBM+ proposed model. There were three capabilities the USAF wanted to obtain from this structure (Navarra et al., 2007):

- To predict any weapon system's mission capability
- To proactively maintain readiness
- To design for integrated system life cycle management and intrinsic reliability

Many organizations have identified difficulties implementing CBM programs (Jardine et al., 2006). Similarly, the USAF struggled with implementing these practices as well. According to Navarra et al. (2007), the premise was to have operational data captured during flight and post-flight inspections automatically downloaded into LIMS-EV. Raw data would come from sensors on the aircraft or from maintainers on the flight line. These data, along with event data, could be analyzed by the Enterprise Predictive Analysis Environment, whom would build predictive algorithms resulting in a remaining useful life estimate for major components on the airframe. However, the major problem was integrating pedigree data directly from sensors into the Global Combat Support System-Data Services data warehouse (Navarra et al., 2007). As such, analysts were forced to resort to using small samples for statistical estimates or simulation data for prognostics.

Previous USAF researchers have also identified issues with regard to reliability failure data in USAF systems. Hogge (2012) attempted to calculate failure distributions of USAF end items, yet stated in his research that the only time to failure data the USAF collected was mean time between failures. He goes on to discuss the issue with mean time between failure being that this calculation is both left and right censored. Furthermore, the mean time between failure calculation is not a depiction of a part's entire useful life. Without that information, a reliability distribution cannot be computed. Further, he illustrates that the USAF tracks usage hours for equipment, usually aircraft or engines, however there is no usage tracking mechanism for most subsystems.

Current CBM+ USAF guidance is extremely sparse. The central document describing today's CBM+ efforts is a two page fact sheet which provides a general description of CBM and CBM+. It states that CBM+ is a meaningful shift away from a reactive, unscheduled maintenance approach to an evidence of need before failures approach (U.S. Air Force, n.d.). Additionally, the fact sheet provides a few examples of how CBM+ can and is used throughout the USAF. Of note, the source alludes to the USAF currently using sensors that monitor and record equipment operating parameters to facilitate remote analysis. Specifically the sheet references the CBM+ application to the F-35 because of its unique Automated Logistics Information System. However, even as recent as 2016, this automated logistics system is not yet fully operational (GAO, 2016).

Therefore, this system was not currently a viable resource option for collecting data. Subsequently, it became a priority to identify where other similar CBM+ analysis was occurring throughout the USAF. A 2014 study on the impacts of CBM in the military was completed by the Australian military. This land centric analysis showed that there are three main impacts (Gallash, Ivanova, Rajesh, & Manning, 2014):

- CBM will extend equipment's useful life while reducing the total cost
- CBM will increase fleet operational availability and mission effectiveness
- CBM will reduce the maintenance burden

It is reasonable to extrapolate these same benefits within an aviation context. Ellis (2008) believed that CBM should only be applied where condition monitoring techniques are available in a cost-effective means. Prajapati et al. (2012) asserted aviation as being a cost-effective CBM area both because of the value the aviation community places on safety, the capital intensiveness of aircraft, and the value to be gained from extending the life of the system. The USAF followed that business model by stipulating that the F-35 have condition monitoring capability from the beginning of its design, therefore making it more cost effective than adding sensors later (U.S. Air Force, n.d.). Further, Swanson (2001) corroborates the benefit to fleet operational availability, as equipment would then only taken out of service when direct evidence necessitates maintenance.

Evidence of what Gallash, et al. (2014) postulated was exemplified all the way back in a 1980s U.S. Coast Guard contract, specifying engine condition monitoring requirements for the HH-65A. This contract delineated each of the condition monitoring sensors already on the helicopter's engine that could be used for analysis, and spelled out the type of data analysis they were going to be able to use based on the condition monitoring signals (Aerospatiale Helicopter Corporation, 1980). At that time engine sensors would allow experts to perform CBM analysis on engine torque, gearbox temperature, oil pressure, oil filter impending bypass quantity, gas temperature, and generator speed.

The Army also recognized the need to move away from a scheduled maintenance, but knew it did not have the IT system in-place to do so. An effort was made in 2005 to canonize the IT requirements that would allow Army analysts to perform CBM diagnostics and prognostics (Figure 6). First, they identified the fundamental data needs—a comprehensive and synchronized view of a component's lifecycle (Henderson & Kwinn, 2005). From this, their analysts could aggregate trends of problem occurrences within major systems. Then these trends could be juxtaposed to an individual component's life history where reliability forecasts could be stipulated based on a component's current condition. One of the major issues their report noted was a disparity between maintenance and supply codes. Specifically they recognized the importance of having a link between work unit code (which is primarily used in the maintenance community) and national stock numbers (used by the supply community) (Henderson & Kwinn, 2005). Without this link, analysts would lack the ability to pinpoint which aircraft system a specific component belongs to, thereby limiting the ability to drill down to analyze multiple layers of a weapon system. Further, another critical shortcoming the Army's legacy systems lacked was a unique part identification. They describe this as a requisite capability in order to track a specific item through its lifecycle. Without a unique identification, they stipulate that "CBM implementation will be limited" (Henderson & Kwinn, 2005).

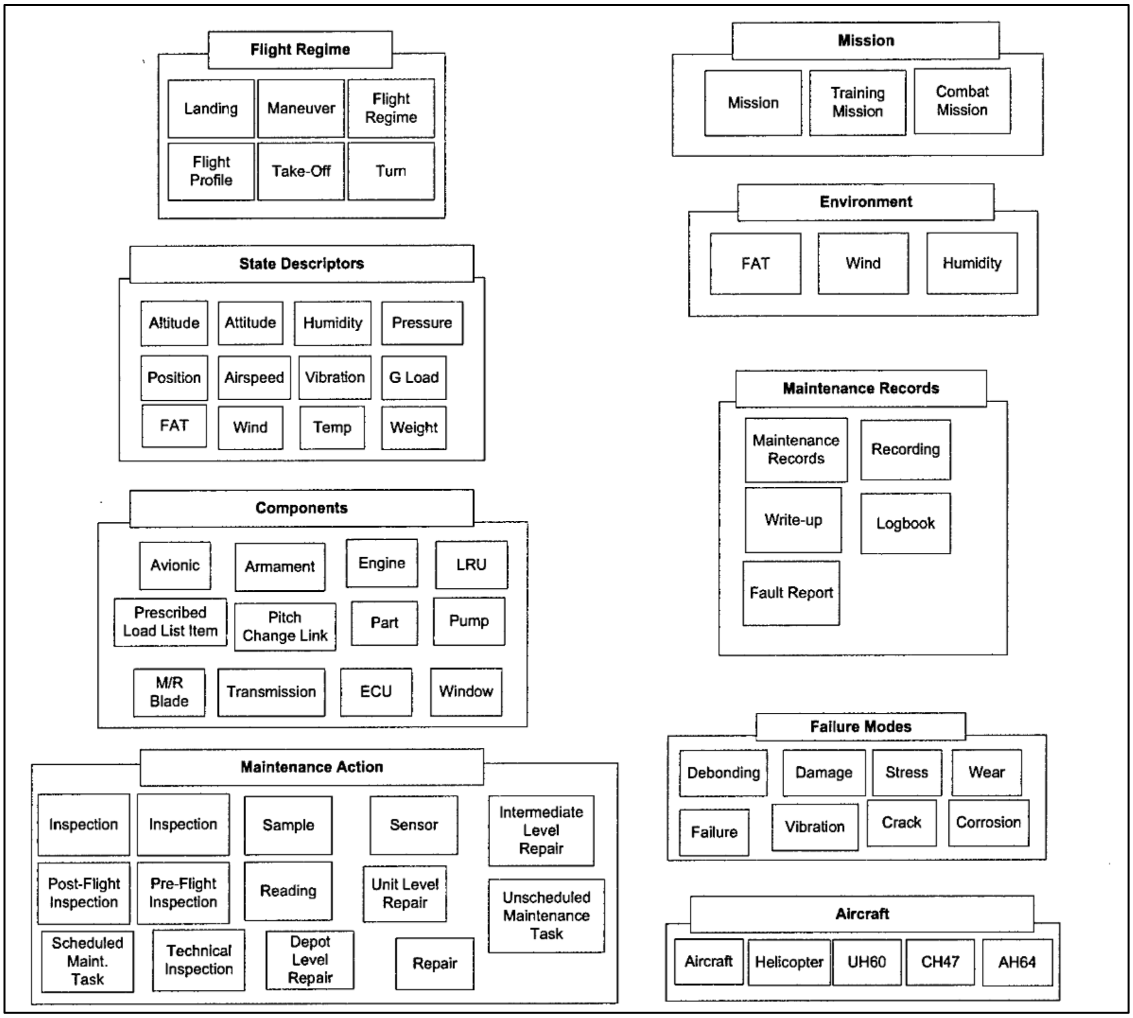


Figure 6: Affinity Diagram of CBM Data Warehouse Components (Henderson & Kwinn, 2005)

The U.S. Navy's pursuit of a CBM strategy led them to use the Integrated Mechanical Diagnostic-Health Usage Management System (IMD-HUMS). This system enabled Reeder to perform CBM analysis on phase inspection maintenance on the MH-60S helicopter. The background of his study was similar to this thesis, in that the U.S. Navy had been working to implement CBM methods for over two decades, however still primarily relied upon inspection cycles (Reeder, 2014). This notion led him to study the effects of an evidence based inspection cycle relative to the baseline phase inspection cycle by comparing data already collected in IMD-HUMS. A gap analysis between the baseline and the CBM alternative method led to the conclusion that the alternative was superior in multiple areas. The first area assessed showed that the added flight hours available per labor hour during phase inspections rose from 0.35 flight hours per phase labor hour, to 1.07 flight hours per phase labor hour (Reeder, 2014). The second area showed a reduction in post-phase vibration analysis thru evidence based inspections of engine and drive train systems. Results showed available flight hours increased by 3.24% (Reeder, 2014). The availability gain came from eliminating post-phase scheduled inspections. Further, maintenance labor hours decreased by an average 1,270 hours per phase cycle. Lastly, there might be a hesitance to move away from what had been the status-quo schedule inspection cycle, so Reeder included a safety analysis. His investigation showed that 60% of all mechanical failures from the preceding five years came from human error. Therefore, by reducing the number of human occurrences to perform maintenance, you reduce the amount of potential human error. He concluded that there was no evidence to show that his alternative need-based phase model would compromise safety in a meaningful way.

CBM Forecast Methods

A time-dependent proportional hazards model (PHM) is a common method used in survival analysis, and can be used to assess both event data and condition monitoring data together (Jardine et al., 2006). The PHM is calculated as:

$$h(t) = h_0(t)\exp(\gamma_1 x_1(t) + \cdots + \gamma_p x_p(t)) \qquad (2)$$

where $h_0(t)$ is a baseline hazard function, $x_1(t), \ldots, x_p(t)$ are covariates from condition variables, that are a function of time, and $\gamma_1, \ldots, \gamma_p$ are coefficients. Then, a maximum likelihood estimator method can be used to find the γ_i coefficients for the PHM from event data and condition monitoring data (Jardine, Anderson, & Mann, 1987). The necessary inputs for this method are a hazard function, and condition indicator covariates. The PHM produces a hazard distribution that is descriptive of the item being assessed.

Another common method that uses both event data and condition monitoring data is a hidden Markov model (HMM). A significant contribution was made by Wang in developing a model for combining both continuous and categorical state descriptors into one HMM. His model is based on a two-stage approach separating a component's life into a normal working zone and a potential failure zone (Wang, 2007). Further, he shows analytically how continuous and categorical descriptors can be combined in a maximum likelihood estimator to model which state a component is in, and the probabilistic time to failure (Wang, 2007). This research is influential because of its ability to model the TTF distribution from practical state descriptors.

Moubray (1997) formed a method known as the P-F interval method, which uses condition monitoring data to predict the failure probability of a component. In this method, a P-F interval is the time between a potential failure (P) and a functional failure (F). This method was enhanced by Goode et al. by combining reliability data with condition monitoring data, to predict the time to failure of steel mill plant machinery (Goode, Moore, & Roylance, 2000). They did this by separating condition monitoring observations into two regions a stable zone and a failure zone, where two distinct failure distributions can be observed. Based upon these observations, a component's remaining useful life can be predicted by a reliability-based model for parts in the stable zone, a combination of a condition monitoring indicator, and a reliability model for components in the failure zone (Goode et al., 2000).

Several researchers have established a Bayesian approach that can be updated by conditional monitoring information. Gebraeel, et al. laid the foundation for this area of study with a technique called the Bayesian Degradation Signal Model. Their approach had two key elements. The first was to use population parameters to form a prior failure distribution. This would predict when and how many bearings would fail. The second element was real-time condition monitoring data, which showed the degradation of an individual bearing (Gebraeel, Lawley, Li, & Ryan, 2005). Their research demonstrated that if the population's failure was properly modeled, real-time condition monitoring could then be used to compute a residual-life distribution for that particular bearing.

Tracht, et al., (3013) were able to formulate a forecasting approach using a supervisory control and data acquisition (SCADA) program that predicted spare parts demand. Their method, noted as an "enhanced forecast model," was a PHM capable of incorporating time dependent covariates, as well as temperature and age conditions. The significance of this work was showing how SCADA software could be used to formulate an accurate binomial PHM distribution.

Kalman filters can also be applied to condition based prognostic models. One example was demonstrated by Swanson, who used Kalman filtering to track the changes in condition monitoring data across a time horizon (D. Swanson, 2001). With this, Swanson was able to both detect fault and make useful life predictions. He postulates that when fault characteristics are accelerating away from a stable operating condition, there is a probable chance of imminent failure which can serve as an indicator (D. Swanson, 2001). Furthermore, tracking the rate of change of a part’s condition allows the ability to make a prediction.

A summary the CBM forecasting methods can be found in Appendix B: Diagnostic and Prognostic CBM Summary.

Summary

This chapter examined spare parts forecasting both in the USAF and at large. Several alternative USAF demand forecasting methods were presented that illustrate how alternative variables than flying hours can be predictive of parts demand. Further, a history of CBM+ in the DoD was discussed to illustrate what the original goal was, and where the program is currently. An academic view of CBM prognostic techniques was discussed to show what types of data and analyses the DoD could implement when the proper data is available. Lastly, several forecast error calculations were presented to explain why mean absolute scaled error is more suitable for spare parts forecasting.

III. Methodology

Chapter Overview

This chapter will explain how the PBM works, and how it will be applied in this research. It will start by identifying the explanatory variables and the model's assumptions. Then, the statistical background of how to calibrate the model's parameters will be explained. Following this, a detailed effort will be made to delineate the data cleaning and filtering steps taken to narrow down to a select list of NIINs used in this study. Finally, calculations for forecast accuracy will be presented along with a discussion on multivariate statistics that will be applied to evaluate the suitability of one forecast method over another.

PBM Basics

A majority of the methodology used in this research effort was leveraged from a research effort completed by Wallace and Lee (2000), which first tried to consider how physical stressors on an aircraft reflect in maintenance removal actions. The approach taken in this research will apply a similar tactic looking at NIIN level demand patterns. LMI's model originally included four independent variables:

Flying Hours (FH)

The LMI model treated flying hour-induced removals as a discrete Poisson distribution, where the number of flight-induced removals produced in time t_f has parameter $\lambda_f t_f$. A normal approximation to the Poisson distribution can then be used to calculate the number of removals with mean and variance of fling-hour-induced removals both equal to $\lambda_f t_f$ (Wallace et al., 2000).

Cold Cycles (CC)

A cold cycle was the approach taken to account for removals induced from a sortie. The term cycle is used to frame the effects of both the take-off and the landing inherent to each sortie, regardless of what is done during the course of that sortie. The number of cold cycles will equal the number of sorties in a given time period. This aspect was modeled as a normal approximation to a binomial distribution where $N_{cc}$is the number of cold cycles and P_{cc} is the probability of a removal per cold cycle. This means that this process can be modeled with mean $N_{cc}P_{cc}$, and variance $N_{cc}P_{cc}(1 - P_{cc})$ (Wallace et al., 2000).

Warm Cycles (WC)

It could be assumed that the effects of a touch and go landing are different than the stress from a cold cycle, which includes starting up the jet and shutting it down with each sortie. Therefore, this variable will equal the number of landings minus the number of sorties in a given time period. This aspect will also be modeled as a normal approximation to a binomial distribution where $N_{wc}$is the number of warm cycles and P_{wc} is the probability of a removal per warm cycle. This process is therefore modeled with mean $N_{wc}P_{wc}$, and variance $N_{wc}P_{wc}(1 - P_{wc})$ (Wallace et al., 2000).

Ground Cycles (GC)

This aspect of the LMI model describes strain on an aircraft that would come from the ground environment, mostly being environmental influences such as temperature, humidity, or precipitation. This variable is computed as possessed hours minus flying hours in a given time period, divided by 24 hours to convert hours into a daily cycle. Similarly to cold and warm cycles, ground cycles are also modeled as a normal approximation to a binomial distribution. Mean and variance are then calculated as $N_{gc}P_{gc}$ and $N_{gc}P_{gc}\left(1 - P_{gc}\right)$, respectively (Wallace et al., 2000).

Model Mean and Variance

The methodology taken in this effort utilizes the same four independent variables, however assess the effects on a different dependent variable, aircraft parts demand. Therefore, the same variable computations will be used and aggregated as:

$$\mu_i = \lambda_f t_f + N_{cc}P_{cc} + N_{wc}P_{wc} + N_{gc}P_{gc} \tag{3}$$

$$\sigma_i^2 = \lambda_f t_f + N_{cc}P_{cc}(1 - P_{cc}) + N_{wc}P_{wc}(1 - P_{wc}) + N_{gc}P_{gc}(1 - P_{gc}) \tag{4}$$

where i is the index indicating each time period (Wallace et al., 2000).

Model Assumptions

The PBM has two main assumptions. The first assumption is that the four explanatory variables are independent from one another. If any two independent variables are collinear, then one should be removed as to not over influence the model. This will be evaluated by a pairwise regression to tell if each pair of variables has a strong correlation.

The second assumption is that spare parts failure can be attributed to the four independent variables in high enough quantities to be approximated as a normal distribution. This assumption reduces the computational complexity behind estimating the number of failures in a time period. Wallace and Lee (2000) use this assumption in their research, and results were found to be very accurate.

Model Calibration: Maximum Likelihood Estimation

In order to use the PBM forecast, the parameters from the four independent variables must be fine-tuned to the appropriate failure probability. Due to homoscedasticity in demand, a simpler method such as linear regression is not possible. Therefore, a maximum likelihood estimation will be used to calibrate the respective probability parameters. Maximum likelihood estimation is a well-established method that uses conditional probability to determine a distribution's parameter value, given that a set of data came from that particular distribution. For example, consider the likelihood equation:

$$L(\theta) = f(x_1, x_2, x_3 \dots x_n; \theta) \tag{5}$$

This is the joint probability of a distinct set of outcomes $x_1, x_2, x_3 \dots x_n$. From the rules of conditional probability given that each outcome is independent, the likelihood probability of outcomes becomes:

$$\begin{aligned} L(\theta|x_i) &= f(x_1|\theta) \cdot f(x_2|\theta) \cdot f(x_3|\theta) \cdot \dots \cdot f(x_n|\theta) \\ &= \prod_{i=1}^{n} f(x_i|\theta) \end{aligned} \tag{6}$$

Then by taking the natural logarithm of the equation, the function becomes additive, which is much easier for computational purposes as shown in Equation 7:

$$l = \sum_{i=1}^{n} \ln[f(\,x_i|\theta)] \tag{7}$$

If solving this problem numerically, the next step would be to find where this function is maximized by finding its derivative with respect to θ, and then setting it equal to zero. The value where the maximum likelihood occurs will be the optimal value of θ for the given dataset. However, this operation is easily performed in Microsoft Excel (version 2013) by using the Solver function to solve this as an optimization problem. In this instance, because there are four parameters to be calibrated, the optimization problem becomes:

$$Max\colon \sum_{i=1}^{n} \ln[N(demand_i|\mu_i,\sigma_i)] \tag{8}$$

where *n* is the number of periods in the calibration horizon, and $N(demand_i|\mu_i,\sigma_i)$ assumes a normal approximation with parameters μ and σ_i from Equation 3 and Equation 4. The change variables will be $\lambda_f, P_{cc}, P_{wc}, P_{gc}$.

Sliding Scale

The concept of a sliding scale was not in LMI's original PBM study. However, it was developed out of necessity to be able to forecast into the future when a different flying profile would be used. To elaborate, consider the original premise behind the PBM model. It was to show that parts failure is driven by what physical stresses are induced on the aircraft. Their research uncovered how a large increase in combat flying hours did not keep the proportional relationship with demand. From this, they postulated that the effects on parts failure are noticeably different on training missions than on combat missions. Their later research used an approach that allowed an analyst to forecast a future periods' demand, by choosing a new proportion of combat missions to training missions (Silver & Cincotta, 2008). The basic premise is that the model uses the actual flying profile to determine the average sortie duration for peacetime missions and combat missions separately. Similarly, it also calculates the average landing per sortie for peacetime missions and combat missions, respectively.

A major assumption in this research will rely on using the actual flying profile in a forecasted period as if it were as forecast parameter. In a real application of the PBM method, the flying profile would be another forecast parameter similar to total flying hours. However, in order to isolate this model's forecast potential, it will be assumed that the forecasted flying profile was what was actually flown for each time period predicted into the future.

Next, the respective average sortie duration and landings per sortie values could be used to linearly extrapolate a future time period's number of sorties and number of touch-and-go landings, again broken out for peacetime and wartime. Subsequently, there needs to be a similar methodology of calculating ground cycles. Since the original model does not assume a difference between ground cycles in training versus in combat, this single parameter only needs to be adjusted for the forecast period's number of flying hours. This can easily be done by assuming the number of unit possessed hours as the prior period which was known, subtracting the forecast period's number of flying hours, and then dividing by 24. The next step would be to sum the total number of sorties and "touch-and-go's" that could then be used as forecast inputs against the failure rate parameters calibrated by the maximum likelihood estimator. A list of equations used in this process is delineated in Appendix C: Sliding Scale Equations.

Data

Sources

Two primary data sources would be used to collect data, with the first being the parts failure data maintained in D200A. With the help of the Requirements Integration

Process Improvement Team, AFSC/LGPS, a filter of B-1 only NIINs was used to select quarterly OIM data for B-1 NIINs. Using Microsoft Access (version 2013), a query was then built to aggregate base-level demand, and to select file maintained data (manual override corrections) when applicable over original data inputs. Base-level demand (more accurately defined as Total OIM Demand) is computed as the number of parts Repaired This Station (RTS) plus the number of parts Not Repaired This Station (NRTS) plus the number of Condemnations as shown in Equation 9: (Air Force Materiel Command, 2011)

$$Total\ OIM\ Demand = RTS + NRTS + Condemnations \tag{9}$$

The other primary data source was LIMS-EV. The suite Weapon System View provided the amount of ground hours by month from 2012-2016. The suite Business Objects (also known as GCSS-Data Services) was used to query the flying hours, the number of landings, the number of sorties, and the mission profile of each sortie, again by month from 2012-2016. This data was aggregated into quarters, then separated by mission profile of training sorties and combat sorties. Landings, flying hours, and sorties were ignored from test flights and demos, as they were less than 6% of total flying hours and the logic in this methodology would be difficult to validate the correlation to parts failure due to the exploratory nature of test sorties.

Data Cleaning and Filtering Selected NIINs

Researching demand impacts by Federal Supply Class (FSC) is a classification method that was not found in any similar research effort. This could be because without assessing FSC with respect to a physical use aspect, it simply would not have been a logical argument. However, with the methodology used in this research, it now becomes possible to evaluate the potential correlation between the category a part is, and its demand pattern with relation to how an aircraft is used. In order to select FSCs for research, a method of highest demand was used. The first step was to use Microsoft Excel 2013's Pivot Table to aggregate total demand from 2012-2016 by FSC. From there, a Pareto chart was made to order those FSCs from highest percentage of total demand to lowest. The top FSCs that accounted for 90% of B-1 demand were selected for evaluation under the assumption that these parts accounted for the vast majority of B-1 demands.

To further purify the demand signal, it was necessary to exclude all common use items from the analysis. A common use item is a NIIN that is used on multiple aircraft. As the purpose in this research is to tie B-1 flying operations to B-1 demand, it is necessary to ensure demand from other aircraft are not being included in the demand pattern. The D200A system does not partition what demand comes from which aircraft. With that, the only way to partition out only B-1 demand would be by creating a query in GCSS-Data Services from the supply system universe by counting supply transactions. However, by writing a new query without regard to similar business rules that D200A uses to count demands it leaves multiple opportunities for miscounting B-1 demand that would not line up with how D200A counts base-level demand. Therefore, it was determined best to exclude common use NIINs from this research. Out of 5,164 B-1 NIINs, 166 NIINs were identified as common use items, and therefore will not be considered for further analysis. This leaves 4998 NIINs in the study.

After filtering and selecting the NIINs for analysis, it was important to confirm no errors occurred during this process. The primary application the USAF's forecasting unit uses for analysis is the Forecast Analysis Comparison Plus (FACT+). A preformatted report based on D200 business rules was pulled and matched against filtered NIINs discussed above, to confirm no demand data had been disorganized during cleaning. By corroborating that the filtered demand data matches the FACT+ data, it enables later comparative analysis from the FACT+ system, which contains the actual USAF forecasts. Now, a measurement of accuracy can be compared between the USAF's actual forecast accuracy and the PBM method.

The next step will be to have a B-1 expert confirm which FSCs can be categorized by one specific type of part. Beginning with the NIINs under the top FSCs that account for 90% of B-1 demand, the data was further refined by selecting only the top three NIINs of each FSC by total demand. From there, this list of parts can be categorized by a B-1 maintainer into categories that can be compared. Category examples included mechanical, electronic, pneumatic, hydraulic, etc. Category comparisons were then made to test the forecast accuracy of each separate group.

Demand Patterns

Another categorical framework that was used to test the accuracy of the PBM were demand patterns. There are four demand patterns categorized in spare parts literature: smooth, intermittent, erratic, and lumpy (Lowas III, 2015). These categories can be determined based on a two parameter matrix shown in Figure 7.

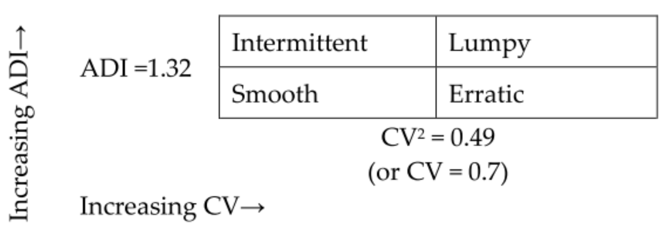


Figure 7: Demand Pattern Matrix *(Lowas III, 2015)*

There are two easy calculations in this process. The first is average demand interval (ADI), which represents how frequently at least one demand will be observed. As shown in Equation 10, this is calculated as:

$$ADI = \frac{\#\ of\ periods}{\#\ of\ nonzero\ demand\ periods} \tag{10}$$

The second factor is the coefficient of variation (CV), and is a measure of variability relative to a sample's mean. This is shown in Equation 11:

$$CV = \frac{\sigma}{\mu} \tag{11}$$

where σ is the standard deviation and μ is the mean. The cutoff limits separating each category are ADI = 1.32, and CV= 0.7. Once categories have been identified for each NIIN, then a random sample can be taken from each category to select five NIINs to compare one demand pattern category to another.

Slow Trends

As with many forecasting techniques such as time series regression or some exponential smoothing methods, it is a common practice to account for trends in response variables. A common phenomenon in spare parts is called the bathtub effect where across a systems' lifecycle it may observe a heightened amount of failures in the beginning, which may eventually level off, followed by another interval of increased failures. A downfall of both the proportional model and the PBM is that they do not have a mechanism to correct for a trend when forecasting multiple periods into the future. Therefore, a shear transformation on the demand data, when trends are present, will compensate for slow developing trends (Wallace et al., 2000). A simple graph of demand across time will provide a sufficient method of evaluating trends that warrant this action.

There are five steps to perform this transformation. The first is to fit a trend line to the data. This can be done by adding the trend line equation when charting the demand in Microsoft Excel. The second step is to perform the shear transformation on the original data using Equation 12:

$$Quarter'_i = Quarter_i$$
$$Demand_i' = Demand_i - (Quarter_i - Quarter_c)m \tag{12}$$

where $Quarter_i$ is the time period, $Quarter_c$ is the mid-point in the calibration time interval, and m is the slope from the trend line. Next, run the maximum likelihood estimator to calibrate the model failure parameters based on the transformed failure data. The fourth step is to then compute the predicted removals. Finally, transform the predicted removals a second time using Equation 13:

$$Quarter''_i = Quarter_i$$
$$Demand_i'' = Demand_i + (Quarter_i - Quarter_c)m \tag{13}$$

USAF Forecast Method

Previously, there was a discussion on how the USAF uses an eight quarter moving average as the primary means by which it forecasts spare parts. This section will cover the calculation used in such a case. To be more exact, the USAF uses what it calls a *factor* method. This method has the effect of calculating the average demand per flying hour over eight quarters as shown in Equation 14:

$$8Q\ Moving\ Average: Factor_{T+\tau} = \frac{\sum_{i=T-8}^{T} \#\ demands\ in\ quarter_i}{\sum_{i=T-8}^{T} \#\ flying\ hours\ in\ quarter_i} \tag{14}$$

where T is the last time period where demand was observed, and τ is the index for the time period being forecasted for in the future. The four quarter moving average also uses the above method, however it only uses four periods of observations to calculate the *factor*. This rate is what they call a *factor*. This new rate is then multiplied by the forecasted number of flying hours in the period of which the forecast is being made. This concept is also frequently referred to as a proportional method because the *factor* is merely the proportional number of demands to flying hours. The next step in the proportional method is to forecast the number of demands. This is done by multiplying the *factor* by the predicted flying hours in a future period.

Experiments

Test #1. Mechanical versus Electrical Forecasting Accuracy

There will be two tests performed in this research. The first is going to be a comparison of PBM forecast accuracy between each part category. Each FSC is categorized into labels such as mechanical, electronic, pneumatic, hydraulic, etc. These FSCs categories are verified by a B-1 maintenance expert NIIN by NIIN to form a homogenous FSC category. This enables the analyst to group like items together and compare forecast accuracy between them. Additionally, this test includes comparisons with the USAF’s standard eight quarter and four quarter moving average methods. This aspect allows a direct comparison between the PBM and the status quo forecast methods, leading to a finite conclusion of the PBMs potential forecasting benefit.

Test #2. Demand Pattern Comparison

The second test is a comparison of forecast accuracy by demand pattern. In a similar method as the first test, this analysis allows the analyst to determine the suitability of the PBM method across a variety of demand signals. This test again includes comparisons between the PBM method and the USAF's eight quarter and four quarter moving averages.

Forecast Error

In the literature review there was a discussion covering the differences between the USAF's demand forecast accuracy measurement, mean absolute percent error, and mean absolute scaled error (MASE). Additionally, it was explained why MASE was the chosen measurement for forecast accuracy in this study. Equation 15 shows the formal calculation for MASE:

$$Scaled\ Error: q_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n}|Y_i - Y_{i-1}|}$$

$$MASE = mean(|q_t|) \tag{15}$$

where e_t is the error at time *t*, and the denominator of the *scaled error* is the mean absolute error of a naïve forecast method (uses previous time period's demand as next period's forecast) from the training set. A benefit of using MASE not mentioned in the literature review is that because it is a scale-free calculation, the MASE of multiple parts can be averaged to compare one group to another (Hyndman, 2006).

Comparative Statistics

After deriving a CBM forecast it became important to test if there is a significant difference in forecast accuracy between the CBM forecast method and a baseline method.

The MASE is the measure of comparison between the three forecast methods for each NIIN. The mean MASE with sample size *n* was compared; where *n,* is the number of NIINs in each aggregated forecast comparison method. More specifically, when comparing mechanical and electrical components, *n* equals three, because there are three mechanical NIINs that are being compared with three electrical NIINs. When comparing the four demand patterns (smooth, intermittent, erratic, and lumpy) *n* equals ten as there will be ten NIINs in each demand category.

In order to test the difference in sample means, multivariate statistics were completed between the CBM forecast and an eight quarter moving average forecast. Further, hypothesis tests were conducted to show the evidence supporting the null hypothesis that there is no difference between forecast methods.

The first step of testing for differences between means of small samples is to test for equal variances. This test uses the null hypothesis that both population variances are equal. Then the test statistic is calculated by dividing the larger of the two sample variances by the smaller sample variance. This test statistic is then compared against an $\alpha = 0.05$ from the F-distribution. If the test concludes that the two population variances are equal, then when calculating sample variance in the next step, a pooled variance calculation can be used.

The second step is to calculate a confidence interval around the difference between the two sample means. This is calculated with Equation 16:

$$\bar{x}_1 - \bar{x}_2 \pm t_{d.f.,\alpha/2}\sqrt{s_p^2\left(\frac{1}{n_1} + \frac{1}{n_2}\right)} \tag{16}$$

where

$$s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}$$

and d.f. is $n_1 + n_2 - 2$. When the confidence interval does not contain zero, then the null hypothesis is rejected, and the conclusion is that the two populations are not equal. This test is conducted at the 95% significance level. The conclusion of this test is the apex of this study, because it provides a scientific method upon which to show how significantly these three forecast methods either are or are not different from one another.

Conclusion

The methodology chapter explained in detail the background of the PBM and the mathematical formulations that drive its forecasts. A discussion was also presented on how to evaluate demand forecast patterns, and explained the industry standard used to categorize them. Further, a detailed description of data sources along with the method used to filter and select individual NIINs for further study was offered. A summary of how the USAF calculates its forecasts, its forecast accuracy, and the marginal benefit of forecasts methods relative to the baseline were discussed. Finally, multivariate analysis methods were discussed which will support a conclusion made about which forecast method is more accurate.

IV. Analysis and Results

Chapter Overview

This chapter will focus on answering the four investigative questions presented in the introduction. The first will address known CBM forecasting methods. The next question seeks to bring to light data that could be used in a CBM method. The third investigative question will pair the answers from questions one and two together, and result in a way to test CBM forecasting using USAF spare parts data. The last question will use two tests as a means to determine the forecast accuracy of a particular CBM method against the USAF's existing methods.

Investigative Question 1

Investigative question one was primarily explored in the CBM Forecast Methods section of the literature review. To summarize the results, there were six primary methods that have been shown to produce a demand forecast. More specifically, what is most beneficial about these methods is that they produce either a time to failure distribution or remaining life distribution. From these distributions, analysts can apply general statistics to evaluate the probability of a failure given a particular part has survived up to a given time period.

Of these six CBM forecast methods, two stand out as more practical to use due to their simplicity. The first was developed by Jardine et al., (1987), which used a standard hazard function that is updated based on a part's condition indicator values. The second notable method is from Gebraeel et al., (2005). This technique specifically allows for the use of real-time sensors to depict the condition of a part. This information can then periodically update the remaining life curve.

Investigative Question 2

The second investigative question assessed known data sources within the USAF to explore what could be used in a CBM methodology, with the expressed intent on leveraging the USAF's data warehouse--Global Combat Support System-Data Services. The literature review underscored several USAF forecasting methods that assessed parts demand correlating with the number of sorties, landings, mission type, and aircraft age. These aspects are event data (with the exception of age), and all are relatively easy to obtain from the data warehouse. It was this researcher's prerogative to explore additional data silos for more potential use. After additional data universes within the data warehouse were explored, a limited set of options remained that were thought to have potential correlation to spare parts demand. Of note were data elements from the maintenance transaction universe that is rooted in Technical Order 00-20-2, the technical manual for maintenance data documentation. As a novice, some components initially explored were:

- Maintenance Transaction Type Codes
- Action Taken Codes
- How Malfunction Codes
- When Discovered Codes
- Type Maintenance Designator Codes
- Time Compliance Technical Order Codes

After receiving corroborating notions from multiple maintainers in the field, it was determined that these codes all have questionable accuracy aspects. It is predominantly thought that this type of data is manually entered, leaving many possibilities for errors.

Also, there is potential for users to enter commonly used codes that will expedite their task completion, versus entering accurate codes that may require more supporting documentation resulting in a more laborious task. These elements together left all experts questioning the soundness of the data.

It should be recognized that there is a significant lack of conditional data available within the USAF's data warehouse. The analyst found no data that was comparable to the condition indicators noted in the literature review section. In order to fully achieve the benefits from CBM, it is imperative to have a data source that can measure the condition a particular part is in at any given time.

Investigative Question 3

The third investigative question in this research sought to identify CBM forecast methods that could use the data elements found in investigative question two. The results of the previous analysis left this research primarily with event data. Unfortunately, the lack of condition indicators eliminated the CBM forecasting methods that were identified in investigative question one. As a result of this, it became a new ambition to determine if event data alone could be applied in a CBM-like format. The method selected was the PBM model based on LMI's previous research, because it still incorporated predictive capability based on what the aircraft executed.

Investigative Question 4

This final question unpacks the quantitative analysis in this research. The subsequent narrative will systematically present the results of the two tests performed using the PBM method as a forecasting tool, and compare its results against an eight quarter moving average.

Summary Statistics

After the common use items were eliminated, 4998 B-1 NIINs were left for analysis. Next, each NIIN was categorized according to its demand pattern in accordance with Figure 7. Figure 8 shows the frequency among these demand patterns.

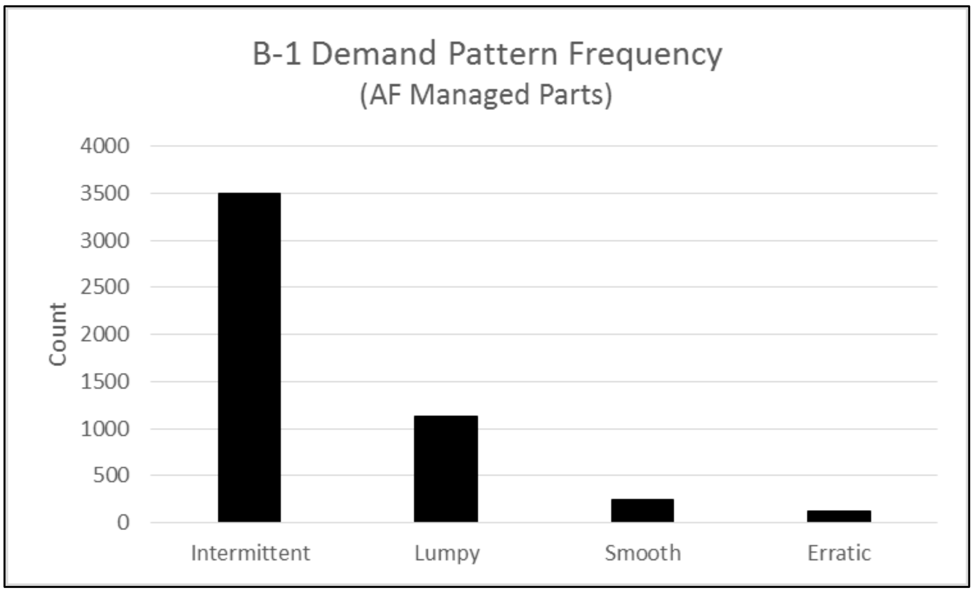


Figure 8: B-1 Demand Pattern Frequency

The next step was to select 10 NIINs at random from each category as a representation of that sub-population on which to perform the forecast method on. Appendix D: Demand Pattern Demand Data shows the demand for each of these parts.

Assumptions

The next step in this analysis is to test the validity of the three assumptions. The first assumption was that the four explanatory variables are independent, and not correlated. This was tested using a pair-wise comparison. Figure 9 shows that of the four variables, sorties is highly correlated with both flying hours and ground cycles. The model included undue influence by keeping sorties in the model, therefore, this variable was excluded from predicting parts failures.

Correlations

	Flying Hours	Sorties	Touch and Go's	Ground Cycles
Flying Hours	1.0000	0.8490	-0.1078	0.6417
Sorties	0.8490	1.0000	0.2809	0.6794
Touch and Go's	-0.1078	0.2809	1.0000	0.1713
Ground Cycles	0.6417	0.6794	0.1713	1.0000

Figure 9: Multicollinearity Test

The second assumption was that part failures can be approximated with a normal distribution. The underlying thought is that the higher the number of demands that a part has, the better a normal approximation will be appropriate for estimating that part's failure parameters in the maximum likelihood estimator. While some parts assessed in this study have relatively few demands, this assumption will be carried throughout because of the mathematical simplicity it affords.

Test #1. Mechanical versus Electrical Forecasting Accuracy

The purpose behind investigating the forecast accuracy of various part classifications was to determine if the stresses on an aircraft affect different part groups in a heterogeneous manner. If true, this would allow for a general precedence that would show how part failures in each category are correlated with different stresses placed on an aircraft. When the top FSCs accumulating 90% of total B-1 demand were verified by the B-1 expert, the resulting categories were less diverse than initially presumed. There were only two categories of parts: mechanical and electrical. Additionally, the B-1 expert recognized issues with the presented list of NIINs grouped by FSC. The fundamental flaw in trying to categorize parts by one classification is that some parts may primarily fit into one category, yet are actuated in another way. Dive Flap (013145809) is an example of this. This part is primarily mechanical, however is actuated hydraulically, making it heterogeneous with other mechanical parts. Therefore, Table 3 should be regarded as an over simplification of true classifications. In an effort to keep to the intent of this research, the list of NIINs was narrowed to parts that could be categorized as purely mechanical or electrical. The next filtering criteria was to select parts based on demand pattern in order to hold that aspect constant across the two samples. The smooth pattern was the most common pattern amongst the already few mechanical parts left, resulting in scoping the analysis down to only assessing smooth demand items. This left three mechanical parts. Finally, for comparison, three smooth demand NIINs from the electrical category were chosen randomly. Demand history for these parts can be located in Appendix E: Mechanical and Electrical Demand Data.

Table 3: FSC Classifications

FSC	Classification	FSC	Classification
1630	Mechanical	5895	Electrical
1650	Electrical	5955	Electrical
1660	Mechanical	5985	Electrical
1680	Electrical	5996	Electrical
2840	Mechanical	5998	Electrical
2915	Electrical	6110	Electrical
2995	Electrical	6130	Electrical
4810	Electrical	6150	Electrical
5821	Electrical	6605	Electrical
5826	Electrical	6610	Electrical
5841	Electrical	6615	Electrical
5865	Electrical	6620	Electrical

The results in Table 4 show that a non-transformed four quarter moving average method was the most accurate among the six overall. Results also show that in the first two items where there is a very strong negative slope, the transformed forecasts perform better relative to their non-transformed counterparts, with the exception of the four quarter moving average. This is to be expected since the benefit of a smaller average horizon is that it by nature accounts for the most recent trend. In the case of a negative trend, the eight quarter horizon will typically have larger observations in the beginning that pull the average higher than what will be accounted for in the trending forecast period. This aspect is exacerbated in the non-transformed PBM model which is calibrated based on a 16 quarter time horizon. This serves as an excellent example of when there is as strong trend, how the shear-transformation application can substantially improve the forecast accuracy of the PBM method.

Table 4: Test #1 Forecast Error Results

		Non-Transformed			Transformed			
Category	NIIN	PBM	8QMA	4QMA	PBM	8QMA	4QMA	Slope
Mechanical	015780463	2.29	0.71	0.62	0.90	0.78	0.78	-8.72
Mechanical	013145809	2.52	1.21	0.60	1.34	0.34	0.15	-7.91
Mechanical	011659072	0.88	1.19	0.96	2.21	2.20	2.47	-1.74
Electrical	011491452	1.60	2.84	3.17	1.54	2.80	1.35	0.01
Electrical	015489586	0.68	0.67	0.65	0.81	1.02	1.18	-0.87
Electrical	014395852	0.62	0.83	0.48	1.34	0.55	0.91	1.55
	Average MASE	1.43	1.24	1.08	1.36	1.28	1.14	

This next section will discuss the comparison of forecast accuracy by part category. Table 5 shows the results of all six forecast methods aggregated by part category.

Table 5: Aggregate MASE by Part Category

	Non-Transformed			Transformed			
	PBM	8QMA	4QMA	PBM	8QMA	4QMA	Avg. MASE
Mechanical	1.90	1.04	0.73	1.48	1.11	1.14	1.23
Electrical	0.96	1.45	1.44	1.23	1.45	1.14	1.28

A comparison of means test was performed on this data. First, an F-test was completed to validate the assumption that these two populations have equal variances (Table 6). Based on a α of 0.05, it is concluded that these variances are equal, and therefore can be pooled. Next, a confidence interval is calculated on these two population means (Table 7). Since this confidence interval does not include zero at the 95% confidence interval, it is concluded that these two population means are not equal. Furthermore, from this test it can be stated that electrical components have a higher forecast error associated with all six forecast methods than mechanical parts do. The complication with this result is that though statistically significant, the methodology used to arrive at the selected NIINs proved a less than ideal application of this model, and therefore would make it difficult to extrapolate these results into future forecasting applications.

Table 6: F-Test for Equal Variances

F-Test Statistic	0.08
α	0.05

Table 7: Test for Equal Means

$\bar{x}_{Mech.}$	1.23
$\bar{x}_{Elec.}$	1.28
d.f.	10
s_p^2	0.10
t-dist.	0.06

Confidence Interval	
Upper	Lower
-0.06	-0.04

Test #2. Demand Pattern Comparison

This second test was used to evaluate the ability of the PBM method across various demand patterns. As discussed previously in the literature review, an item's demand pattern plays a vital role in forecast accuracy. Therefore, this aspect will show the robustness of the PBM method by testing its accuracy across a range of categories. Additionally, it should be noted that the main measure of forecast accuracy improvement or diminishment will be the non-transformed eight quarter moving average. As discussed in the literature review, the eight quarter moving average is the USAF's primary method of forecasting base-level demand; being used over 80% of the time.

Smooth

Table 8 displays the results of the first set of forecasts in this test. A breakout of non-transformed and shear transformed forecasts are displayed along with the slope of the historical demand used to calibrate the model. For smooth demand items, the non-transformed PBM model performed the most accurate, with the transformed PBM also performing better than the status quo methods. Specifically, the non-transformed PBM showed a 4.43% decrease in forecast error over the eight quarter moving average, while the transformed PBM realized a 2.05% decrease. When comparing non-transformed forecasts against the transformed methods it is evident that the transformed methods did not perform as well. This is likely because in the sample used here the parts all show a very weak to negligible trend.

Table 8: Smooth Demand Forecasts

	Non-Transformed			Transformed			
NIIN	PBM	8QMA	4QMA	PBM	8QMA	4QMA	Slope
012630536	1.29	1.00	0.95	0.72	1.62	1.66	-0.70
011433525	0.90	0.69	0.62	0.59	0.28	0.28	0.20
015097158	1.32	1.93	1.80	2.10	2.46	2.31	-0.15
012704772	0.53	0.73	0.85	1.25	1.23	1.23	-0.25
011491452	1.75	2.84	3.17	1.54	2.80	3.13	0.01
011478410	2.35	1.01	0.86	2.52	1.23	0.99	0.10
012398983	1.17	2.06	1.82	1.10	1.95	1.72	0.06
013194674	0.72	0.75	0.72	0.56	0.80	0.77	-0.20
013751527	0.41	0.36	0.40	0.44	0.39	0.44	0.04
011829763	0.91	0.50	0.68	0.81	0.43	0.54	0.05
Avg. MASE	1.13	1.19	1.19	1.16	1.32	1.31	

Lumpy

The next demand pattern analyzed was the lumpy demand signal. The test results in Table 9 show the transformed eight quarter moving average to be the most accurate method--11% more accurate than non-transformed eight quarter moving average. However, the transformed PBM produced a narrowly less accurate result. Furthermore, in this sample the status quo, non-transformed eight quarter moving average, performed the least accurate of all six models. It is possible in this sample that NIIN 015824217 is an outlier and therefore influencing the averages of each category more heavily than those of the rest of the sample. Though the historical data for this part met the lumpy criteria, it is evident once reviewing its actual demand during the forecast period that the part's pattern became very irregular. To elaborate, from 2012-2015 this item had 11 periods with zero demands, 3 periods with less than 10 demands, and two periods with a demand greater than 60. This prompted the shear-transformed models to calibrate based on a very recent upward trend. Then when actual demand history averaged 68 demands per period during the forecasting horizon, the transformed forecasts were already accounting for this recent change in demand pattern. This resulted in the transformed models performing significantly more accurate than the non-transformed models.

Table 9: Lumpy Demand Forecasts

	Non-Transformed			Transformed			
NIIN	PBM	8QMA	4QMA	PBM	8QMA	4QMA	Slope
013994172	1.02	0.66	0.69	1.26	0.94	0.96	0.03
015499544	2.45	2.21	2.53	2.74	2.62	2.85	0.04
011730600	2.30	2.40	2.40	2.30	2.39	2.39	0.00
013023453	2.39	1.24	1.23	1.13	1.06	1.08	-0.01
015548051	2.82	2.70	2.71	2.91	2.86	2.88	0.03
011642197	0.42	0.28	0.29	0.61	0.30	0.25	0.02
015824217	4.41	6.36	4.93	1.52	2.75	2.14	3.88
015824221	0.24	0.36	0.55	1.92	1.34	1.94	0.72
011505162	0.41	0.43	0.58	0.52	0.56	0.76	0.03
012321676	0.57	0.53	0.42	0.42	0.42	0.35	-0.03
Avg. MASE	1.70	1.72	1.63	1.53	1.52	1.56	

Intermittent

Next, the intermittent demand forecasts were assessed (Table 10). In this test the results show both PBM models as having performed 33% - 34% less accurate than the proportional model. The model that performed the best was the non-transformed four quarter moving average, while the non-transformed eight quarter moving average performing the second best. These results are logical because one would expect that when demands are sparse then using a slope as a future predictor is less reliable. Additionally, as these results show, the intermittent demand signal simply is not a good calibration mechanism for the PBM method.

Table 10: Intermittent Demand Forecasts

	Non-Transformed			Transformed			
NIIN	PBM	8QMA	4QMA	PBM	8QMA	4QMA	Slope
016525025	1.95	2.58	2.66	3.34	2.84	2.34	0.23
011862809	6.06	4.35	4.92	5.93	5.69	6.07	0.02
016175632	1.17	1.82	0.87	2.09	1.15	1.68	0.28
012110135	0.51	0.75	0.61	1.91	1.49	1.16	0.06
012137727	1.02	1.08	1.08	1.30	0.99	0.97	0.11
015626911	0.65	1.09	0.55	1.79	1.26	1.35	0.56
016525309	2.04	1.65	1.66	2.51	2.21	2.27	0.21
011862810	2.71	1.88	1.88	1.95	1.88	1.88	-0.01
011433521	0.31	0.28	0.29	0.54	0.55	0.53	0.08
012112088	6.22	1.57	1.57	1.45	1.51	1.49	0.02
Avg. MASE	2.26	1.70	1.61	2.28	1.96	1.97	

Erratic

The final demand pattern to analyze is the erratic pattern. The non-transformed eight quarter moving average was decisively the most accurate forecast method for parts with erratic demand as shown in Table 11. The PBM models forecasted at least 85% worse than the status quo. However, it should be noted that all forecast models showed a significantly smaller forecast error than in other demand patterns.

Table 11: Erratic Demand Forecasts

	Non-Transformed			Transformed			
NIIN	PBM	8QMA	4QMA	PBM	8QMA	4QMA	Slope
012058322	0.67	0.94	0.90	0.72	1.08	1.02	-0.06
013731249	1.53	1.17	1.19	2.83	2.12	2.00	1.44
015006333	0.50	0.38	0.46	0.35	0.54	0.57	-0.08
011491450	0.16	0.17	0.14	0.45	0.48	0.30	-0.45
011838951	2.70	0.38	0.36	0.49	0.40	0.40	-0.25
015452484	0.64	0.76	1.07	1.52	0.91	0.79	0.62
012664261	0.41	0.13	0.28	0.47	0.55	0.56	-0.49
011982203	0.71	0.20	0.46	0.89	0.26	0.34	0.10
011807465	1.33	0.17	0.17	0.24	0.31	0.26	-0.29
011933136	1.98	0.61	0.59	1.13	0.81	0.79	-0.09
Avg. MASE	1.06	0.49	0.56	0.91	0.74	0.70	

Overall Demand Pattern Comparison

When comparing the accuracy between models, Table 12 shows intermittent patterns with the worst accuracy, and erratic patterns with the best. Additionally, it is worth highlighting that the non-transformed four quarter moving average outperformed the status quo, non-transformed eight quarter moving average method by 2%. This evidence points to the significance of using multiple methods. Finally, the two PBM models performed the worst overall, with the transformed model performing slightly better than the non-performed model.

Table 12: Demand Pattern Comparison

	Non-Transformed			Transformed			
Pattern	PBM	8QMA	4QMA	PBM	8QMA	4QMA	Avg. MASE
Smooth	1.13	1.19	1.19	1.16	1.32	1.31	1.22
Lumpy	1.70	1.72	1.63	1.53	1.52	1.56	1.61
Intermittent	2.26	1.70	1.61	2.28	1.96	1.97	1.96
Erratic	1.06	0.49	0.56	0.91	0.74	0.70	0.75
Avg. MASE	1.54	1.27	1.25	1.47	1.39	1.39	1.38

Now that two PBM forecast methods have been identified as outperforming the status quo, this next section will test for significance and present a relative comparison. The first comparison will be testing for a significant difference between the non-transformed PBM forecast accuracy and the non-transformed eight quarter moving average method in the smooth demand category. Similar to the approach taken to test for significance between the mechanical and electrical MASE results, this analysis will also begin with a test for equal variances. As shown in Table 13, these two samples do not show evidence to reject the null hypothesis, leading to the conclusion that they do have equal variances. Finally, the confidence interval shown in Table 14 shows that these are indeed significantly different in populations.

Table 13: Smooth Demand F-Test for Equal Variances

F-Test Statistic	0.17
α	0.05

Table 14: Smooth Demand Test for Equal Means

$\bar{x}_{PBM}$	1.13
$\bar{x}_{8QMA}$	1.19
d.f.	18
s_p^2	0.50
t-dist.	0.06

Confidence Interval	
Upper	Lower
-0.07	-0.03

The second test for significance is on lumpy demand patterns between the transformed PBM forecast method and the non-transformed eight quarter moving average method. As before, this analysis begins with a test for equal variance. Again, as shown in Table 15, this test concludes that these populations do have equal variances. Subsequently, the confidence interval shown in Table 16 supports the conclusion that the transformed PBM method is significantly more accurate than the status quo method.

Table 15: Lumpy Demand F-Test for Equal Variances

F-Test Statistic	0.19
α	0.05

Table 16: Lumpy Demand Test for Equal Means

$\bar{x}_{PBM}$	1.53
$\bar{x}_{8QMA}$	1.72
d.f.	18
s_p^2	2.71
t-dist.	0.06

Confidence Interval	
Upper	Lower
-0.23	-0.14

Another way to explain the PBM model's forecast accuracy relative to the eight quarter moving average is by determining the percent change in forecast accuracy between the two. Figure 10 illustrates this well. It can be seen that overall the PBM (both non-transformed and transformed) performed significantly worse than the baseline. However, for smooth and lumpy demand patterns there was a significant improvement in accuracy. Finally, Figure 10 clearly shows that for intermittent and erratic patterns the PBM well under performs the status quo method.

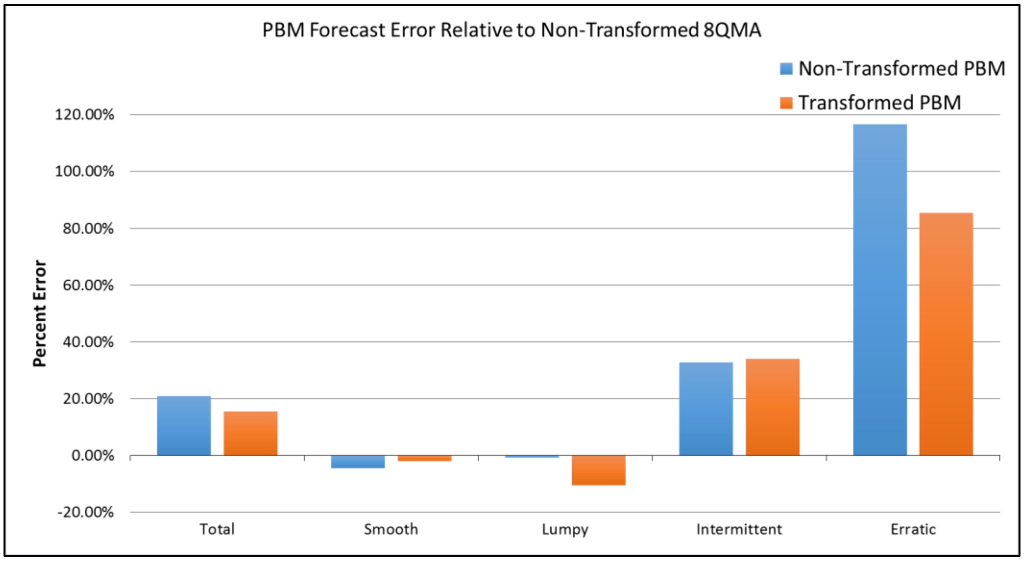


Figure 10: PBM Forecast Error Relative to Non-Transformed 8QMA

The last area in this analysis explored for possible extrapolation potential was the potential benefit of using the shear-transformation forecasts over non-transformed forecasts methods. When aggregating forecast accuracy across all demand patterns Figure 11 shows that while not a significant difference, there is a slight benefit to the non-transformed forecasts over transformed forecasts.

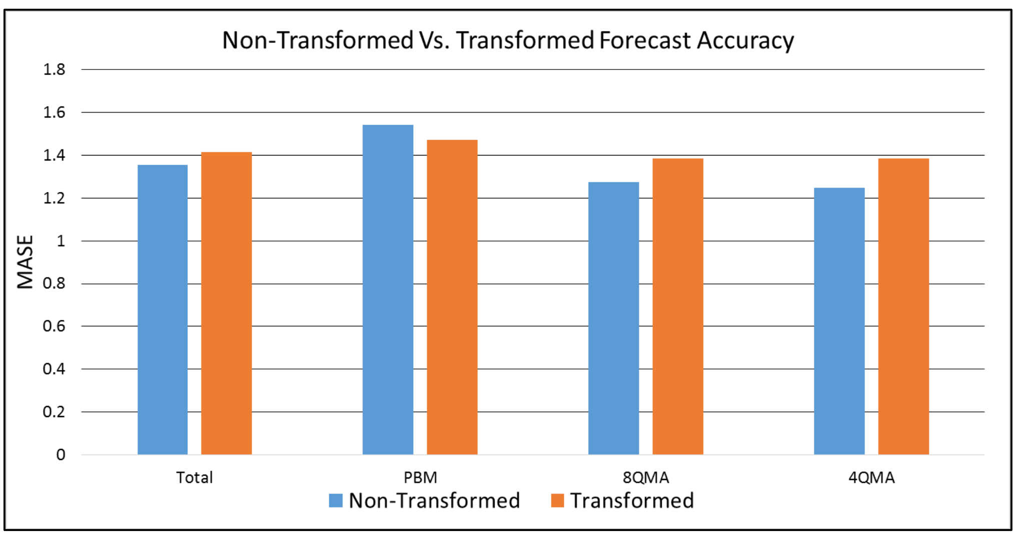


Figure 11: Non-Transformed Versus Transformed Forecast Accuracy

However, in the case of lumpy demand patterns there was a significant difference as shown in Figure 12. The explanation for this was not transparent, however, this result was likely influenced by the potential outlier (NIIN 015824217), which as discussed earlier saw a large error reduction by accounting for the trend in the transformed methods.

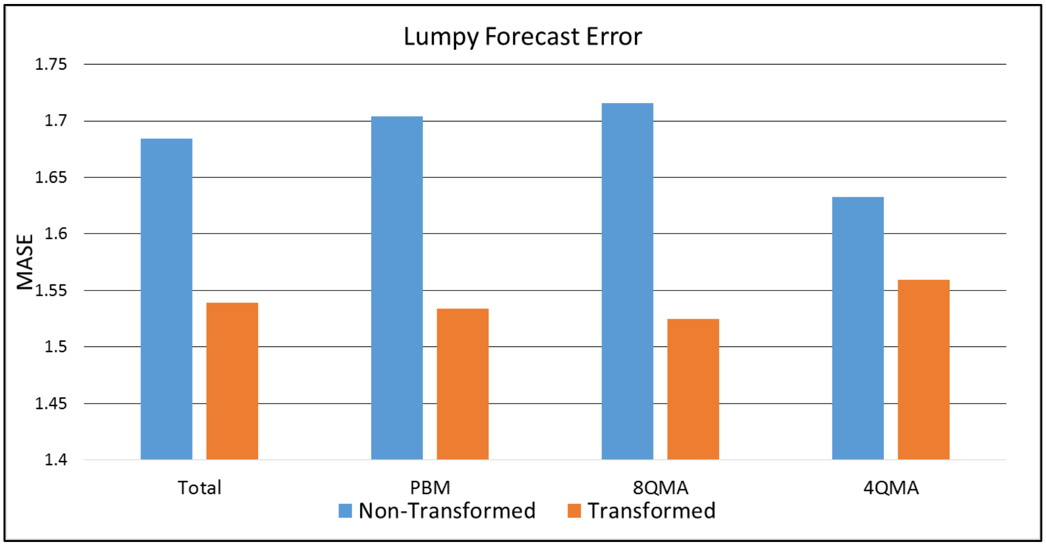


Figure 12: Lumpy Forecast Error

An effort was made to separate all parts with a significant slope versus those will an insignificant slope to determine if there were additional cases where a trend greatly influenced the forecast accuracy. Out of the 40 NIINs in this study, only six showed a positive or negative slope greater than 0.5 demands per period. When looking at those six NIINs together, the MASE results still showed the non-transformed forecasts with a five percent better accuracy measure.

Summary

This chapter answered the four investigative questions posed in the introduction. The first question used the literature review as the substantive evidence that defined the common CBM forecasting methods in academic literature today. Question two sought to identify data in the USAF's central data warehouse in an effort to find both event and condition indicator data. After finding only event data it was recognized that a substantial loss of CBM capability would be missed without the better quality data. Question three assessed what could be done with the data obtained, and funneled efforts toward the PBM. The final investigative question was answered through two separate tests. The first test looked at evaluating forecast accuracy based on component make-up. It was found that B-1 parts primarily fell into two categories, mechanical or electrical. This made the test results less practical than originally thought. The second test established overall forecast accuracy comparisons between the PBM and an eight quarter moving average. Then this test addressed differences in accuracy by demand pattern.

V. Conclusions and Recommendations

Chapter Overview

The objective of this chapter is to tie together large scale conclusions from this research effort. Additionally, it quantifies the significance of this research, and frames the implications of the potential impacts of this research. Then a list of recommended actions are presented to persuade stakeholders what further measures could advance the impact this research has on benefiting the USAF. Lastly, a discussion of future research suggests other follow-on studies.

Conclusions of Research

This research effort began with the ambition to explore the art of the possible, by capitalizing on the USAF's data warehouse. A superior competency seemed to divide new sophisticated forecast methods based on data analytics with the archaic and simple methods the USAF uses for spare parts. It was this notion that made this topic seem ripe for improvement.

The first investigative question identified the major CBM forecast methods that could be used in the application of forecasting aircraft parts. Two particular methods were recommended as seminal works that should be looked to as baseline models in any organization using CBM. The first was developed by Jardine et al., (1987). Their method took a standard hazard function, and updated this distribution based on a particular part's condition indicator values. The second method developed by Gebraeel et al., (2005), has the added benefit of using real-time sensors to update a remaining life curve. Both instances, along with all of the CBM forecast methods discussed in the literature review are predicated on having information on the condition of a particular part. This is where the largest set-back in pursuing a true CBM method came.

Investigative question two focused on using the USAF's data warehouse, Global Combat Support System-Data Services, to find key data frames that could hold potential in a CBM format. As thoroughly discussed earlier, a void of condition indicators was identified. However, recognizing the ample event data, there was still hope for utility in this data source. Question three then sought to compare what CBM methods could be applied given the data at hand. A model established by contractors at LMI had proved very robust in other applications of research. Because of this, their PBM forecast method looked to be a novel pursuit given only event data.

Question four investigated the statistical evidence comparing the USAF's primary forecasts method against a CBM like technique. It did this through two tests. The first test assessed the PBM's capacity to differentiate forecast accuracy between electrical and mechanical components. Though the results of this test proved statistically significant, the overall method of identifying purely electrical and purely mechanical components was found to be less substantive than originally hoped. The second test focused on comparing the PBM against the USAF's eight quarter and four quarter moving average forecasts. The overall test results showed that the PBM well under performed the status quo. However, when broken out by smooth demand, the non-transformed PBM out performed all other methods. Additionally, for lumpy demand parts, the transformed PBM method performed significantly better than the standard eight quarter moving average.

Significance of Research

There are three significant aspects of this research. The first shows that a CBM method using solely event data can be effective. A contribution to academic literature is that all other CBM forecast methods found required specific beginning and end life cycle data to form a reliability distribution. A greatly simplified explanation of why the PBM seems to work is that instead of forming a reliability distribution based on a sample of failure data, the PBM uses a conditional Bayesian sight-picture to calibrate failure parameters that in its own way form the reliability distribution. This is done through the use of a maximum likelihood estimator.

The second significant contribution from this research was found in the second test of investigative question four. As stated above, there were two specific instances where the PBM method outperformed the USAF's primary forecasting method. It was identified in the introduction that forecast error accounts for $5.5 billion worth of inventory across all USAF managed parts. Of the smooth and lumpy demand patterns where the PBM was significantly more accurate, the PBM would have reduced the dollar value of forecast error on B-1 parts by $12.6 million or effectively 2.46% of error by dollar value. If this premise was applied across all weapon systems the result would be a substantially larger dollar value.

The impact of a more accurate forecast method has further implications as well. When considering a supply chain as a system, the primary methods used to overcome forecast error are increased safety stock and faster order delivery. To the USAF this means increased carrying costs, and increased expediting costs. Therefore, the true impact of even minimal forecast improvements would go far beyond accurate appropriation of funds.

Recommendations for Action

As a result of this research, it is recommended to consider three primary actions. First, the forecast accuracy results found on smooth and lumpy demand items should be validated with larger samples and across all airframes. It is possible that forecast accuracy based on factors of flying hours, number of landings, and number of ground cycles could have wide ranges. Additionally, other weapon systems may not show a dependent correlation between the number of flying hours and the number of sorties, thus resulting in adding the number of sorties as an explanatory variable.

The second recommend action is to suspend the use of demand forecast accuracy as the central measurement of forecast accuracy in the USAF. As discussed in Chapter II, there are several critical oversights with this calculation making it unsuitable especially for intermittently demanded items. Therefore, it is recommended that the USAF adopt the use of MASE as the primary forecast error calculation it its place. The analytical performance of this tool is far superior, and should prompt immediate use of MASE.

The last recommendation is to consider an increased use of a four quarter moving average. Though not thoroughly discussed in the results section, it was shown that the most accurate forecast method across all demand patterns was the four quarter moving average. Currently, the USAF uses this forecast method on only 15% of the items it manages. This research suggests there should be a much larger application of this method than currently used.

Recommendations for Future Research

There are three recommended future topics at the conclusion of this research:

Recommendation 1: Potential conditional information sources

Data use is a widely talked about topic throughout the USAF. Because of this, several initiatives are in infancy that may solve the missing link the USAF would need to implement true CBM methods. The first is the F-35's Automated Logistics Information System. New processes are improving regularly with the fielding of this technology. This system is possibly the greatest opportunity for conditional data due to the substantial number of sensors the jet was designed with. Another opportunity to obtain USAF conditional data comes from a flight operations data collection system referred to as Military Flight Operations Quality Assurance (Megatroika, Galinium, Mahendra, & Ruseno, 2015). At one point in this research effort it seemed possible to obtain raw sensor data from the government contractor who maintained this system for the B-1 aircraft. However, a substantive wait led to a need to put aside that pursuit. If a researcher were to pursue this course early and with the right sponsor, then this path may prove fruitful.

A future project allegedly in work by the Air Force Research Laboratory is a "Digital Thread Digital Twin" program, however, recent updates on this project were hard to uncover (Kobryn, 2014). The basic idea is that there is a data surrogate for every materiel system. This digital twin allows analyst to perform simulated tests or large scale data analytics such as CBM forecasting.

***Recommendation 2:* CBM Inventory Policy**

The second recommendation falls under a very sparsely researched topic. As new and as limited of an application as CBM is throughout maintenance organizations today, a notion of a spare parts inventory model based on CBM inputs is even rarer. Picture a system that would place an order for a part two weeks before a part would fail based on sensors on a part that would tell the system its diminishment. To some, this would be the holy grail of inventory management by effectively eliminating the need for safety stock inventory all together. A novel approach was an age-dependent supply replenishment policy developed by the U.S. Coast Guard in 2006. When compared to the non-age dependent policy, the age-dependent policy reduced average total cost by 22% (Deshpande, Iyer, & Cho, 2006). It should be noted that the Coast Guard's IT systems specifically track end items by serial number and by usage, thus allowing such a practice.

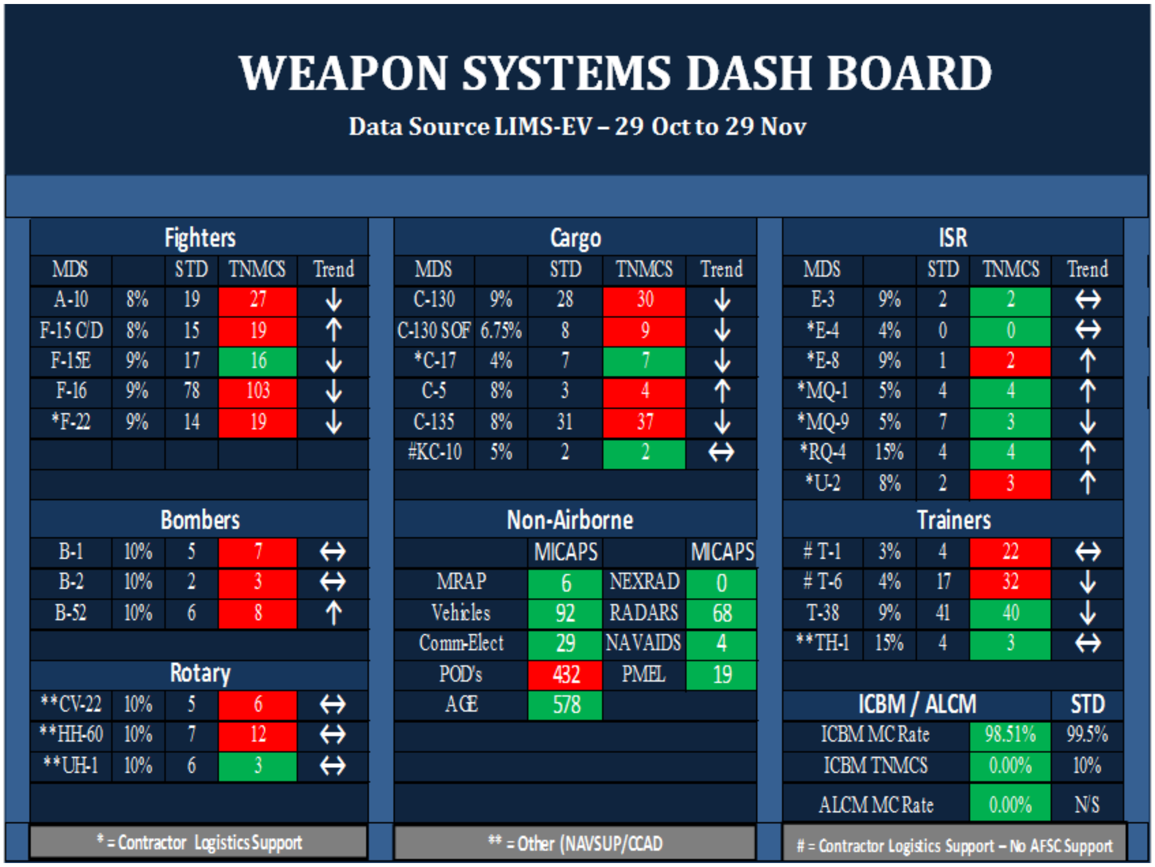
***Recommendation 3:* PBM Sliding Scale Analysis**

The final recommended research area is to explore the reliance of the PBM's dependence on the sliding scale forecast parameter. As explained in the third chapter of this report, the PBM scale requires an analyst to forecast both flying hours and a flying profile ratio between training sorties and combat sorties. The aspect of sliding scale forecast error was not assessed in this research. Rather, it was assumed that each forecasted time period's actual flying profile (known only in hind-sight) was what was actually predicted. By making this assumption it eliminated variance due to forecasting a different flying profile than what was executed.

Summary

It is the belief of this researcher that CBM has a wide and influential application throughout the USAF, and should be considered a high priority in the maintenance and the logistics fields to seek more applications. This research has explored what CBM is defined as, and how academia views it. Also, this research has addressed previous initiatives the DoD has engaged in an effort to establish a robust CBM program. After identifying data collection gaps between where the USAF currently is and where academia suggests, a novel event data approach to CBM forecast was explored. The results of this analysis show a limited yet still influential application of the PBM forecasting method. Finally, the precluding detailed discussion on recommended actions and recommended future research serve as new opportunities to continually advance the application of CBM throughout the DoD.

Appendix A: Weapon Systems Dash Board



WEAPON SYSTEMS DASH BOARD

Data Source LIMS-EV – 29 Oct to 29 Nov

Fighters

MDS		STD	TNMCS	Trend
A-10	8%	19	27	↓
F-15 C/D	8%	15	19	↑
F-15E	9%	17	16	↓
F-16	9%	78	103	↓
*F-22	9%	14	19	↓

Bombers

B-1	10%	5	7	↔
B-2	10%	2	3	↔
B-52	10%	6	8	↑

Rotary

**CV-22	10%	5	6	↔
**HH-60	10%	7	12	↔
**UH-1	10%	6	3	↔

* = Contractor Logistics Support

Cargo

MDS		STD	TNMCS	Trend
C-130	9%	28	30	↓
C-130 SOF	6.75%	8	9	↓
*C-17	4%	7	7	↓
C-5	8%	3	4	↑
C-135	8%	31	37	↓
#KC-10	5%	2	2	↔

Non-Airborne

	MICAPS		MICAPS
MRAP	6	NEXRAD	0
Vehicles	92	RADARS	68
Comm-Elect	29	NAVAIDS	4
POD's	432	PMEL	19
AGE	578		

** = Other (NAVSUP/CCAD

ISR

MDS		STD	TNMCS	Trend
E-3	9%	2	2	↔
*E-4	4%	0	0	↔
*E-8	9%	1	2	↑
*MQ-1	5%	4	4	↑
*MQ-9	5%	7	3	↓
*RQ-4	15%	4	4	↑
*U-2	8%	2	3	↑

Trainers

# T-1	3%	4	22	↔
# T-6	4%	17	32	↓
T-38	9%	41	40	↓
**TH-1	15%	4	3	↔

ICBM / ALCM		STD
ICBM MC Rate	98.51%	99.5%
ICBM TNMCS	0.00%	10%
ALCM MC Rate	0.00%	N/S

= Contractor Logistics Support – No AFSC Support

Figure 13: December 2016 Operations Summary Snapshot

Appendix B: Diagnostic and Prognostic CBM Summary

Author	Article Name	Inputs	Outputs	Technique	Significance
Jardine, A., Anderson, P., & Mann, D. (1987)	Application of the Weibull Proportional Hazards Model to Aircraft and Marine Engine Failure Data	- Age-dependent baseline hazard function - Condition indicators	PHM distribution	PHM	Used MLE to find the parameters of Weibull PHM distribution
Moubray, J. (1997)	*Reliability-Centered Maintenance* (ed 2)	- Condition indicators - "On-Condition Task" interval	P-F Interval	P-F Interval	Established framework to estimate TTF
Goode, K., Moore, J., & Roylance, B. (2000)	Plant machinery working life prediction method utilizing reliability and condition-monitoring data	- Condition Indicators - Weibull parameter estimates	TTF distribution	P-F Interval	Enhanced Moubray's P-F Interval with a Weibull distribution
Swanson, D. (2000)	A General Prognostic Tracking Algorithm for Predictive Maintenance	- Condition Indicators	Hazard distribution	Kalman Filters	Used Kalman Filters to detect changes in indicators
Murray, J., Hughes, G., & Kreutz-Delgado, K. (2005)	Machine Learning Methods for Predicting Failures in Hard Drives: A Multiple-Instance Application	-Self-Monitoring and Reporting Technology (ie. many simultaneous condition indicators)	Fault detection classification	Compared support vector machines, rank-sum, mi-BM (among others)	Proposed efficient/accurate multiple-instance learning algorithm for fault detection
Gebraeel, N., Lawley, M., Li, R., & Ryan, J. (2005)	Residual-Life Distributions From Component Degradation Signals: A Bayesian Approach	- Population reliability distribution parameters - Condition Indicators	Residual-life distribution	Bayesian Degradation Signal Model	Real-time sensor based failure model
Wang, W. (2007)	A Two-Stage Prognosis Model in Condition Based Maintenance	- Categorical & continuous condition indicators	TTF distribution	Discrete/Continuous Hidden Markov Model	Combined continuous and categorical data into state descriptor variable
Tracht, K., Goch, G., Schuh, P., Sorg, M., & Westerkamp, J. (2013)	Failure probability prediction based on condition monitoring data of wind energy systems for spare parts supply	- SCADA condition Indicators	PHM distribution	Enhanced PHM	Used SCADA data as covariates in binomial PHM distribution

Appendix C: Sliding Scale Equations

Peacetime Average Sortie Duration (ASD_{PT}) $= \frac{\#\,Peacetime\ Sorties}{\#\,Peacetime\ Flying\ Hours}$

Wartime Average Sortie Duration (ASD_{WT}) $= \frac{\#\,Wartime\ Sorties}{\#\,Wartime\ Flying\ Hours}$

Peacetime Average Landings Per Sortie (LPS_{PT}) $= \frac{\#\,Peacetime\ Landings}{\#\,Peacetime\ Sorties}$

Wartime Average Landings Per Sortie (LPS_{WT}) $= \frac{\#\,Wartime\ Landings}{\#\,Wartime\ Sorties}$

Predicted Peacetime Flying Hours (PTFH^)

$$= User\ defined\ future\ period's\ Peacetime\ Flying\ \% * Future\ period's\ Flying\ Hours$$

Predicted Wartime Flying Hours (WTFH^)

$$= User\ defined\ future\ period's\ Wartime\ Flying\ \% * Future\ period's\ Flying\ Hours$$

Predicted Peacetime Cold Cycles (PTCC^) $= \frac{(PTFH^\wedge)}{(ASD_{PT})}$

Predicted Wartime Cold Cycles (WTCC^) $= \frac{(WTFH^\wedge)}{(ASD_{WT})}$

Predicted Cold Cycles (CC^) $= PTCC^\wedge + WTCC^\wedge$

Predicted Peacetime Warm Cycles (PTWC^) $= (LPS_{PT} - 1) * PTCC^\wedge$

Predicted Wartime Warm Cycles (WTWC^) $= (LPS_{WT} - 1) * WTCC^\wedge$

Warm Cycles (WC^) $= PTWC^\wedge + WTWC^\wedge$

Ground Cycles (GC^) $= (Possessed\ Hrs_{t-1} - Flying\ Hours_t)/24$

*Note, this research assumes the user knows the forecast year's flying profile mix of PTFH and WTFH. Also, Possessed Hours is assumed to remain constant from last known year in order to forecast into future years.

Appendix D: Demand Pattern Demand Data

Demand Pattern	NIIN-SGM	Noun.	2012 Q1	2012 Q2	2012 Q3	2012 Q4	2013 Q1	2013 Q2	2013 Q3	2013 Q4	2014 Q1	2014 Q2	2014 Q3	2014 Q4	2015 Q1	2015 Q2	2015 Q3	2015 Q4	2016 Q1	2016 Q2	2016 Q3	2016 Q4
Smooth	012630536	COMPUTER,F	39	21	27	20	13	13	15	22	19	21	20	18	10	10	21	20	9	8	17	12
Smooth	011433525	CONTROL BO	1	4	8	6	4	2	5	10	1	4	6	9	4	4	9	7	6	4	5	7
Smooth	015097158	ACTUATOR,E	8	6	7	4	4	4	3	4	2	4	2	1	6	5	4	5	2	3	7	6
Smooth	012704772	PCA #3 157	2	8	6	5	8	4	3	1	0	2	8	2	2	2	1	3	3	2	5	3
Smooth	011491452	PUMP,SUBME	9	6	10	7	9	8	8	2	10	13	11	7	6	6	9	9	12	11	14	14
Smooth	011478410	CYLINDER A	3	8	10	8	9	15	8	14	12	15	10	7	9	8	11	7	3	5	1	0
Smooth	012398983	FREQUENCY	13	13	5	10	5	16	13	10	3	6	8	15	16	17	11	5	18	16	10	17
Smooth	013194674	COUPLER,AN	4	3	8	4	4	6	5	3	6	1	6	4	4	1	4	0	1	4	4	0
Smooth	013751527	COMPUTER,F	16	10	20	5	12	3	7	8	9	8	23	5	15	18	6	13	5	2	5	5
Smooth	011829763	INDICATOR,	1	4	4	2	4	5	3	7	5	2	4	6	3	1	1	7	6	2	3	2
Lumpy	013994172	PCA 2 9-S	0	0	0	0	1	1	0	0	0	1	0	0	0	1	0	1	1	0	0	0
Lumpy	015499544	ACTUATOR,E	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	2
Lumpy	011730600	AMPLIFIER,	0	0	0	1	0	0	0	1	0	1	0	0	1	0	0	0	0	0	4	1
Lumpy	013023453	CIRCUIT CA	0	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	1	0	0
Lumpy	015548051	POWER SUPP	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	2	1	0	0
Lumpy	011642197	CONTROL,IN	1	0	3	2	1	2	0	2	1	3	3	1	5	2	0	0	0	1	1	1
Lumpy	015824217	WHEEL,LAND	0	0	0	0	0	0	0	0	0	0	1	8	0	7	64	111	72	44	76	79
Lumpy	015824221	BRAKE,MULT	0	0	0	0	0	0	0	0	0	0	0	1	1	26	12	2	5	4	3	5
Lumpy	011505162	VALVE,HYDR	1	1	2	2	2	0	1	0	0	1	2	0	1	0	3	3	1	1	0	0
Lumpy	012321676	CONTROL UN	2	0	0	1	0	0	0	0	2	0	1	0	0	0	1	0	0	0	0	1
Intermittent	016525025	DRIVE UNIT	0	0	0	0	0	0	0	0	3	3	3	2	2	1	2	4	0	3	2	2
Intermittent	011862809	TANK,HYDRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0
Intermittent	016175632	POWER CONT	0	0	0	0	0	0	0	0	0	2	1	0	0	3	3	7	3	2	2	3
Intermittent	012110135	VALVE,SOLE	0	0	0	0	0	0	2	0	1	1	2	2	2	0	0	0	1	0	0	0
Intermittent	012137727	SWITCH,RAD	0	0	2	2	0	0	0	2	2	1	3	1	0	3	2	2	1	3	0	2
Intermittent	015626911	COMPUTER,F	0	0	0	0	0	1	7	3	2	3	3	5	8	8	3	10	8	5	4	4
Intermittent	016525309	DRIVE UNIT	0	0	0	0	0	0	0	0	2	3	2	2	3	1	2	3	3	3	1	0
Intermittent	011862810	TANK,HYDRA	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Intermittent	011433521	TURBINE,AI	0	0	3	0	1	0	1	0	0	0	4	1	1	2	2	1	1	1	1	0
Intermittent	012112088	VALVE,OXYG	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	1	0	1
Erratic	012058322	VALVE,SHUT	3	5	0	1	10	1	3	6	0	2	3	3	1	4	1	4	8	2	5	3
Erratic	013731249	EXTINGUISH	0	10	7	9	25	6	18	20	38	27	4	32	40	34	22	11	3	0	1	0
Erratic	015006333	PCA 11 BL	1	3	1	3	1	0	3	5	2	2	0	2	1	0	1	1	1	2	1	0
Erratic	011491450	PUMP,SUBME	13	3	30	22	5	4	7	14	4	6	2	6	8	4	16	10	8	4	2	5
Erratic	011838951	ANTI-ICE M	6	6	2	3	4	4	15	7	5	5	1	1	2	0	3	4	1	2	2	0
Erratic	015452484	PROCESSOR,	1	2	1	2	2	3	8	8	11	6	7	21	10	3	10	6	15	5	7	7
Erratic	012664261	OSCILLATIN	11	7	9	8	2	2	7	7	1	3	11	1	4	0	2	1	3	2	2	1
Erratic	011982203	CIRCUIT CA	12	3	2	3	5	4	0	0	6	13	15	12	18	0	1	1	8	5	3	3
Erratic	011807465	ELECTRONIC	2	3	8	5	9	3	8	4	3	2	0	2	2	1	2	2	1	1	0	1
Erratic	011933136	CIRCUIT CA	2	4	1	1	4	4	3	4	0	0	3	2	2	1	1	2	3	0	1	1

Appendix E: Mechanical and Electrical Demand Data

Part Category	NIIN-SGM	Noun.	2012 Q1	2012 Q2	2012 Q3	2012 Q4	2013 Q1	2013 Q2	2013 Q3	2013 Q4	2014 Q1	2014 Q2	2014 Q3	2014 Q4	2015 Q1	2015 Q2	2015 Q3	2015 Q4	2016 Q1	2016 Q2	2016 Q3	2016 Q4
Mechanical	015780463	FLAP,INLET	294	293	218	218	226	247	176	297	125	183	215	165	131	118	156	192	92	98	55	16
Mechanical	013145809	FLAP, DIVE	226	243	191	157	154	166	139	196	165	430	152	161	124	166	58	11	27	11	0	4
Mechanical	011659072	NOSE WHEEL	78	41	29	40	42	23	29	28	16	12	33	16	23	33	31	28	26	20	29	33
Electrical	011491452	PUMP,SUBME	9	6	10	7	9	8	8	2	10	13	11	7	6	6	9	9	12	11	14	14
Electrical	015489586	CIRCUIT CA	34	26	31	26	21	12	3	7	17	23	12	18	7	16	21	18	12	15	2	12
Electrical	014395852	GENERATOR	11	3	11	18	9	11	15	17	20	13	15	23	36	45	12	30	27	22	24	13

Appendix F: Quad Chart

A Condition Based Maintenance Approach to Forecasting B-1 Aircraft Parts

Capt Joshua D. DeFrank
Co-Advisor: Capt Michael P. Kretser
Co-Advisor: Dr. Alan W. Johnson
Department of Operational Sciences (ENS)
Air Force Institute of Technology

Background:

- Condition Based Maintenance (CBM) uses an evidence based approach to determine when to perform maintenance actions
- Evidence can be gathered by sensors or from performing tests that measure the remaining life or performance of a part
- AF part forecasts are based on a 8 quarter moving average (8QMA) proportional to flying hours

Problem:

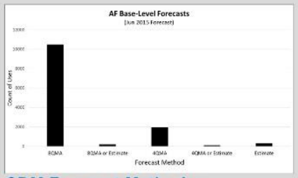
- Current forecast methods result in $5.5B worth of error at 57% accuracy
- CBM offers new approaches to improve forecast accuracy

Investigative Questions:

1. What established prognostic CBM methods produce a demand forecast?
2. What data does the AF currently collect that fits under CBM?
3. What CBM forecast methods can be used by the AF with current IT systems?
4. How well does a CBM forecast compare to the AF's current forecast method?

AIR FORCE INSTITUTE of TECHNOLOGY

Methodology



IQ1. CBM Forecast Methods:

- Two of six stood out:
  - A Proportional Hazards Model produces a hazard distribution
  - A Bayesian Degradation Signal Model produces a remaining life curve
- All CBM forecasts require condition monitoring data

IQ2. CBM Data:

- Search focused on GCSS-Data Services data warehouse
- Corroborated with several AF offices performing CBM analysis
- AF primarily collects event data (sortie duration, action taken codes, etc.)
- Results of maintenance tests performed at base level are not transferred into a central database

IQ3. What CBM forecast can be used:

- Condition monitoring data was required for all true CBM methods
- A CBM-like physics-based approach uses event data to predict parts failures

IQ4. Physics-Based Model (PBM) Forecast:

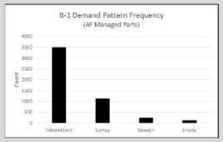
Flying Hours	$\mu = \lambda_f t_f$	$\sigma = \lambda_f t_f$
Sorties	$\mu = N_{cc} P_{cc}$	$\sigma = N_{cc} P_{cc}(1 - P_{cc})$
Touch & Go's	$\mu = N_{wc} P_{wc}$	$\sigma = N_{wc} P_{wc}(1 - P_{wc})$
Ground Days	$\mu = N_{gc} P_{gc}$	$\sigma = N_{gc} P_{gc}(1 - P_{gc})$

$$\mu_i = \lambda_f t_f + N_{cc} P_{cc} + N_{wc} P_{wc} + N_{gc} P_{gc}$$

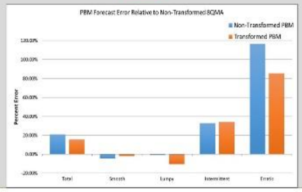
$$\sigma_i^2 = \lambda_f t_f + N_{cc} P_{cc}(1 - P_{cc}) + N_{wc} P_{wc}(1 - P_{wc}) + N_{gc} P_{gc}(1 - P_{gc})$$

$$Max\ Log\ Likelihood = \sum_{i=1}^{n} \ln\left[N(demand_i | \mu_i, \sigma_i)\right]$$

- PBM uses a Sliding Scale to adjust for different percentages of combat vs. training missions flown each forecast period
- A shear transpose was used to account for slope in historic demand



	Non-Transformed			Transformed			
Demand Pattern	PBM	8QMA	4QMA	PBM	8QMA	4QMA	Avg. MASE
Smooth	1.13	1.19	1.19	1.16	1.32	1.31	1.22
Lumpy	1.70	1.72	1.63	1.53	1.52	1.56	1.61
Intermittent	2.26	1.70	1.61	2.28	1.96	1.97	1.96
Erratic	1.06	0.49	0.56	0.91	0.74	0.70	0.75
Avg. MASE	1.54	1.27	1.25	1.47	1.39	1.39	1.38



Contributions:

- Identified error calculation more practical for parts forecasting: mean absolute scaled error
- Condition monitoring data is not readily available in AF's central data warehouse
- 4 quarter moving average was overall the most accurate method—AF should increase its use
- PBM Forecast outperformed the AF's primary forecast method in two categories:
  - Smooth: 4.43% error reduction
  - Lumpy: 10.60% error reduction
  - Combines for estimated $12.6M error reduction for B-1 parts

Future Research:

- Apply identified CBM forecast methods on F-35 ALIS data
- Use PBM on DLA managed parts
- Explore PBM's reliance on a Sliding Scale when ratio of combat vs. training missions is unknown

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14. ABSTRACT
United States Air Force (AF) aircraft parts forecasting techniques have remained archaic despite new advancements in data analysis. This approach resulted in a 57% accuracy rate in fiscal year 2016 for AF managed items. Those errors combine for $5.5 billion worth of inventory that could have been spent on other critical spare parts. This research effort explores advancements in condition based maintenance (CBM), and its application in the realm of forecasting. Then it evaluates the applicability of CBM forecast methods within current AF data structures. This study found large gaps in data availability that would be necessary in a robust CBM system. The Physics-Based Model was used to demonstrate a CBM like forecasting approach on B-1 spare parts, and forecast error results were compared to AF status quo techniques. Results showed the Physics-Based Model underperformed AF methods overall, however outperformed AF methods when forecasting parts with a smooth or lumpy demand pattern. Finally, it was determined that the Physics-Based Model could reduce forecasting error by 2.46% or $12.6 million worth of parts in those categories alone for the B-1 aircraft.

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