

**United States Military Academy
West Point, New York 10996**

Condition-Based Maintenance (CBM): A Working Partnership between Government, Industry, and Academia

**OPERATIONS RESEARCH CENTER OF EXCELLENCE
TECHNICAL REPORT #DSE-TR-0614
DTIC #: ADA449019**

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Professor and Head, Department of Systems Engineering

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The Operations Research Center of Excellence is supported by the Assistant Secretary of the Army
(Financial Management & Comptroller)

This Research was sponsored by: The U.S. Army Aviation and Missile Command

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Abstract

While a large number of partnerships form as defensive measures in response to fierce global competition, distress over future uncertainties, and a lack of alternative methods to ensure continued survival, synergistic partnerships are characterized as being cooperative learning experiences that benefit all the parties involved. The best partnerships are those that develop into strategic alliances helping to capture and create value that would otherwise have been difficult to realize if not for the mutually shared goals and resources of the partnership. In this paper, we discuss how government, industry, and academia are able to converge upon a new maintenance paradigm aimed at benefiting our nation's military forces. In particular, representatives from all three domains are working together to determine how condition-based maintenance (CBM) can best serve U.S. Army aviation and bolster our soldiers engaged in the war against terrorism. Described as is a set of maintenance processes and capabilities aimed at improving U.S. Army aviation fleet's operational readiness and reducing soldiers' maintenance burden, CBM leverages advanced technologies to help generate enhanced diagnostics for key components on-board a select number of AH-64 Apache, UH-60 Blackhawk, and CH-47 Chinook helicopters. The near real-time assessment of data from the embedded sensors seeks to provide the U.S. Army with a more effective and efficient way to conduct maintenance based on need rather than scheduled periods, the capability to perform supply chain actions in a more proactive manner, and the ability to optimize the competing demands of warfighting and planned maintenance. In short, CBM attempts to improve the way the U.S. Army approaches maintenance, transforming it from the industrial age of the 20th Century into the information age of this new century. We believe that through the successful partnering of government, industry, and academia, we will be able to exemplify how CBM is demonstrating business transformation for the U.S. Army.

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Acknowledgements

This project was funded under the direction and leadership of Mr. Robert Brown, G-3 Condition-Based Maintenance Lead, U.S. Army Aviation and Missile Command. This study follows on the research and work that Major Mark Gorak and Major Steve Henderson had conducted in previous years. The authors would like to gratefully acknowledge the enduring impact and immense contributions that Mr. Bill Braddy, Ms. Mary Katherine Akamatsu and Mr. Ron Steele of Westar Corporation have provided. The authors are also indebted to Aviation Engineering Directorate's Mr. Randy Buckner, Major Allen Pilgrim, and Mr. Chris Perry for their valued assistance and support on the project. Finally, the authors wish to thank Professor Patricia Jacobs and Professor Donald Graver at the Naval Postgraduate School for their support, insights, and lasting contributions.

Table of Contents

Abstract.....	iii
About the Authors.....	iv
Acknowledgements	v
Table of Contents	vi
Chapter 1: Introduction	7
Chapter 2: Using the SEMP to Foster Mutual Cooperation.....	8
Chapter 3: A Roadmap for Getting the Most out of a Partnership	10
Chapter 4: The Promising Path Forward for CBM	12
Chapter 5: Conclusions	13
Endnotes.....	15
Appendix A: List of Abbreviations	16
Exhibit 1: Rapidly Attaining Low Hanging Fruit.....	17
Exhibit 2: Delivering on Unique Skill Sets	27
Exhibit 3: Driving Toward Greater Mutual Understanding	127
Exhibit 4: Researching Common Areas of Interest.....	135
Distribution List.....	145
REPORT DOCUMENTATION PAGE – SF298	146

Chapter 1: Introduction

“Partnership. n. A relationship between individuals or groups that is characterized by mutual cooperation and responsibility, as for the achievement of a specified goal.”

--American Heritage Dictionary

Over the past several years, the Operations Research of Excellence (ORCEN) in the Department of Systems Engineering at the United States Military Academy (USMA) has worked with the U.S. Army Aviation and Missile Command (AMCOM) on research projects aimed at enhancing our military aviation capabilities. Previous works by Major Mark Gorak [1] and Major Stephen Henderson [2] have helped to lay the foundation for the current partnership between government, industry, and academia that aims to improve the U.S. Army’s helicopter maintenance paradigm. Under the direction of the AMCOM, support of the Westar Aerospace and Defense Group, and academic research focus of the ORCEN, we continue to strengthen our mutual interest in determining how CBM can best advance our military into the information age of the 21st Century.

We approached this year’s joint venture as a mutually beneficial arrangement that would generate not only tangible results for our partners, but also relevant and significant studies for us as military operations research faculty members. Being new to the partnership, we employed the Systems Engineering and Management Process (SEMP) that we teach to cadets at USMA—a structured problem solving process useful in the design of multidisciplinary, large-scale, and complex engineering problems graphically portrayed in Figure 1—to ensure a swift and prompt integration of appropriate interests, capabilities, and resources [3]. While the application of the SEMP can vary significantly from project to project, reflecting local practices and expectations, we believe that such variance often provides opportunities to adopt new ideas and new ways of

approaching an issue. As a new maintenance paradigm that leverages advanced technologies and introduces new processes, CBM is an ideal project for the application of the SEMP.

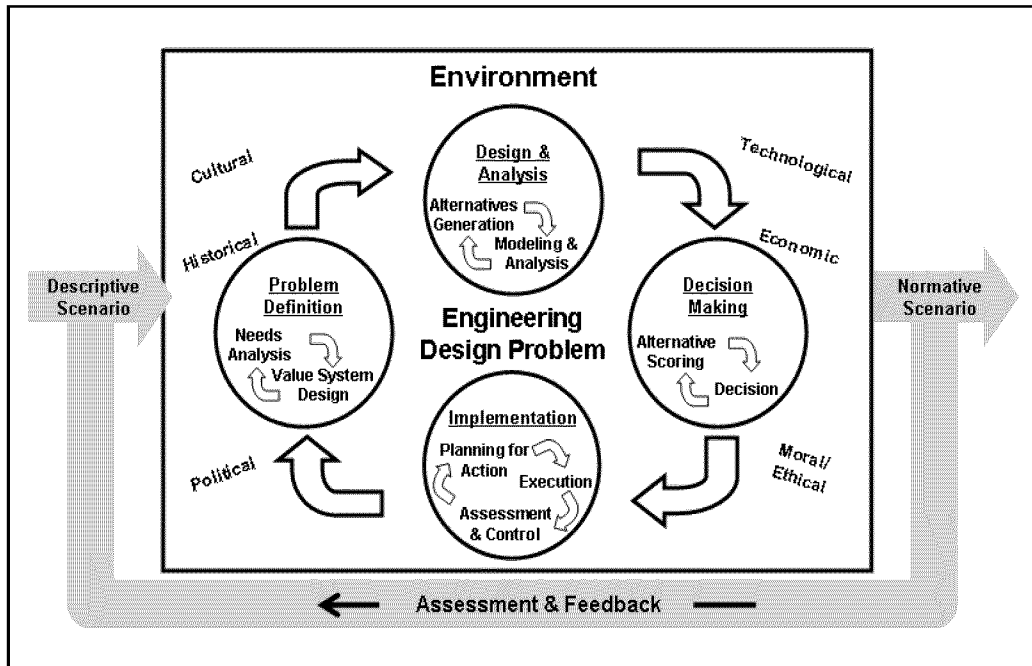


Figure 1: The SEMP Framework [4]

Chapter 2: Using the SEMP to Foster Mutual Cooperation

As a design methodology and problem solving framework, the SEMP provides us with a coherent and structured process for defining and agreeing on shared goals and objectives, nominating areas for research focus, and selecting appropriate analytical tools, processes, and methodologies for achieving project deliverables. We used the problem definition phase of the SEMP to ensure our unique skills and analytical capabilities would be utilized in ways that best complements our partners' expectations. Much of this initial phase was spent ironing out project deliverables that truly satisfied the partners' needs and requirements. This initial phase of the project also helped foster mutual cooperation in the following ways:

- Alleviated much of the anxiety with getting the initial statement of work (SOW) produced, especially in terms of addressing milestones, timelines, and project deliverables;
- Provided a deliberate and methodical method for generating common understanding of capabilities and limitations among partners;
- Prevented partners from feeling locked into a set of pre-defined objectives and goals, especially for projects where dynamic exchange is to be expected;
- Empowered ORCEN analysts with the capability of refining the initial SOW into a project contract that they can take ownership of with agreement from the partners;
- Encouraged partners to communicate to one another their expectations and goals,
- Allowed for partners to come up with a SOW based on system needs, common interests, and shared responsibilities.

Furthermore, the growth of such mutual cooperation diminished the likelihood that the CBM partnership would turn into a short-lived reactive association and increased the chances of it developing into a proactive partnering, and perhaps even a strategic alliance. Table 1 provides examples and characteristics of the various types of partnerships that exist in government, industry, and academia. While the use of the SEMP does not guarantee the creation of longer-term alliances, it does help to communicate common expectations and shared responsibilities that, in turn, help avert purely reactive associations from forming.

Table 1: Partnerships Types and Characteristics

	Government	Industry	Academia
Reactive Associations	Political Expediency Military Necessity	Fierce Competition Fear of Uncertain Future	External Locus of Control Credentialing
Proactive Partnering	Balance of Core Competencies Longer-Term Partnerships	Focus on Core Competencies Longer-Term Mergers	Internal Locus of Control Fruitful Collaboration
Strategic Alliances	Shared Resources	Common Vision	Mutual Respect

Chapter 3: A Roadmap for Getting the Most out of a Partnership

Thriving partnerships and successful project deliverables are predicated upon the four key dimensions of preparation, promotion, implementation, and documentation. Figure 2 illustrates that these four dimensions are not mutually exclusive and depicts the elements that comprise each of the dimensions. Central to overall success is the organizational commitment to the program. While it is difficult to predict how committed our government will be to CBM in the future, AMCOM's current level of effort and focus bodes well for its near-term prospects. Not only has AMCOM provided considerable resources in the promotion of CBM, both in terms of time as well as funding, it has formulated clear objectives and goals for CBM. As a result, AMCOM has helped to establish a common vision for the direction of CBM and has brought industry and academia together to work on preparing, documenting, and implementing a viable strategy for how to best incorporate CBM into the military.

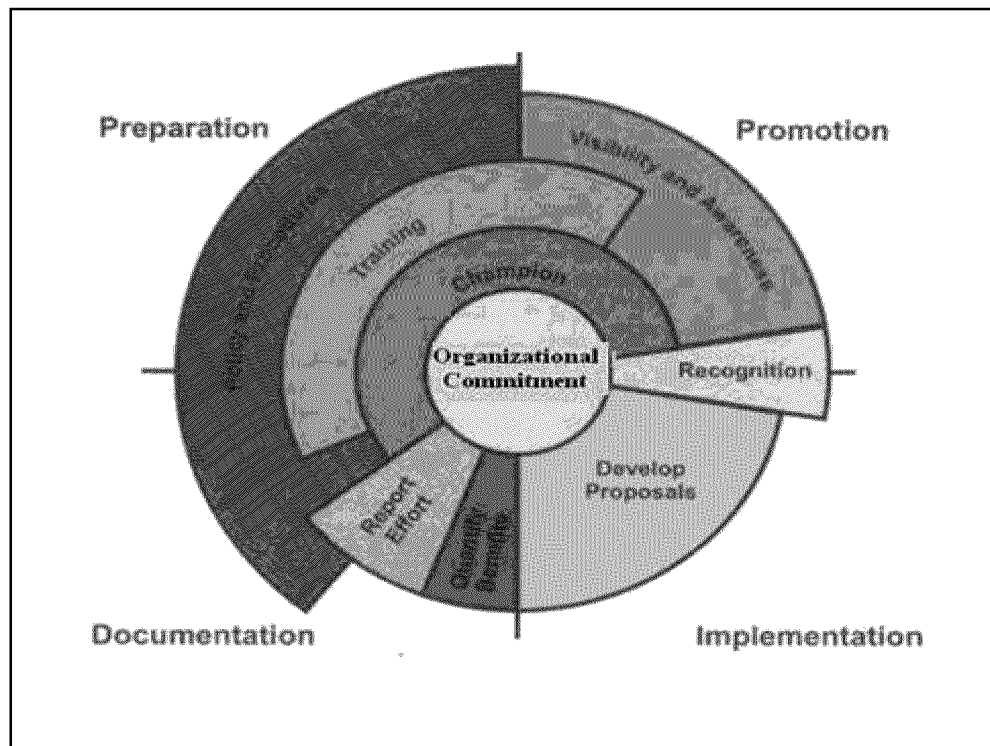


Figure 2: Functional Elements of Successful Products and Partnerships [5]

With the substantial weight of the vast resources under its charge, AMCOM has been the key governmental agency overseeing the direction of CBM. AMCOM has taken steps to advance partnerships with industry and academia so that it is able to leverage the core competencies distinctive within each of these two domains. Industry tends to possess valued competencies such as speed, responsiveness, efficiency, practical expertise, and entrepreneurial thinking. Academia, on the other hand, tends to maintain valued competencies such as research capabilities, technical expertise, and advancement of new ideas. Therefore, all three domains enter the CBM partnership with the understanding that each is able to focus on its own unique competencies—the government with its resources and vision, industry with its speed and practicality, and academia with its theories and strength in conducting research.

In keeping with this common understanding pertaining to the CBM partnership, the ORCEN agreed to undertake project deliverables that did not fall on the critical path of CBM advancement. As a result, the ORCEN was able to conduct research that ranged from answering specific questions, such as how to leverage simulation capabilities into the CBM paradigm (see Exhibit 1—Rapidly Attaining Low Hanging Fruit), to initiating a pilot study on initial CBM helicopter data (see Exhibit 2—Delivering on Unique Skill Sets). Additionally, the ORCEN was able to integrate information on CBM from both government agencies as well as corporate participants to help better articulate the intended vision for this new military maintenance paradigm (see Exhibit 3—Driving Toward Greater Mutual Understanding). Lastly, the ORCEN was able to collaborate with Westar Corporation, a key industry partner, on developing new and more meaningful metrics under a CBM paradigm (see Exhibit 4—Researching Common Areas of Interest). All four of these deliverables represent distinct research projects the ORCEN has undertaken to help contribute to the advancement of CBM as an Army transformation initiative.

Chapter 4: The Promising Path Forward for CBM

Not only does CBM provide an entirely different way of conducting maintenance for the U.S. Army, it introduces a great number of potential research partnerships between government, industry, and academia. Areas that lend themselves directly to further study include production operations management (e.g., supply chains, inventory control, lean thinking, and just-in-time processes), quality control (e.g., six sigma, 5S, root cause analysis, and failure modes effects analysis), statistical methodologies (e.g., hypothesis testing, multivariate analysis, pareto analysis, and stochastic analysis), continual process improvements (e.g., theory of constraints, value stream mapping, tear-down analysis, value engineering, and benchmarking), and problem solving techniques (e.g., design of experiments, modeling and simulation, data mining, and data farming). Under the watchful direction of the government, speedy and efficient application of resources from industry, and varied ideas and research focus of academia, CBM provides a large wealth of possibilities for continued proactive partnerships. Figure 3 illustrates the synergistic growth of knowledge that can occur as a result of the successful partnership of all three domains.

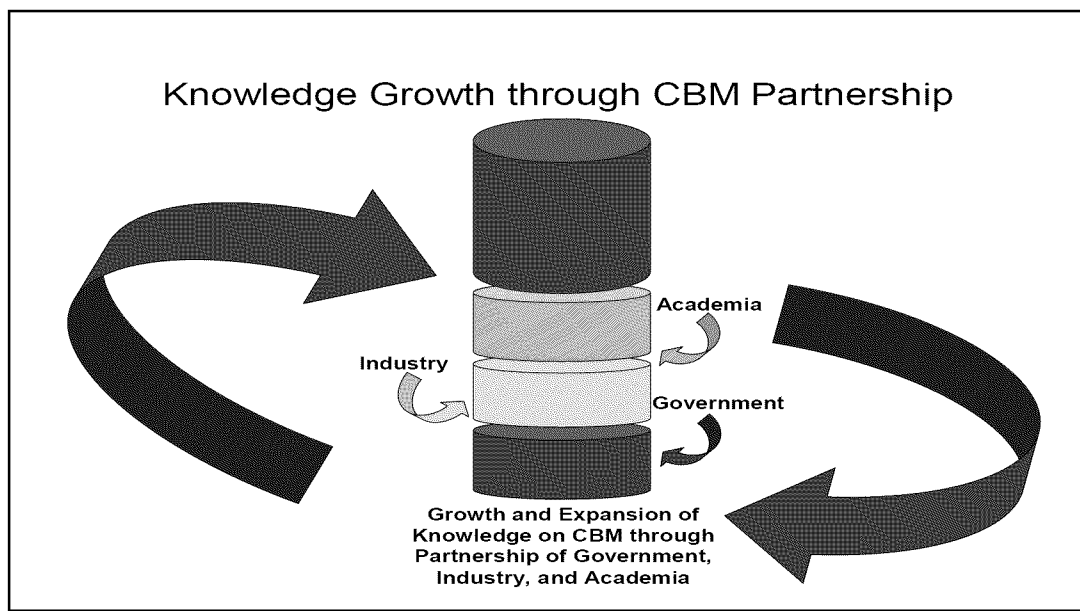


Figure 3: Growth and Expansion of Knowledge through the CBM Partnership

A positive Matthew Effect is likely to result from the knowledge gained through the CBM partnership [6]. As more collaborative engagements between the partners develop, the more trust builds among government, industry, and academia. As this trust grows, the greater the confidence each partner will have in each other's capabilities. Each domain's individual contribution will help to add not only to the existing body of knowledge pertaining to CBM, but more importantly, will help to catalyze the other domains into pursuing further analysis. As a result, new systems and processes, improved diagnostics and prognostics, and enhanced control mechanisms and maintenance approaches will likely result from the study of CBM. And as a consequence, the U.S. Army becomes the key beneficiary from the growth and expansion of such knowledge.

Chapter 5: Conclusions

According to Foley, "The means of production is less and less the sweat of our brow, or the leveraging of our muscle power with steam or water or electric power, or mindless repetition of work on the assembly line. Rather, the means of production increasingly is the leveraging of our intellectual power with computers" [7]. It is our belief that our partnership on CBM is helping to leverage computational power and technological advances to make the task of maintenance more effective and more efficient for our military forces. We also believe our partnership on CBM is helping to advance the tenets of Army Transformation. As former Army Chief of Staff General Eric Shinseki and former Army Secretary Thomas White have stated: "Soldiers on point for the nation transforming this, the most respected army in the world, into a strategically responsive force that is dominant across the full spectrum of operations . . . The Army's Vision [consists of] People, Readiness, Transformation—and our efforts to change

quickly into a more responsive, deployable, agile, versatile, lethal, survivable, and sustainable force” [8]. The introduction of the CBM paradigm will help to promote military transformation, and the partnership of government, industry, and academia is helping to demonstrate how we can leverage each domain’s unique skills and capabilities towards the fulfillment of the Army Vision in this new century.

Endnotes

- [1] M. Gorak. "Lead-the-Fleet: Transitioning Army Aviation Maintenance from a Time Based System to a Usage Based System" **Operations Research Center of Excellence Technical Report**, #DSE-TR-0406, DTIC #ADA426343, June 2004.
- [2] S. Henderson. "A Data Warehouse to Support Condition Based Maintenance (CBM)." **Operations Research Center of Excellence Technical Report**, #DSE-TR-0509, DTIC #ADA434357, May 2005.
- [3] United States Military Academy, Department of Systems Engineering (Eds.). **Readings for Systems Engineering & Engineering Management**. Mason, OH: Thomson Customer Publishing, 2004, p. 2.
- [4] Ibid.
- [5] Adapted from D Wilson. "Value Engineering in Transportation." **Achieving Value**. Dayton, Ohio: SAVE International, Volume 1, Number 1. Winter 2006.
- [6] R. Merton. "The Matthew Effect in Science." **Science**, 159(3810): 56-63, 1968, accessed August 8, 2005 from www.garfield.library.upenn.edu/merton/matthew1.pdf.
- [7] J. Foley. Forward to D. Hix and H.R. Hartson, **Developing User Interfaces: Ensuring Usability Through Product & Process**, New York: John Wiley & Sons, Inc., 1993, p. v.
- [8] E. Shinseki and T. White. "The 2003 United States Army Posture Statement," letter dated February 11, 2003, accessed April 3, 2006 at www.army.mil/aps/2003/letter/index.html.

Exhibit 1: Rapidly Attaining Low Hanging Fruit

White Paper
Operations Research Center of Excellence
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17 August 2005
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How to Leverage Computer Simulation in Condition-Based Maintenance: Capabilities are Determined by the Availability and Accessibility of Data

Executive Summary

Many companies are discovering that they can leverage computer simulation to help improve their competitiveness and help achieve cost savings. Simulation modeling is becoming an important enabling technology that is enhancing numerous functions such as engineering and operations, logistics, research and development, risk analysis, process design, and information systems. Government agencies are also adopting computer simulation techniques to assist in areas such as accident analyses, operator training, environmental protection, and efficiency studies.

In the past, tailor-made computer simulators were developed from scratch and used almost exclusively by mathematicians and programmers who held the expertise to utilize and understand such time-consuming and expensive systems [15]. As computers have gained greater processing power at more affordable prices, however, a greater number of users are taking advantage of simulation capabilities. As a result, a greater number of companies are now able to leverage computer simulation to tackle even more demanding problems. And as a greater number of applications are being developed, computer simulation is helping to provide benefits such as [10, 15]:

- Higher quality manufacturing through reduced costly mistakes
- Reduced risk and improved safety
- Shorter commissioning time of new products
- Increased operational capacity and usage

- Savings in training costs of personnel
- Extension of equipment life
- Increased confidence in major decisions

Since these benefits all appear to tie directly to the goals of condition-based maintenance (CBM), the question of whether or not computer simulation makes sense for the U.S. Army aviation's new maintenance paradigm ought to be apparent (refer to page 3 for CBM goals). Not only does computer simulation have the potential to improve many functions within CBM, it also has the ability to help promote the CBM vision of achieving optimal operational readiness of the aviation fleet. Consequently, rather than focusing on trying to answer *whether* computer simulation modeling can be used to enhance CBM, it is perhaps more worthwhile to focus on *how* to best introduce computer simulation modeling into the CBM process in the most effective manner. This paper presents three major alternatives for addressing how to introduce computer simulation techniques into CBM:

- Develop computer simulation tools in-house that are tailored specifically to U.S. Army Aviation and Missile Command (AMCOM) engineering requirements
- Use existing commercial simulation software tools, such as Crystal Ball and Palisades Decision Tools, for analysis of existing data
- Outsource the modeling functions to external agencies with established dependability, responsiveness, and expertise in computer simulation

Although these three alternatives are very distinct courses of action, there should be no reason to think that each one cannot play a role in advancing the CBM paradigm. It is very likely that the best decision for incorporating simulation into CBM will include elements of all three alternatives. But regardless of the decision, it is important to recognize that the success of computer simulation techniques in CBM depend largely on the availability and accessibility of suitable data.

Introduction--What Are Computer Simulations and What Can We Gain from Them?

Computer simulations are designed to provide insights into the dynamic behavior of systems as they vary over time [8, 16]. Traditionally, the formal modeling of systems has been via mathematical models that attempt to find analytical solutions to problems based on a set of

defined parameters and initial conditions. Computer simulations are often used as adjuncts to modeling systems in which analytical solutions are not possible or those that are very difficult to answer. There are many different types of computer simulation, but the common feature they all share is their attempt to generate a sample of representative scenarios for a model in which a complete accounting of all possible states of the model would be prohibitive or impossible [9, 13].

One of the principal advantages with computer simulation is its capacity to model and represent the behavior of complex systems over time in a rapid, convenient, and cost-effective manner [14, 15]. Without computer simulations, analysts would have to rely upon sophisticated mathematical theories, or test actual devices and observe how they behave under controlled conditions to learn about and make improvements in the design or process [4]. Another important feature of computer simulation is its ability to emulate every significant step that occurs in a process and identify significant interactions between resources in a process. This enables analysts to gain insights about the impact of potential decisions or changes on that process. A good simulation model equips the analyst with a visual representation of what will happen in the process if changes are made to it, and it gives the analyst a record of those changing system performance measures as they are examined under various scenarios [13, 14].

Simulation has been used most extensively in situations where the real system cannot be used for experiments. Computer simulation is also an appropriate analysis tool when [3, 15]:

- The real system does not yet exist
- The experiments would involve high economical risks
- The experiments would be dangerous
- The experiments cannot be controlled or carried out
- The process variables are too difficult to be measured through experimentation
- The measurements are too noisy
- The experimenting with the real system is expensive
- The system cannot be easily accessed
- The dynamics and response of the system under actual conditions are too slow
- The proper conditions for the experiment are difficult to fulfill
- The variables of the system cannot be easily manipulated in an experiment

Appendix A lists both a wide-range of industry sectors employing computer simulation techniques as well as a number of practical applications that have been developed through computer simulation.

Why Does Computer Simulation Make Sense for CBM?

Computerized dynamic simulation models are useful for verification of both conceptual and detailed process designs [15]. Because they make in-house pre-testing of automation systems, user interfaces, and operational procedures possible in a relatively quick, efficient, and economical manner, computer simulation appears to be an ideal tool for enhancing the CBM paradigm. According to DoD Directive 5000.1, the stated objectives of CBM are [5, 12]:

- Predict equipment failures based on real-time or near real-time assessments of equipment condition obtained from embedded sensors
- Reduce maintenance down time
- Increase operational readiness by repairing or replacing system components based on actual condition of components rather than on a scheduled or time-phased basis

As such, computer simulation can help to facilitate in the development of both enhanced diagnostics as well as predictive prognostics which serve to “improve maintenance agility and responsiveness, increase operational availability, and reduce life cycle total ownership costs” [7]. Because the effectiveness of computer simulation models is contingent upon large amounts of data, the profuse amount of information generated from the embedded sensors across the aviation fleet will serve to provide even more legitimacy to both the models and results of CBM computer simulations. Furthermore, benefits from computer simulation need not be limited to the operations, support, and sustainment phases of the life cycle for aviation assets. From system acquisition to retirement and disposal, computer simulation can help provide robust analysis to nearly all phases of the Total Life Cycle Systems Management--especially when faced with decreased testing budgets, more complicated systems, more software-intensive systems, more upgrades to existing systems as part of “evolutionary procurement,” and greater interest in system reliability, availability, and maintainability [2].

What Challenges are Associated with Incorporating Computer Simulation into CBM?

There are, however, numerous costs involved with the introduction of computer simulation modeling that we need to be cognizant of. These costs include [1, 10, 16]:

- Computer hardware--despite steady reduction in prices
- Simulation software testing, development, and maintenance
- Software training
- New business process training
- Additional labor needed to attain proficiency in new software and business processes
- Culture change implementation

Although the introduction of computer simulation is not intended to replace other forms of analysis, it may initially be difficult to convince analysts to immediately employ new modeling techniques that they may not be familiar with and have relatively little confidence in.

It is also important to consider the limitations of simulation modeling. Since all simulation models contain simplifications and assumptions that limit their accuracy, computer models attempting to capture some aspect of reality must, therefore, be imperfect and incomplete as well [9]. Consequently, computer simulations will not eliminate all faults or failures in the aviation fleet. The diagnostic and prognostic capabilities derived from simulation modeling are only as useful as the data from which the models originate. Finally, even though simulation can help to reduce defects through statistical process controls such as Six-Sigma [13, 16], simulation will not fully replace operational testing [2]. Oftentimes, simulation works best as a modeling tool that helps complement, enhance, and substantiate other analytical methods.

How Do We Best Introduce and Leverage Computer Simulation in CBM?

There are essentially three distinct alternatives we can consider to implement computer simulation within CBM. The pros and cons for each alternative are provided below:

- Develop computer simulation tools in-house that are tailored specifically to U.S. Army Aviation and Missile Command engineering requirements (Develop In-House):

- + Simulation tool conforms exactly to specified requirements and
 - + Developed so that there will be less apparent need for training on user interfaces
 - With software design and testing, takes arguably the longest time to implement
 - High upfront development costs
 - Unlikely to be flexible enough to exploit unspecified requirements
 - Likelihood of product obsolescence
- Use existing commercial simulation software tools, such as Crystal Ball and Palisades Decision Tools, for analysis (Use Existing Commercial Tools):
 - + Commercially available with demonstrated use within industry
 - + Available software support and expert guidance
 - + Multiple user training opportunities available
 - + Relatively inexpensive compared to in-house development
 - + High likelihood of being able to keep up with product upgrades
 - + Conformance with industry and academic standards
 - May not be entirely compatible with existing data
 - Models may not be congruent with existing paradigms and analytical frameworks
 - Requires operator training
 - May not be proficient enough to exploit the software capabilities
- Outsource the modeling functions to external agencies with established dependability, responsiveness, and expertise in computer simulation (Outsource to Experts):
 - + Able to leverage existing expertise in industry or academia for immediate results
 - + Limited long-term software development, sustainment, and training costs
 - + Possibility of forming long-term relationships with proven partners
 - In the long run, may not be able to capture and reproduce demonstrated capabilities
 - May require time-intensive reverse engineering to verify conclusions
 - Requires a certain degree of trust with external agencies
 - Potential to become reliant on proprietary software

A helpful way to compare these three potential solutions is to examine the pros and cons of each alternative in an evaluation matrix format [17], as shown in the table below:

Table 1: Evaluation Matrix to Help Decide Best Way to Leverage Simulation Capabilities

Criteria:	Alternatives:		
	Develop In- House	Use Existing Commercial Tools	Outsource to Experts
Ability to Tailor Software Specifications	+++	0	0
Cost	---	+++	+++
Time to Develop Software	---	+++	+++
Amount of Required Training & Education	---	+++	0
Time to Implement Capabilities	---	+++	+++
Compatibility with Existing Data	+++	---	0
Congruence with Existing Paradigms	+++	---	0
Verification of Simulation Results	+++	+++	---
Flexibility to Adapt to Unknown Requirements	---	+++	0
Likelihood of Product Obsolescence	---	+++	+++
Reliance on Long-Term Support Relationships	0	+++	---
Legend:	+++ = Positive	0 = Neutral	--- = Negative

Clearly all three alternatives have their advantages and disadvantages, and it is highly unlikely that a single alternative will provide the best way to implement computer simulation for CBM. What this chart does provide, however, is a way to determine how to gradually introduce computer simulation to different portions of the CBM paradigm. As such, the best solution is probably to simply choose a particular alternative for a portion of the CBM process that satisfies its specific characteristics, needs, and requirements. One advantage that such a gradual approach provides to CBM is the ability to incrementally learn from what works and what doesn't. Another advantage to this diversified approach is that as more work is conducted via computer simulation, analysts will increasingly learn more about the capabilities and limitations of simulation. As a result, they will be able to become both better consumers of simulation tools as well as better advocates for the future use and implementation of simulation capabilities.

Conclusion—What Conditions Make it Possible for CBM to Exploit Computer Simulation?

Computer simulation is a very powerful tool that can be successfully applied to nearly all areas of CBM and nearly all stages of Total Life Cycle Systems Management. It can help to save considerable time and significant costs in the development of effective diagnostics and prognostics for improving the overall readiness of the U.S. Army aviation fleet while simultaneously reducing the maintenance man-hours currently imposed on our soldiers. However, it is the accessibility and availability of suitable data that will determine what computer simulation capabilities will be used to help enhance the CBM paradigm [10]. Limited data that is cumbersome to retrieve severely hampers the value of not just computer simulation, but just about all analytical techniques. Under the current aviation maintenance paradigm, only a small percentage of the existing data is being exploited to better improve fault detection and optimize the operational readiness of our aviation fleet. Accordingly, it is not hard to image that a disproportionately small portion of our analysts' time is being used for actual analysis while the bulk remainder of their time is spent simply trying to gain access to the appropriate data and data sources. A data architecture that can help to remedy this shortcoming will serve as a key development in providing CBM with its enhanced analytical promise.

It will, however, take time to train and educate analysts on the robust capabilities of computer simulation. Yet, once the CBM architecture begins to materialize, computer simulation will almost assuredly play a vital role in the program. Furthermore, a positive Matthew Effect [11] is likely to develop between simulation capabilities and CBM outcomes. As more valid data becomes readily available and accessible, the more confidence there will be in the construction of the simulation models that draw upon the data; the better the models become, the more certainty there will be in the simulation results; the better the simulation results become, the more trust there will be in the recommendations inferred from those results; the better the conclusions that can be applied to the aviation fleet, the better the CBM program will become; and the better the program becomes, the more CBM can demonstrate that is able to improve aviation maintenance, increase warfighting readiness, and save taxpayer dollars. Consequently, it is not too difficult to image how a virtuous cycle begins to cultivate among simulation capabilities and the CBM paradigm for U.S. Army aviation maintenance.

Exhibit 1, Appendix A:

Table 1. Industrial Uses and Applications of Computer Simulations

The Broad Field of Computer Simulation Uses	
Industry Sectors	Simulation Applications
Aircraft	Advanced Control of Manufacturing
Avionics	Product Simulation
Biomedical	Rapid Prototyping
Chemicals	Efficiency Studies
Construction, Civil	Waste Minimization
Financial	Business Process Models
Flight Training	Financial Analysis
Food & Beverage	Ordering Policies for Inventory System
Hospitals	Human Aspects, Ergonomics
Insurance	Environmental Protection
Machine Tools	Life Cycle Analysis and Prediction
Mechanical Engineering	Accident Analysis
Medical	Process Design and Engineering
Metals Processing	Logistics
Military	Research and Development
Minerals	Risk Analysis and Risk Mitigation
Oil & Gas Exploration	Software Testing
Paper & Pulp	Training of Users / Operators
Pharmaceuticals	Reengineering of Business Processes
Power Generation	Service Organization Design
Rubber & Plastics	Communication Network Protocols
Ship Building	
Space Exploration	
Transportation	
Utilities	

Table derived from SimServ Website: <http://www.sim-serv.com/simulation.php>. Additional data taken from Law, A., and W. Kelton. (2000). *Simulation Modeling and Analysis*, 3rd ed. Boston: McGraw Hill.

References

- [1] Benefits and Costs of Process Simulation. (n.d.). Retrieved on 1 August 2005 from Modern Machine Shop Online Website: <http://www.mmsonline.com/articles/0200rt1.html>.
- [2] Cohen, M., J. Rolph, and D. Steffey (Eds.). (1998). *Statistics, Testing, and Defense Acquisition*. Washington, D.C.: National Academy Press.
- [3] Computer Simulation. (n. d.). Retrieved on 9 August 2005 from Wikipedia Website: http://en.wikipedia.org/wiki/Computer_simulation.
- [4] Cook, T, and R. Russell. (1993). *Introduction to Management Science*, 5th ed. Englewood Cliffs, NJ: Prentice Hall.
- [5] Department of Defense. (2003). Directive No. 5000.1 dated May 12, 2003. Retrieved on 11 August 2005 from <http://www.dtic.mil/whs/directives/corres/pdf2/d50001p.pdf>.
- [6] Department of Defense. (2003). Instruction Memorandum No. 5000.2 dated May 12, 2003. Retrieved on 20 July 2005 from <http://www.dtic.mil/whs/directives/corres/pdf2/i50002p.pdf>.
- [7] Deputy Under Secretary of Defense for Logistics and Material Readiness. (2002). Memorandum dated 25 Nov. 2002. Retrieved on 1 August 2005 from http://akss.dau.mil/dag/Guidebook/IG_c5.2.1.2.asp.
- [8] Hughes, W (Ed.). (1997). *Overview of Military Modeling for Decision Making*, 3rd ed. Military Operations Research Society, Inc.
- [9] Law A., and W. Kelton. (2000). *Simulation Modeling and Analysis*, 3rd ed. Boston: McGraw Hill.
- [10] Macfarlane, I., D. Fry, and P. Leigh-Jones. (2005). Applying Simulation for Better Diagnostic Instrument Design. Retrieved on 1 August 2005 from <http://www.devicelink.com/ivdt/archive/05/01/003.html>.
- [11] Merton, R. (1968). The Matthew Effect in Science. *Science*, 159(3810): 56-63. Retrieved on 8 August 2005 from <http://www.garfield.library.upenn.edu/merton/matthew1.pdf>.
- [12] Office of the Inspector General, Department of Defense. (2003). Logistics: Condition Based Maintenance-Plus, Report No. D-2003-125(PDF), Project No. D2003LH-0025.000. Retrieved on 20 July 2005 from <http://www.dodig.osd.mil/audit/reports/fy03/03-125.pdf>.
- [13] Render, B., R. Stair, and M. Hanna. (2006). *Quantitative Analysis for Management*, 9th ed. Upper Saddle River, NJ: Pearson Prentice Hall.
- [14] Sauter, V. (1997). *Decision Support Systems*. New York: John Wiley & Sons, Inc.
- [15] Simulation. (n. d.) Retrieved on 1 August 2005 from Sim-Serv Website: <http://www.sim-serv.com/simulation.php>.
- [16] Taylor, B. (1996). *Introduction to Management Science*, 5th ed. Englewood Cliffs, NJ: Prentice Hall.
- [17] United States Military Academy, Department of Systems Engineering (Ed.). (2004). *Readings for Systems Engineering & Engineering Management*. Mason, OH: Thomson Custom Publishing.

Exhibit 2: Delivering on Unique Skill Sets



**NAVAL
POSTGRADUATE
SCHOOL**

MONTEREY, CALIFORNIA

**DECISION ANALYSIS TO SUPPORT CONDITION-BASED
MAINTENANCE PLUS**

by

Major Stephen E. Gauthier

June 2006

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Patricia A. Jacobs

Thesis Co-Advisor:

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Second Reader:

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THESIS

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REPORT DOCUMENTATION PAGE		<i>Form Approved OMB No. 0704-0188</i>	
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington DC 20503.			
1. AGENCY USE ONLY (Leave blank)	2. REPORT DATE June 2006	3. REPORT TYPE AND DATES COVERED Master's Thesis	
4. TITLE AND SUBTITLE: Decision Analysis to Support Condition-Based Maintenance Plus		5. FUNDING NUMBERS	
6. AUTHOR(S) Gauthier, Stephen E.			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000		8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES) Operations Research Center of Excellence (ORCEN) West Point, NY 10996-1905		10. SPONSORING/MONITORING AGENCY REPORT NUMBER	
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.			
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution is unlimited		12b. DISTRIBUTION CODE	
13. ABSTRACT (maximum 200 words) This thesis provides a stochastic modeling tool to assist in the component selection process for Army Aviation's Condition-Based Maintenance Plus (CBM+) program. This work is in conjunction with the Operations Research Center of Excellence (ORCEN) at the United States Military Academy to assist in providing insight for the U.S. Aviation and Missile Command (AMCOM). The component selected for this thesis is the AH-64/UH-60 T701C Turbine Helicopter Engine. Data analysis of the failure data indicated that a nonhomogeneous Poisson process appropriately modeled the failure characteristics of this engine. A Microsoft Excel simulation utilizing Crystal Ball version 5.5 compares an engine monitored by CBM+ versus the traditional Legacy system of maintenance. This simulation provides information on diagnosed faults, mission aborts, repair times, false positives, and logistical implications. This simulation is generic and can be used in comparing CBM+ candidate components for future inclusion into the CBM+ program. Results suggest when considering a component for inclusion in the CBM+ program important factors to consider are even the smallest false positive rate can invalidate process, large sensor probability of detection isn't necessary for beneficial results, and by entering a component into the CBM+ the on hand component requirements can be greatly reduced.			
14. SUBJECT TERMS Army Aviation Condition-Based Maintenance, AH-64/UH-60 T701C Turbine Engine, Nonhomogeneous Poisson Process, Visual Basic for Applications (VBA) Coding		15. NUMBER OF PAGES	16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified	19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified	20. LIMITATION OF ABSTRACT UL

Approved for public release; distribution is unlimited

DECISION ANALYSIS TO SUPPORT CONDITION-BASED MAINTENANCE PLUS

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B.S., United State Military Academy, 1993

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
June 2006

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ABSTRACT

This thesis provides a stochastic modeling tool to assist in the component selection process for Army Aviation's Condition-Based Maintenance Plus (CBM+) program. The CBM+ program uses measurements from sensors to monitor the health (resistance to failure) of components replacing the Legacy process of scheduled inspections and maintenance. This work is in conjunction with the Operations Research Center of Excellence (ORCEN) at the United States Military Academy to assist in providing insight for the U.S. Aviation and Missile Command (AMCOM). AMCOM is currently developing CBM+ from its current early stages into a program that will revolutionize maintenance procedures for the Army's helicopter fleet.

The subsystem selected for this thesis is the AH-64/UH-60 T701C Turbine Helicopter Engine. The times to occurrences to serious diagnostics symptoms requiring maintenance action were collected from the Army's Aviation and Missile Research, Development, and Engineering Center (AMRDEC). Data analysis indicates that a nonhomogeneous Poisson process appropriately models the times between the occurrences of serious diagnostic symptoms for this engine. A Microsoft Excel simulation utilizing Crystal Ball version 5.5 compares an engine monitored by CBM+ versus the traditional Legacy system of maintenance. This simulation provides information on diagnosed faults, mission aborts, repair times, false positives, and logistical implications.

This simulation is generic and can be used in comparing CBM+ candidate components for future inclusion into the CBM+ program. Results suggest that the sensor's false alarm rate and the reliability/maintainability of the CBM+ sensor are important factors to consider. Since the CBM+ sensor is continually monitoring a component's condition, a modest sensor probability of detection of an impending failure can result in fewer mission aborts than those that arise in the Legacy system. The ability and speed of the logistics system to recognize and respond to sensor measurements indicating impending failure affect the potential success of CBM+.

ACKNOWLEDGMENTS

This thesis was developed over the course of nine months with the gracious assistance and invaluable guidance of numerous individuals and agencies. My appreciation is extended to everyone who answered an email or telephone call, helped me locate subject matter experts, funded travel, or participated in numerous meetings.

Professor Patricia Jacobs and Professor Donald Gaver, thank you for your superb mathematical talents and insights. Your thoughts, ideas, and experience truly guided the direction of this journey and as a young analyst attempting to learn this craft I could not have hoped for better mentors. Your example of work ethic and focus will stay with me for years to come.

LTC Simon Goerger, as my second reader and future boss at ORCEN thank you for enabling me to work with MAJ Ernest Wong on this very important Army project.

Mr. James Keebler at Aviation and Missile Research, Development, and Engineering Center (AMRDEC) provided data which without this thesis would not have been possible.

Mr. Eric Bechoefer at B.F. Goodrich Corporation provided me with critical contacts and telephone numbers when I needed them the most.

LT Jason Kratz provided invaluable assistance in proofreading and streamlining my VBA code.

And finally to my family who have shouldered the burden of having a husband and dad “deployed” for the past months to the computer laboratory in Glasgow Hall. To my wife, Elizabeth, thank you for all of your love and patience while I worked on this thesis. Without your support I could not have done this. Ellis, Eli, and Isaac, thank you for making sure that I occasionally put my thesis away and went on walks to get ice cream, launched stomp rockets, and chased whistle balloons.

EXECUTIVE SUMMARY

U.S. Aviation and Missile Command (AMCOM) has initiated a program to monitor Army helicopter component health (resistance to failure) through a network of sensors installed on aircraft. This sensor network forms the foundation for a maintenance philosophy known as Condition-Based Maintenance Plus (CBM+). This thesis provides a stochastic modeling tool to assist in the component selection process for Army Aviation's CBM+ program. This work is in conjunction with the Operations Research Center of Excellence (ORCEN) at the United States Military Academy to assist in providing insight for the U.S. Aviation and Missile Command (AMCOM). AMCOM is currently developing CBM+ from its current early stages into a program that will revolutionize maintenance procedures for the Army's helicopter fleet. The CBM+ program uses measurements from sensors to monitor the health of components replacing the Legacy process of scheduled inspections and maintenance. Furthermore, Army Aviation's CBM+ program is a collection of maintenance processes and capabilities derived, in large part, from real-time assessment of weapon system condition, obtained from embedded sensors and/or external tests and measurements. Currently, aircraft parts are replaced based on results of scheduled maintenance inspections of the Legacy maintenance system. Under CBM+, the condition of components will be monitored and the components replaced when sensors show indications of possible failure and extended wear.

Not all components will benefit from being part of the CBM+ program. Stochastic modeling and simulation are used to develop a tool to assist in the component selection process for CBM+ program. This work is in cooperation with the Operations Research Center of Excellence (ORCEN) at the United States Military Academy supporting AMCOM.

The subsystem selected for this thesis is the AH-64/UH-60 T701C Turbine Helicopter Engine. The times of occurrences of serious diagnostics symptoms requiring maintenance action were collected from the Army's Aviation and Missile Research, Development, and Engineering Center (AMRDEC) and analyzed to provide input to the development of a simulation model. The resulting Microsoft Excel simulation utilizing Crystal Ball version 5.5 compares an engine monitored by CBM+ versus the traditional Legacy system of maintenance. The output of the simulation provides information on diagnosed faults, mission aborts, repair times, false positives, and logistical implications.

This simulation is generic and can be used in comparing CBM+ candidate components for future inclusion into the CBM+ program. Results from the simulation study suggest that since a sensor is continually monitoring the component, it doesn't have to be highly accurate in diagnosing impending failures in order to produce fewer mission aborts than the Legacy maintenance system. However, it is extremely important to minimize the number of false positives when using CBM+ sensor otherwise the Legacy maintenance system outperforms CBM+ with respect to total inspection/repair time.

I. INTRODUCTION

A. CONDITION-BASED MAINTENANCE PLUS

U.S. Aviation and Missile Command (AMCOM) is interested in monitoring Army helicopter component health through a system of sensors and monitors placed onboard aircraft. Component health is defined as a component's ability to provide the proper mechanical action it was designed and engineered to accomplish. This program is in response to a Department of Defense (DoD) strategy which states that all services should seek "operational supportability" in system development and demonstration. (DoD 5000.2, 2003) Over the past year, approximately twenty different aircraft components were monitored by sensors; the components are installed on different types of airframes. The AH-64 Apache, UH-60 Blackhawk, and CH-47 Chinook were selected since these are the aircraft that are included in the Army's force modernization plan. This sensor network forms the foundation for a maintenance philosophy known as Condition-Based Maintenance (CBM).

According to Defense Acquisition Guidebook dated 20 December 2004 "the goal of CBM is to perform maintenance only upon evidence of need. CBM tenets include: designing systems that require minimum maintenance; need-driven maintenance; appropriate use of embedded diagnostics and prognostics through the application of Reliability-Centered Maintenance (RCM); improved maintenance analytical and production technologies; automated maintenance information generation; trend based reliability and process improvements; integrated information systems providing logistics system response based on equipment maintenance condition; and smaller maintenance and logistics footprints." (Department of Defense, 2003) A more specific form of CBM exists and that is known as Condition-Based Maintenance Plus (CBM+). CBM+ "expands on these basic concepts, encompassing other technologies, processes, and procedures that enable improved maintenance and logistics practices. CBM+ can be defined as a set of maintenance processes and capabilities derived, in large part, from real-time assessment of weapon system condition, obtained from embedded sensors and/or external tests and measurements. The design specifications should identify early teaming with systems engineering to clearly define and understand the operating envelope in order to design in Built-In-Test (BIT) and Built-In-Self-Test (BIST) mechanisms including false alarm mitigation." (Department of Defense, 2006) False alarm mitigation is accomplished by

using sensor equipment that provides for enhanced capability for fault detection, isolation, and repair time minimization. The purpose of this enterprise is to provide cost-effective warning of potential catastrophic failure or mission abort.

AMCOM's mission statement is "to transform Army Aviation maintenance to Condition-Based Maintenance, by converting condition and usage data into maintenance actions". (AMCOM Web Site, 2006) Currently, aircraft parts are replaced based on a system of scheduled maintenance inspections. CBM+ would drastically change this system. Under CBM+, components would now be monitored and replaced only when sensors show indications of ill health or possible imminent failure and extended wear. AMCOM contacted the Operations Research Center of Excellence (ORCEN) at the United States Military Academy to assist in providing additional insight into this important area of research. This thesis is produced in conjunction with ORCEN in an effort to provide AMCOM with a stochastic model and simulation that will be useful in aiding decisions concerning the potential introduction of aircraft components to CBM+.

Currently, only passive sensors are employed on Army aircraft. After each flight the crew chief downloads data from the sensors onto a recording device. The crew chief then transfers the data to a laptop computer for that specific aircraft. All of the crew chiefs' laptop computers feed into a desktop computer at the unit's Production Control office. The Production Control office is the controlling node for all maintenance activities of an Army Aviation unit. B.F. Goodrich contact teams are at specific sites and are assisting these Production Control offices with interpreting the data. Based on these interpretations these data can trigger repair or replacement of components. The data are then sent from the Production Control office to a data warehouse which is currently undergoing construction by the Westar Corporation. From this data warehouse AMCOM reviews the data and monitors the development of CBM+.

B. OBJECTIVES

The objective of this thesis is to utilize stochastic modeling and simulation to aid in determining which aircraft components should be included in CBM+ Microsoft Excel 2003 and Crystal Ball version 5.5 were chosen as the software package for the simulation of this model. (Ragsdale, 2004) Crystal Ball version 5.5 is an Excel-based Monte Carlo simulation application produced by Decisioneering Incorporated. The components that have been selected to use

CBM+ were chosen as a test bed to make sure that the CBM process results in a decrease of the maintenance burden on the soldier, an increase in platform availability and readiness, and a reduction of operations and support costs. (Brown, 2005) Since AMCOM is in the earliest phases of CBM+, it acquired sensors to track and monitor aspects that its engineers hypothesized would have a useful probability of providing the most beneficial results in terms of improving operational readiness and reduction of maintenance related costs. Now that results have been generated there needs to be a component selection system established that will be used when CBM+ is implemented across the Army aviation fleet.

The simulation used in this thesis compares a CBM+ monitored airframe to a non-CBM+ monitored airframe. The measures of performance include mitigation of mission aborts, time spent repairing components, and time spent awaiting replacement component arrival. Through this comparison it is possible to determine which components to enter into the program based on the greatest reduction of mission aborts and possible gain in mission performance and operational readiness. This can be a useful tool for AMCOM to use in future decision making.

C. LEGACY AND CONDITION-BASED MAINTENANCE PLUS REGIMES

A Legacy unit that conducts maintenance using the conventional maintenance regime is currently in place at all Army aviation units. A CBM+ unit conducts the Legacy maintenance regime but also has the benefit of CBM+ sensors installed on specified components. Both regimes employ intensive scheduled maintenance and reactive unscheduled maintenance. The use of CBM+ monitoring promises to reduce numerous time-intensive scheduled maintenance actions, reduce the unexpected nature of unscheduled maintenance, and increase operational readiness. (Department of the Army, 2004) An example of this is Air Worthiness Release (AWR) dated 16 June 2005, which deleted mandatory inspection requirements for six different CBM+ monitored components on AH-64 Apache and UH-60 Blackhawk helicopters. This AWR saved Maintenance Man Hours (MMH) per inspection, downtime per aircraft, and Time Between Overhaul (TBO) for components. This AWR is the first of many of its kind that will transition Army Aviation from the present rigid, time-intensive, and reactive Legacy maintenance regime to a prediction-based CBM+ maintenance regime.

D. METHODOLOGY

This thesis is divided into six chapters and follows this structure. Chapter One, “Introduction”, describes the background, objectives, and methodology of this work. Chapter Two, “Aircraft System Structure and Data”, discusses in detail the aircraft components that are currently monitored by Condition-Based Maintenance Plus and the available data describing their performance, failure, and repair. This chapter describes the maintenance procedures used by Army aviation units and the repair times associated with these actions. Chapter Three, “Stochastic Models for Comparing Legacy Maintenance and Condition-Based Maintenance Plus”, details the model structures, and gives example cases of the stochastic model that is used in this thesis. Chapter Four, “Legacy Maintenance and Condition-Based Maintenance Plus Simulation”, describes the architecture, characteristics, assumptions, and results of the simulation used in this thesis. Chapter Five, “Data Analysis”, presents the results of the analysis of the simulation output as different components are monitored and compares average operational readiness and repair times. Finally, Chapter Six, “Conclusions and Recommendations”, summarizes the findings of this thesis and possible uses for this thesis in future decision making.

II. AIRCRAFT SYSTEM STRUCTURE AND DATA

A. GENERAL DESCRIPTION OF AIRCRAFT TYPES AND COMPONENTS

This chapter will discuss in detail the aircraft components that are currently in the Condition-Based Maintenance Plus program or are under consideration for inclusion. Any available data describing their performance, failure, and repair are listed. Furthermore, this chapter describes the maintenance procedures used by Army aviation units and the costs associated with these actions; all CBM+ sensors currently use vibratory information to monitor these components. The three different types of aircraft presently monitored by CBM+ are the AH-64 Apache, UH-60 Blackhawk, and the CH-47 Chinook.

1. AH-64 Apache Helicopter Information

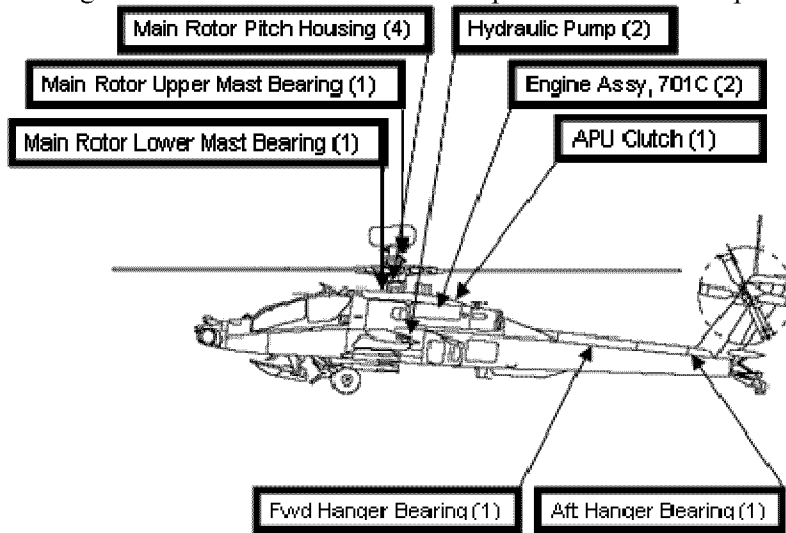
The AH-64 Apache helicopter is a twin-engine, tandem-seat, aerial weapons platform. (TM 1-1520-251-10, 2002) Its primary mission is to provide attack and reconnaissance capabilities in support of the ground tactical plan. There are currently thirteen components of eight different types monitored by CBM+ on the AH-64. A listing of AH-64 Apache CBM+ components is listed in Table 1.

Table 1. AH-64 Apache CBM+ Component Listing

AH-64 COMPONENT NOMENCLATURE	NSN	PART NUMBER	FEDLOG NOMENCLATURE
APU Clutch	3010-01-515-8483	3617950-1	CLUTCH ASSEMBLY, FRICTION
Engine Assembly, 701C	2840-01-284-4011	6071T24G01	ENGINE, AIRCRAFT, TURBO-SHAFT
Utility Hydraulic Pump	4320-01-158-0893	7-311810022-3	PUMP, AXIAL PISTONS
Forward Hanger Bearing	3130-01-333-8491	7-311350008-5	BEARING UNIT, BALL
Aft Hanger Bearing	3130-01-333-8490	7-211350007-5	BEARING UNIT, BALL
MR Pitch Housing	1615-01-235-5845	7-311411215-13	HOUSING ASSEMBLY
MR Upper Mast Bearing	3110-01-215-4794	7-311411202-5	BEARING, ROLLER, TAPERED
MR Lower Mast Bearing	3110-01-179-7335	7-114110011	BEARING, ROLLER, TAPERED

Depicted below in Figure 1 is the location of these components on the AH-64 Apache extracted from Figure 2-2 of TM 1-1520-251-10. The number in parenthesis indicates the total number of that type of component on the aircraft.

Figure 1. Location of AH-64 Apache CBM+ Components



2. UH-60 Blackhawk Helicopter Information

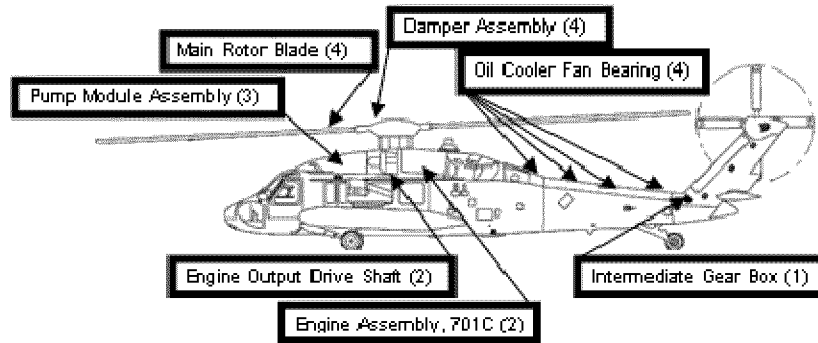
The UH-60 Blackhawk helicopter is a twin-turbine engine, single-rotor, semimonocoque fuselage helicopter. Its primary mission is the tactical transport of troops, supplies and equipment. Its secondary missions include training, mobilization, development of new and improved concepts, and support of disaster relief. (TM 1-1520-237-10, 2003) There are currently nineteen components of eight different types monitored by CBM+ on the UH-60. A listing of UH-60 Blackhawk CBM+ components is listed in Table 2.

Table 2. UH-60 Blackhawk CBM+ Component Listing

UH-60 COMPONENT NOMENCLATURE	NSN	PART NUMBER	FEDLOG NOMENCLATURE
Oil Cooler Fan Bearing	3110-01-329-8573	110KSZZ-401	BEARING,BALL,ANNULAR
Main Rotor Blade	1615-01-106-1903	70150-09100-043	BLADE,MAIN ROTOR
Pump Module Assembly	4320-01-207-7228	70652-02300-050	MODULE ASSY,PUMP
Damper Assembly	1615-01-285-3024	70106-08100-046	DAMPENER,FLUTTER
Engine Assembly, 701C	2840-01-284-4011	6071T24G01	ENGINE,AIRCRAFT,TURBO-SHAFT
Engine Output Drive Shaft	2835-01-123-7648	70361-08004-043	DRIVE SHAFT ASSEMBLY,ROTARY WING
Intermediate Gear Box	1615-01-074-5152	70357-06300-042	GEAR BOX ASSEMBLY

Depicted below in Figure 2 is the location of these components on the UH-60 extracted from Figure 2-2 of TM 1-1520-237-10. The number in parenthesis indicates the total number of that type of component on the aircraft.

Figure 2. Location of UH-60 Blackhawk CBM+ Components



3. CH-47 Chinook Helicopter Information

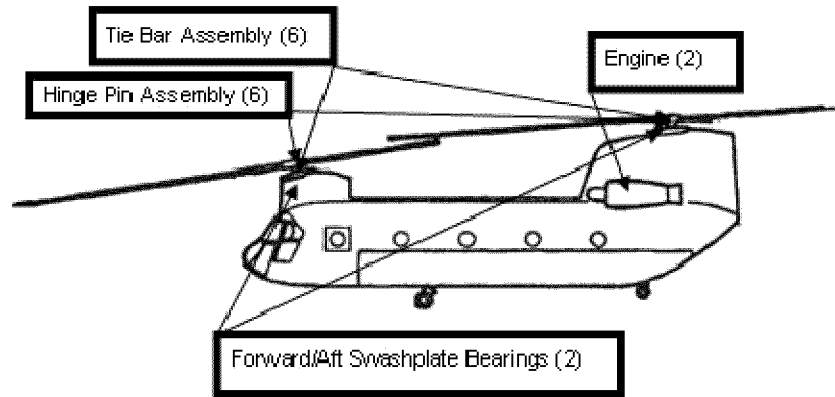
The CH-47 Chinook is a twin-turbine engine, tandem-rotor helicopter. Its primary mission is the transportation of cargo, troops, and weapons during day, night, visual, and instrument conditions. (TM 1-1520-240-10, 2003). There are currently sixteen different components of four different types on the CH-47 monitored by CBM+. A listing of CH-47 Chinook CBM+ components is listed in Table 3.

Table 3. CH-47 Chinook CBM+ Component Listing

CH-47 COMPONENT NOMENCLATURE	NSN	PART NUMBER	FEDLOG NOMENCLATURE
Hinge Pin Assembly	5315-01-295-7008	114R2197-7	PIN,HOLLOW
Tie Bar Assembly	1615-00-740-6480	114R2155-1	TIE BAR ASSEMBLY,LAMINATED
Engine, Gas Turbine	2840-01-458-5361	2-001-020-39	ENGINE,AIRCRAFT,TURBO-SHAFT
Fwd/Aft Swashplate Bearings	3110-00-141-3750 3110-01-356-0489	114RS308-1 114RS308-2	SWASHPLATE BEARING

Depicted below in Figure 3 is the location of these components on the CH-47 extracted from Figure 2-1-1 of TM 1-1520-224-10. The number in parenthesis indicates the total number of that type of component on the aircraft.

Figure 3. Location of CH-47 Chinook CBM+ Components



B. SPECIFIC DESCRIPTION OF COMPONENT CHARACTERISTICS

Brief descriptions of the components of interest on the AH-64 Apache referenced from TM 1-1520-251-10 are:

1. Auxiliary Power Unit Clutch is a subcomponent of the Auxiliary Power Unit (APU) which provides both hydraulic pressure, pressurized air, and electrical power for the operation of systems onboard the AH-64 whether the engines are operating or not. The APU is required to start the main engines unless the AH-64 is assisted with an Auxiliary Ground Power Unit (AGPU).

2. 701C Engine Assemblies are the main engines for the AH-64. The engines are front drive turbo shaft engines of modular construction. One horizontally mounted engine is housed on either side of the AH-64 aft of the main transmission above the wing.

3. Utility Hydraulic Pump is a subcomponent of the utility hydraulic system that provides hydraulic power to the flight controls, weapon drives, ammunition systems, and

emergency hydraulic systems. This pump is mounted on the accessory drive case of the main transmission (right side).

4. Forward Hanger Bearing is a component of the tail rotor drive system. A hanger bearing supports the two longest shafts of three shafts that lead from the transmission to the intermediate gear box. There is a fourth shaft that leads from the intermediate gear box to the tail rotor. The forward hanger bearing is located on the end of the second shaft.

5. Aft Hanger Bearing serves the same purpose as the Forward Hanger Bearing; it is located on the end of the third shaft.

6. Main Rotor Pitch Housing is a subcomponent of the rotor head. The pitch housing permits blade pitch changes in response to flight control movements transmitted through the swashplate.

7. Main Rotor Upper Mast Bearing is a subcomponent of the AH-64 mast collocated with the rotor head.

8. Main Rotor Lower Mast Bearing is similar to the upper bearing but located lower.

Brief descriptions of the components of interest on the UH-60 Blackhawk referenced from TM 1-1520-237-10 are:

1. Oil Cooler Fan Bearing is a subcomponent of the tail rotor drive section. The oil cooler cools oil from the engine before it returns it to the oil tank. Shafts from the main transmission connect the oil cooler and also transmit torque to the tail rotor. There are four points where viscous damped bearings are mounted on adjustable plates which support these shafts that lead to the tail rotor.

2. Main Rotor Blades are a subsystem of the main rotor system. A rotor blade has a titanium-spar and is attached to spindles which are retained by elastomeric bearings contained in one-piece titanium hub. The elastomeric bearing permits the blade to flap, lead, and lag.

3. Pump Module Assembly is a component that provides hydraulic pressure to the Blackhawk's hydraulic system. The hydraulic pump module assemblies are a combination of a hydraulic pump and a hydraulic fluid reservoir.

4. Damper Assembly is located between the main rotor blade and the main rotor head. Main rotor dampers are installed between each of the main rotor spindles modules and the hub to restrain leading and lagging motions of the main rotor blades during rotation and to absorb rotor head loads when starting the aircraft. Each damper has a small hydraulic fluid reservoir.

5. 701C Engine Assemblies are the main engines for the UH-60. The engines are front drive turbo shaft engines of modular construction. One horizontally mounted engine is housed on either side of the UH-60. These are the same engines that are mounted on the AH-64 Apache.

6. Engine Output Drive Shaft is a subcomponent of the UH-60 power train system. It transfers torque generated by the engine to the main transmission.

7. Intermediate Gear Box is a subcomponent of the UH-60 power train system. It is mounted at the base of the tail pylon. It transmits torque and reduces shaft speed from the main module gear box to the tail rotor gear box.

Brief descriptions of the components of interest on the CH-47 Chinook referenced from TM 1-1520-224-10 are:

1. Hinge Pin Assembly is a component of the rotor system. The rotor head consists of a hub connected to three pitch-varying shafts by three horizontal hinge pins. These pins permit blade flapping. Stops on the top and bottom of the hub limit the blade flapping motion.

2. Tie Bar Assembly is located close to the hinge pin assembly. It connects the pitch-varying shafts to the pitch-varying housings on the rotor heads.

3. Engines on the CH-47 are housed in separate nacelles mounted externally on each side of the aft pylon.

4. Forward/Aft Swashplate Bearings rotate and transfer blade pitch changes by the three pitch-varying links to the pitch-varying housing on each rotor blade.

C. MAINTENANCE REGIMES OF COMPONENTS

Army Aviation maintenance regimes are composed of both periodic and on condition maintenance tasks. Prescribed maintenance tasks can be subdivided into five major areas: (AMCOM Proof of Principle, 2005)

1. PM: Maintenance or inspections performed in accordance with normal Preventive Maintenance Checks and Services.
2. On Condition: Maintenance or inspections occurring after the aircraft encounters a specific event or flight in certain environmental conditions.
3. -18: Maintenance or inspections prescribed in maintenance manuals and tracked on the -18 forms kept in the aircraft log book.
4. ASAM: Maintenance or inspections listed in a specific Aviation Safety Action Message.
5. AWR: Maintenance or inspections listed in a specific Air Worthiness Release.

These maintenance tasks are outlined by several different maintenance manuals, log book forms, and messages/releases specific for each airframe type. A component may be inspected as often as every day or at intervals of several hundred hours. Each inspection interval is a unique inspection in the sense that some of the more common inspections are a visual exterior check of a component whereas the more infrequent inspections require removal of the component from the airframe, disassembling it, and conducting a much more thorough inspection. Each inspection has a specific number of maintenance-man hours (MMH) required in order to complete the maintenance task.

Listed below in Tables 4 and 5 are the most time consuming and thorough inspections for each component listed above for the AH-64 Apache and UH-60 Blackhawk. In cases where there are two different interval inspections with the same MMH and clock time requirements the more frequent inspection of the two is listed:

Table 4. AH-64 Apache Maintenance Regime

AH-64 Component	Inspection Interval	Reference	Maint Type	MMH
APU Clutch	250 Flight Hours	TB 1-1520-238-20-139	-18	34.4*
Eng Assy, 701C	500 Flight Hours	TM 1-1520-238-PM	PM	20.5*
Utility Hydraulic Pump	250 Flight Hours	TB 1-1520-238-20-139	-18	1.1
Forward Hanger Bearing	500 Flight Hours	TM 1-1520-238-PM	PM	4.4*
Aft Hanger Bearing	500 Flight Hours	TM 1-1520-238-PM	PM	4.4*
Main Rotor Pitch Housing	125 Flight Hours	TM 1-1520-238-23	-18	0.5*
Main Rotor Upper Mast Bearing	500 Flight Hours	TM 1-1520-238-PM	PM	20.4*
Main Rotor Lower Mast Bearing	500 Flight Hours	TM 1-1520-238-PM	PM	20.4*
* If no Maintenance Allocation Chart (MAC) data was available or seemed suspect a review of the appropriate techniques were conducted and a time was allocated by AMCOM Subject Matter Experts				

Table 5. UH-60 Blackhawk Maintenance Regime

UH-60 Component	Inspection	Reference	Maint Type	MMH
Oil Cooler Fan Bearing	700 Flight Hours	TM 1-1520-237-PMI	PM	11.3*
Main Rotor Blade	700 Flight Hours	TM 1-1520-237-PMI	PM	17.2
Pump Module Assembly	700 Flight Hours	TM 1-1520-237-PMI	PM	0.03
Damper Assembly	700 Flight Hours	TM 1-1520-237-PMI	PM	2.5*
Engine Assembly, 701C	700 Flight Hours	TM 1-1520-237-PMI	PM	12.4*
Engine Output Drive Shaft	700 Flight Hours	TM 1-1520-237-PMI	PM	4.9*
Intermediate Gear Box	120 Flight Hours	TM 1-1520-237-23	-18	2.0*
* If no Maintenance Allocation Chart (MAC) data was available or seemed suspect a review of the appropriate techniques were conducted and a time was allocated by AMCOM Subject Matter Experts				

A CH-47 Chinook Maintenance Regime is not listed since a Proof of Principle brief was not conducted on the CH-47 Chinook CBM+ program due to the progression of the CH-47 CBM+ program. Proofs of Principle briefs are the source of maintenance regime information for both the AH-64 Apache and UH-60 Blackhawk. (Brown, 2005)

D. FAILURE/AGE REPLACEMENT CHARACTERISTICS OF COMPONENTS

The Aviation and Missile Research, Development, and Engineering Center (AMRDEC) provided data sets for component failure times. The failure times are the occurrences of serious diagnostic symptoms requiring maintenance actions. The data sets are displayed in Microsoft

Excel format and each data set consists of twenty-one columns. The twenty-two columns are listed below.

1. WUC: Work Unit Code
2. PN: Part Number of component
3. SN: Serial Number of component
4. EI_SN: End Item Serial Number (aircraft tail number)
5. MODEL: The model of aircraft
6. DATE: Date the action was performed
7. REP_NUM: Repair Number-The number of times the part was removed for a causable removal.
8. CEN: Censored-If 1 then installed and still flying, else 0 and component removed
9. LIFE: If CEN=0, the time on the component since new or last causable removal. If CEN=1, the current time on the component.
10. TSN: Time Since New
11. TSO: Time Since Overhaul
12. NOVH: Number of Overhauls
13. F_TYPE: Type of failure
14. FCODE: Failure Code 001 to 999, the reason the part was removed
15. FAILURE: Narrative for the FCODE
16. FAMILY: The fail code grouped into failure family types.
17. PREV_FC: Failure Code on the previous removal
18. REP_UIC: UIC that repaired the item last or original manufacture if REP_NUM=1.
19. REPAIR: Location name of the UIC that repaired the item last.
20. UIC: Unit Identification Code of removing unit
21. LOC: Location of the UIC

22. SN_PREFIX: Serial Number substring as a prefix to perform comparison analysis

In addition to this data, each airframe type has a Technical Manual which states a component's Time Between Overhaul (TBO) and/or component retirement time. These manuals allow the determination of a component's age replacement time if one exists. Listed below in Table 6 are the CBM+ component's estimated mean time between failure (MTBF) and Age Replacement times. The Age Replacement times are derived from the applicable airframes' Technical Manual. The MTBFs listed below are obtained from AMCOM's Proof of Principle briefs prepared in July 2005. (Brown, 2005) The MTBF estimates take into account that some of the data are censored. When both TBO and component retirement times are given by the applicable reference the more restrictive of the two numbers is listed.

Table 6. CBM+ Component MTBF and Age Replacement

AH-64 Component	MTBF	Age Replacement
APU Clutch	900 Flight Hours	On Condition of Failure
Engine Assembly, 701C	1,304 Flight Hours	5,000 Flight Hours**
Utility Hydraulic Pump	464 Flight Hours	On Condition of Failure
Forward Hanger Bearing	834 Flight Hours	2,500 Flight Hours
Aft Hanger Bearing	537 Flight Hours	2,500 Flight Hours
Main Rotor Pitch Housing	257 Flight Hours	5,300 Flight Hours
Main Rotor Upper Mast Bearing	1,250 Flight Hours	1,750 Flight Hours
Main Rotor Lower Mast Bearing	1,250 Flight Hours	9,400 Flight Hours
UH-60 Component	MTBF	Age Replacement
Oil Cooler Fan Bearing	14,425 Flight Hours	700/2,100 Flight Hours*
Main Rotor Blade	1,594 Flight Hours	9,600 Flight Hours
Pump Module Assembly	5,969 Flight Hours	On Condition of Failure
Damper Assembly	6,629 Flight Hours	On Condition of Failure
Engine Assembly, 701C	1,342 Flight Hours	5,000 Flight Hours**
Engine Output Drive Shaft	2,581 Flight Hours	On Condition of Failure
Intermediate Gear Box	6,624 Flight Hours	On Condition of Failure
CH-47 Component	MTBF	Age Replacement
Hinge Pin Assembly	3,393 Flight Hours	1,200 Flight Hours
Tie Bar Assembly	2,925 Flight Hours	4,800 Flight Hours
Engine	602 Flight Hours	2,400 Flight Hours
Forward/Aft Swashplate Bearings	991/867 Flight Hours	1,200 Flight Hours
*700 flight hours when installed at Station 410.5; all others 2,100 flight hours		
**701C Engine Assembly has several components changed at various intervals. 5,000 Flight Hours is the most common age replacement time of the most critical components.		

E. COSTS ASSOCIATED WITH COMPONENTS

Listed below are each component's cost and an estimate of its shipping cost. It is assumed that the components can be divided into three different weight classifications. A component weight is considered to be either *light*, *medium*, or *heavy*. In addition, the component's shipment is either urgent or not urgent. Table 7 displays the approximate costs of shipping components of different weights 2000 miles under urgent and not urgent requirements. These shipping costs, while approximate, are realistic. Although the model and simulation do not include costs for component shipping this must occur in both the Legacy and CBM+ Process; it is important to state these values in recognition that this exists in both processes.

Table 7. CBM+ Component and Shipping Costs

AH-64 Component	FEDLOG Unit Price	OSMIS Weight	Weight Classification	Urgent Shipping Cost	Non-urgent Shipping Cost
APU Clutch	\$27,774.00	Unavailable	Medium	\$1,000	\$500
Engine Assembly, 701C	\$720,974.00	Unavailable	Heavy	\$3,000	\$1,500
Utility Hydraulic Pump	\$9,437.00	Unavailable	Medium	\$1,000	\$500
Forward Hanger Bearing	\$6,941.00	400	Light	\$200	\$50
Aft Hanger Bearing	\$5,673.00	216	Light	\$200	\$50
Main Rotor Pitch Housing	\$6,846.00	894	Medium	\$1,000	\$500
Main Rotor Upper Mast Bearing	\$7,295.00	275	Light	\$200	\$50
Main Rotor Lower Mast Bearing	\$5,126.84	40	Light	\$200	\$50
UH-60 Component	FEDLOG Unit Price	OSMIS Weight	Weight Classification	Urgent Shipping Cost	Non-urgent Shipping Cost
Oil Cooler Fan Bearing	\$290.71	8	Light	\$200	\$50
Main Rotor Blade	\$130,420.00	6500	Medium	\$1,000	\$500
Pump Module Assembly	\$16,771.00	560	Medium	\$1,000	\$500
Damper Assembly	\$9,770.00	500	Light	\$200	\$50
Engine Assembly, 701C	\$720,974.00	Unavailable	Heavy	\$3,000	\$1,500
Engine Output Drive Shaft	\$4,812.00	Unavailable	Medium	\$1,000	\$500
Intermediate Gear Box	\$20,694.00	800	Medium	\$1,000	\$500
CH-47 Component	FEDLOG Unit Price	OSMIS Weight	Weight Classification	Urgent Shipping Cost	Non-urgent Shipping Cost
Hinge Pin Assembly	\$5,520.00	330	Light	\$200	\$50
Tie Bar Assembly	\$11,822.00	120	Light	\$200	\$50
Engine	\$916,406.00	11,650	Heavy	\$3,000	\$1,500
Forward/Aft Swashplate Bearings	Unavailable	Unavailable	Light	\$200	\$50

III. STOCHASTIC MODELS FOR COMPARING LEGACY MAINTENANCE AND CONDITION-BASED MAINTENANCE PLUS

A. IMPORTANT FACTORS FOR CBM+ CANDIDACY

In determining a whether or not to introduce a component into the CBM+ program a number of factors should be considered:

1. How often does the component fail during active flight hours?

It is preferable to introduce a component that fails often versus components that rarely fail.

2. What are the consequences of a component failing?

It is preferable to introduce a component that possesses severe consequences for failure versus a component that is inconsequential in its failure.

3. What is the difficulty level of the inspection that would be alleviated by CBM+?

If an inspection is extremely difficult and resource intensive to perform it would be preferable to have this inspection replaced by CBM+ versus an inspection that is simple and easy to perform.

4. Is a CBM+ sensor feasible for a component?

If measurements cannot be taken to assess the degradation of the component before it fails then that component would not be a good CBM+ candidate. Furthermore, the time from occurrence of measurable evidence of impending failure until failure should be long enough to detect the impending failure and take maintenance action.

5. What is the reliability of the CBM+ sensor, the difficulty of inspecting the CBM+ sensor, and the effect of the CBM+ sensor on performance of the component being monitored? Is there even a CBM+ sensor currently developed for a component? What is the cost of the sensor?

By focusing on the CBM+ sensor it can be determined whether or not the sensor itself may sometimes miss impending failures, give false positives, require intensive maintenance, or impede standard operations. Maintainers are often wary of adding a new system

designed to help them conduct maintenance operations for fear of there now being one more system to maintain.

Stochastic models can be created to assist in identifying information needed to determine characteristics of components that make the component a good candidate for monitoring by CBM+. Such stochastic models compare a single component's performance and associated costs in both the CBM+ and Legacy processes. The models can vary in detail and complexity; transparency and simplicity are desirable.

B. MODEL OVERVIEW

In choosing a model to represent the operating environment of CBM+ it is convenient to let every aircraft component being considered for CBM+ begin in good operating condition. Over time the component's condition/state degrades and eventually the component fails. We consider a component that allows predictive measurements to be made of its condition (failure propensity); these are diagnostic symptoms (DS). If a DS can be recognized by maintenance personnel then this information is a useful indication that the component is beginning to fail. A DS can be detected by a CBM+ sensor or noticed by a maintainer during the conduct of scheduled maintenance, or by the operator.

If conditions for a near-term future failure exist it is essential to recognize the impending failure in order to lessen such a failure's effect. CBM+ sensors recognize impending failure of components by monitoring the component's performance. Specifically the UH-60 IMD-HUMS system notes condition indicators (CIs) based on vibratory analysis of items such as bearings, shafts, and gears. These CIs are rolled up into health indicators (HIs) which are numbers from 0 to 1 displaying the perceived health of that component. (Wright, 2005) This system of CIs and HIs is used to determine the occurrence of DSs. Under the Legacy maintenance system when maintenance personnel conduct a scheduled inspection of an aircraft they are looking for chips, cracks, dents, nicks, wears, incorrect lubrication levels, incorrect pressure outputs (pneumatic and fluids), and other potential faults. These physical inspections determine the occurrence of DSs. A DS may or may not be noticed during the downtime immediately following the mission during which it was generated. All DSs are discovered during inspections during downtimes. (Gaver and Jacobs, 2006)

The following are the components which form a general framework for a Non-Homogeneous Poisson Process (NHPP) model for the occurrence of DSs for both the CBM+ process and the Legacy process:

$N(t)$: number of transitions of components from good condition to poor condition during the time interval $(0, t]$, (number of occurrences of DSs during $(0, t]$); each transition corresponds to the occurrence of one DS. In many cases the times between failures of repairable components may tend to decrease as the components age. Thus $\{N(t); t \geq 0\}$ is assumed to be a nonhomogeneous Poisson process with

$\Lambda(t)$: mean value function of $\{N(t); t \geq 0\}$; that is $E[N(t)] = \Lambda(t)$.

$\lambda(t)$: intensity function of $\{N(t); t \geq 0\}$; that is $\lambda(t) = \frac{d\Lambda(t)}{dt}$.

m : constant mission length

C. A NON-HOMOGENEOUS POISSON PROCESS (NHPP) MODEL

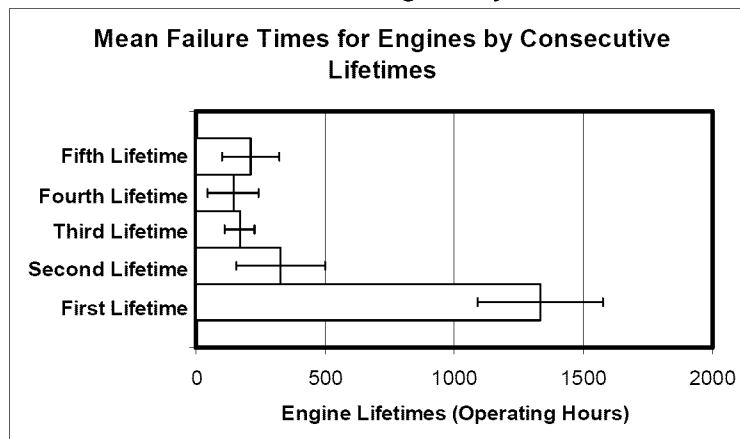
Renewal processes are often used to model times between failures for a system. For a renewal process to apply, the times between successive failures should be independent and identically distributed with an arbitrary distribution. (Ross, 2003) In order to either accept or refute the assumption that the times between failures are independent and identically distributed failure data must be analyzed. The data set that was selected for evaluation is the set of AH-64/UH-60 701C Engine lifetime data. The lifetimes are the times between occurrences of serious diagnostic symptoms requiring maintenance action. The reason for the selection of this data set is that each engine may have several failure times recorded. The data set contains both censored and uncensored lifetime data. Multiple lifetimes for an engine are indicated by the same engine serial number (SN) being listed with consecutive lifetimes (REP_NUM). This gives the opportunity to assess whether or not the successive times between failures for an engine can be approximately represented as independent and identically distributed. If there is evidence that the successive lifetimes are not independent and identically distributed, then a renewal process model for the times between failures is not appropriate.

Analysis of the engine data suggests that the times between failures are not identically distributed. Therefore a Non-Homogeneous Poisson Process (NHPP) model for the failure times is considered. Although the term “failure” is used, these events are actually occurrences of serious diagnostic symptoms that require maintenance action.

The AH-64/UH-60 701C Engine data provided by AMRDEC consists of 3,385 entries in the format outlined in Chapter Two. From this group of 3,385 entries there were 2,045 entries that were first lifetimes, 913 entries that were second lifetimes, 480 that were third lifetimes, and 397 that were fourth lifetimes. These data are not complete with regards to all lifetimes being annotated for all serial numbers. There are missing lifetime data which are not due to censoring. However, some of these missing lifetimes can be inferred from other recorded data. For example, suppose the first lifetime is missing but the second lifetime is recorded along with the time since the engine was new at the time of the second failure. In this case the first lifetime can be inferred by subtracting the second lifetime from the time since new. The engine data considered appear in Appendix A. The engines considered have at least 3 failure times recorded. The columns named WUC, PN, TSO, NOVH, REP_UIC, REPAIR, UIC, LOC, and SN_PREFX have been omitted from the original data set since these factors are not relevant in this analysis, and to make the data set more compact. None of the engines displayed TSO (Time Since Overhaul) and NOVH (Number of Overhauls); therefore these columns are omitted.

In Figure 4 the mean times between failures for the first, second, third and fourth failures with 95% confidence intervals are displayed; censored lifetimes are not included. This figure suggests that the successive lifetimes of an engine are not identically distributed; the time until first failure tends to be much larger than the subsequent times between failures.

Figure 4. Mean Failure Times for Engines by Consecutive Lifetimes



An estimate of the intensity function of a NHPP is obtained by using disjoint time intervals of length 500 hours from 0 to 3,000 hours. Let $N_j(t)$ be the number of failures for engine j during the time interval $(0,t]$.

$$I_j(x, \infty) = \begin{cases} 1 & \text{if the last observation for engine } j \text{ (censored or not) is greater than } x \\ 0 & \text{otherwise} \end{cases}$$

The intensity function in the age interval $[x, x+500]$ where $x \in (0, 500, 1,000, 1,500, \text{etc.})$ is estimated as

$$\frac{\sum_j [N_j(500+x) - N_j(x)]}{500 \sum_j I_j(x)} \quad (\text{Jacobs, 2006})$$

A display of the resulting estimated intensity function is in Appendix B. The log of the estimated intensity function versus log t is also displayed. This latter display suggests that an NHPP with power-law mean value function $\Lambda(t) = \gamma t^\delta$ tends to summarize the data well. The parameters of a NHPP with power-law mean value function of the form $\Lambda(t) = \gamma t^\delta$ are estimated from the engine data using maximum likelihood. The estimates and standard errors are listed in Figure 5. The standard errors are obtained using Fisher information. (Bickel and Doksum, 1977)

Figure 5. NHPP Parameter Estimates

NHPP Parameter Estimates			
Estimate of γ	5.4×10^{-6}	Estimate of δ	1.71
Standard Error	6.3×10^{-7}	Standard Error	0.015
Estimate \pm 2 s.e.	$(4.2 \times 10^{-6}, 6.7 \times 10^{-6})$	Estimate \pm 2 s.e.	(1.68, 1.74)

The estimate of δ is statistically significantly greater than 1, suggesting that failures are more frequent for older engines. The older an engine, the more likely various subcomponents are to fail.

D. MODEL STRUCTURE

The power law NHPP model with the estimated parameters is used in a model to assist in the selection of components for inclusion in the CBM+ process. The model represents the arrival of DSs during each mission, the number of downtimes elapsed until the DSs are discovered, the

repair times associated with the discovery of the DSs, and the chance a component failure will cause a mission abort. This analytical model is taken directly from Gaver and Jacobs (2006).

Let $N(t)$ be the number of transitions of components from good condition to poor condition (occurrence of diagnostic symptoms (DS)) during the operational time interval $(0, t]$. $\{N(t); t \geq 0\}$ is a nonhomogeneous Poisson process with mean value function $\Lambda(t) = E[N(t)]$ and intensity function $\lambda(t) = \frac{d\Lambda(t)}{dt}$. The DSs may not be discovered immediately. The DSs are discovered during inspection during downtimes. Each mission is of length m . Let $N_i = N(mi) - N(m(i-1))$ be the number of DSs to occur during the i th mission. N_i has a Poisson distribution with mean $\Lambda_i = \Lambda(mi) - \Lambda(m(i-1))$. For example if the length of the mission is 4 hours long ($m=4$) and $\Lambda(t) = \gamma t^\delta$, then $\Lambda_i = \gamma(4i)^\delta - \gamma(4(i-1))^\delta$. The computations used to derive the estimates of γ and δ are listed in Appendix C. These estimated values are used throughout the thesis.

Let p_j be the conditional probability a DS is discovered during the j th downtime after the mission within which it first appears, given it has not been discovered before and the DS has not caused a mission abort; the downtime immediately after the mission the DS appears in is labeled downtime 1. In general, $p_1 \leq p_2 \leq \dots$. Assume that whether or not a DS is discovered during a downtime is independent from downtime to downtime and from DS to DS. Suppose also that if a DS is generated during a mission it can critically activate during that mission, causing the mission to fail. This is known as a mission abort. Further, let a_j denote the conditional probability that the DS critically activates during the j th mission after its generation, given it has not been discovered and rectified in advance; a_1 is the probability of critical activation during the mission of its genesis. Let $\mathbf{D}_{i,i+j}$ be the number of DSs that occurred during mission i that are discovered during the j th downtime after mission i before a critical activation; it has a Poisson distribution with mean $\Lambda_i \left[\prod_{k=1}^{j-1} (1-p_k)(1-a_k) \right] (1-a_j) p_j$; that is, $\mathbf{D}_{i,i}$ has a Poisson distribution with mean $\Lambda_i (1-a_1) p_1$; $\mathbf{D}_{i,i+1}$ has a Poisson distribution with mean

$\Lambda_i(1-a_1)(1-p_1)(1-a_2)p_2$, etc. Further, these random variables are currently assumed independent. It is of course possible that critical activation occurs before the DS is discovered and the fault removed. Let $\mathbf{D}_{i,i+j}^*$ denote the number of DSs that are generated during the i th mission that give rise to a critical activation (mission abort) before discovery j missions after they are generated. Clearly $\mathbf{D}_{i,i}^*$ is Poisson with mean $\Lambda_i a_1$, $\mathbf{D}_{i,i+1}^*$ is Poisson with mean $\Lambda_i(1-a_1)(1-p_1)a_2$; etc. (Gaver and Jacobs, 2006)

Assume that DSs that cause mission abort are discovered in the downtime following the aborted mission. The number of DSs discovered during the i th downtime,

$\tilde{\mathbf{D}}_i = \sum_{j=1}^i [\mathbf{D}_{j,j+(i-j)} + \mathbf{D}_{j,j+(i-j)}^*]$, has a Poisson distribution with mean

$$E[\tilde{\mathbf{D}}_i] = \sum_{j=1}^i \Lambda_j \left[\prod_{k=1}^{(i-j)} (1-p_k)(1-a_k) \right] \left[1 - (1-a_{i+1-j})(1-p_{i+1-j}) \right]$$

where an empty product is interpreted as equal to 1. (Gaver and Jacobs, 2006)

The expected number of missions that are not aborted during the first t scheduled missions can be calculated as follows. Let $S(t)$ be the number of DSs that can cause mission abort during mission t ; there is at most one mission abort per mission. Let $s(n)$ be the probability a DS causes a mission abortion during the n th mission after it is generated. Assume $p_i \equiv p$ and $a_i \equiv a$ for all i .

$$s(n) = [(1-a)(1-p)]^{n-1} a \quad (1)$$

$$E[S(t)] = \sum_{i=1}^t \Lambda_i s(t-(i-1))$$

$$Var[S(t)] = \sum_{i=1}^t \Lambda_i s(t-(i-1))$$

$S(t)$ has a Poisson distribution. The probability mission t is aborted is $P\{S(t) > 0\} = 1 - \exp\{-E[S(t)]\}$. Let $A(t)$ be the number of missions that have been aborted during the first t missions. A mission is aborted if at least one DS causes a mission abort.

$$E[A(t)] = \sum_{i=1}^t [1 - \exp\{-E[S(i)]\}] \quad (2)$$

$$VAR[A(t)] = \sum_{i=1}^t [1 - \exp\{-E[S(i)]\}] \exp\{-E[S(i)]\}$$

In the general case

$$s(t) = \prod_{i=1}^{t-1} [(1 - a_i)(1 - p_i)] a_t \quad (3)$$

where an empty product is set equal to 1. (Gaver and Jacobs, 2006)

IV. LEGACY MAINTENANCE AND CONDITION-BASED MAINTENANCE PLUS SIMULATION

A. SIMULATION ARCHITECTURE AND CHARACTERISTICS

This simulation is based on the nonhomogeneous Poisson process model as described in Chapter III. The Visual Basic for Applications (VBA) coding used as a macro within Microsoft Excel 2003 is listed in Appendix D. The Excel workbook consists of four worksheets named “RVs”, “Legacy Process”, “CBM+ Process”, and “Data”.

The purpose of “RVs” worksheet is to receive all variable inputs. The variable inputs for this simulation are:

1. # Replications: This number sets the number of iterations for the simulation to perform.

2. $P_L(h)$: The probability that the Legacy Process will recognize a DS during a downtime that includes an inspection lasting h hours.

3. P_C : The probability that the CBM+ Process will recognize a DS during a downtime.

The number of downtimes until a DS is discovered has a geometric distribution with mean $\frac{1}{P_c}$.

For each DS an independent P_C is drawn from a Beta distribution with mean 0.99 and variance .00037711. The randomization of P_C is determined by a Beta distribution and both α_B and β_B parameters are entered on the worksheet. Initially the Beta distribution is generated using $\alpha_B=25$ and $\beta_B=.25$. The equation for the probability density function of the beta distribution is:

$$f(x; \alpha_B, \beta_B) = \frac{1}{B(\alpha_B, \beta_B)} x^{\alpha_B-1} (1-x)^{\beta_B-1} \text{ for } 0 \leq x \leq 1 \text{ and } 0 \text{ otherwise}$$

where B is the normalizing constant.

4. R_0 : The initial repair time incurred upon a DS discovery.

5. R_1 : The subsequent repair time incurred if DS not discovered after first mission.

6. A_0 : The initial repair time incurred upon a mission abort.

7. A_1 : The subsequent repair time incurred if mission abort causing DS is not discovered after first mission.

8. M_A : For each DS an independent time until the DS results in a mission abort is drawn from a Weibull distribution with shape parameter 1.5 and mean 10. The values of both Weibull parameters α_W and β_W parameters are entered on the worksheet. Initially the Weibull distribution is generated using $\alpha_W=1.5$ and $\beta_W=11.08$. The equation for the probability density function of the Weibull distribution is:

$$f(x; \alpha_W, \beta_W) = \left(\frac{\alpha_W}{\beta_W}\right) \left(\frac{x}{\beta_W}\right)^{(\alpha_W-1)} e^{-\left(\frac{x}{\beta_W}\right)^{\alpha_W}} \quad \text{for } x \geq 0 \text{ and } 0 \text{ otherwise .}$$

9. P_{OH} : This is the probability that the required replacement component is on hand when a DS is discovered or causes mission abort. For each discovered DS, or a DS that causes a mission abort, an independent Bernoulli random number is generated to determine if the replacement component is immediately available or must be ordered from a depot.

10. T_{OH} : If a replacement component is ordered, a time T_{OH} until the replacement component arrives is generated; the time has an exponential distribution.

11. λ_i : The expected number of DSs to occur during mission i having length 4 hours; $\lambda_i = \gamma[(4i)^\delta - (4(i-1)^\delta)]$; the values of gamma and delta are the maximum likelihood estimates obtained from analysis of the engine data.

The “RVs” worksheet generates the number of DSs to occur during each mission; the number of DSs that occur during the i^{th} mission is generated using a Poisson distribution where the mean is determined by the appropriate λ_i . These numbers of DSs are used for both the “Legacy Process” and the “CBM+ Process”. This provides a common arrival process for both the Legacy and CBM+ processes.

The purpose of the “Legacy Process” and “CBM+ Process” worksheets is to provide the cell structure and formula to determine the following information for the two different processes:

1. D_{ij} : The number of downtimes to occur until the j^{th} DS generated during the i^{th} mission is discovered.

2. M_{Aij} : The number of downtimes to occur until the j th DS generated during the i th mission results in a mission abort; for each DS the same time until mission abort is used in the Legacy and CBM+ models.

3. R_{ij} : The total repair time from the j th DS resulting from the i th mission.

4. S_{ij} : The total time awaiting replacement components from the j th DS resulting from the i th mission; for each DS the time is drawn from an exponential distribution with a common mean for both the Legacy and CBM+ models.

The purpose of the “Data” worksheet is to display the results of each simulation replication and then compute the means, standard deviations, and 95% confidence intervals of the results for the Legacy and CBM+ processes. The results that are tabulated for both processes are:

1. $\sum DSs \leq M$: The number of diagnostic symptoms that are detected before the end of the total number of missions observed (M).

2. $\sum DSs > M$: The number of diagnostic symptoms that are detected after the end of the total number of missions observed (M) but were generated during the M missions.

3. $\sum Aborts \leq M$: The number of mission aborts that occur before the end of the total number of missions observed (M).

4. $\sum Aborts > M$: The number of mission aborts that occur after the end of the total number of missions observed (M) that are due to DSs generated during the M missions.

5. $\sum R \leq M$: The sum of repair times that occur before the end of the total number of missions observed (M).

6. $\sum R > M$: The sum of repair times that occur after the end of the total number of missions observed (M) that are due to DS generated during the M missions.

7. $\sum R$: The sum of repair times that occur.

8. $\sum S \leq M$: The sum of time spent awaiting component arrival that occurs before the end of the total number of missions observed (M).

9. $\sum S > M$: The sum of time spent awaiting component arrival that occurs after the end of the total number of missions observed (M) that are due to DS generated during the M missions.

10. $\sum S$: The sum of time spent awaiting component arrival that occurs.

B. DETERMINATION OF P_C and P_L

The number of downtimes until the Legacy or CBM+ process recognizes a DS is a direct result of a process's probability of successfully at detecting a DS. The conditional probability a DS is discovered n downtimes after it is generated in the Legacy process, given it has not been discovered before and has not caused a mission abort, is $P_L(h)$ where h is the maintenance man-hours (MMH) incurred during the downtime; in the CBM+ process the conditional probability a DS is discovered during a downtime, given it has not been discovered before and has not caused a mission abort is a constant P_C ; that is the number of downtimes until a generated DS is discovered has a geometric distribution with probability of success P_C . Initially it is assumed that the CBM+ Process P_C has an expected value of 0.99; this may be an optimistic value. The effect of the variability of the time to discover different DSs is modeled by randomizing P_C using a Beta distribution. For each generated DS the P_C is independently drawn from a Beta distribution having mean 0.99. The mean value of 0.99 is based on a telephone conversation with Mr. Johnny Wright the Deputy Program Manger for B.F. Goodrich Corporation's IMD-HUMS program on January 27, 2006. (Wright, Personal Communication, 2006) He stated that the parameters of the CBM+ sensors were set very conservatively in order to capture all changes in vibratory patterns. Since this is an emerging technology, B.F. Goodrich Corporation wants to ensure that their sensors do not inadvertently miss any vibratory indications that could be used to indicate impending component failure. However, the conservative setting may increase the chance of false alarms. The mean value of P_C will be varied in Chapter 5 in order to explore sensitivity of the simulation results to its value. Furthermore false positives (false alarms) will also be introduced into the simulation in order to observe their impact on the CBM+ process.

The Legacy maintenance schedule of the UH-60 Blackhawk 701C Engine Assembly will be used to describe the specification of the probabilities of the Legacy system discovering a previously generated DS during the downtime with h MMH, $P_L(h)$. Although the 701C Engine Assembly is used by both the AH-64 Apache and the UH-60 Blackhawk the two airframes have different maintenance schedules. Listed in Table 8 below is the maintenance schedule for the UH-60 Blackhawk 701C Engine Assembly maintenance schedule as listed in the AMCOM Proof of Principle briefing from June of 2005. (Brown, 2005)

Table 8. UH-60 Blackhawk 701C Engine Assembly Maintenance Regime

Inspection	Reference	Maint Type	Task or Paragraph	MMH
Pre-Flight	TM 1-1520-237-CL	PM	Not Applicable	0.1
Post-Flight	TM 1-1520-237-CL	PM	Not Applicable	-
Daily	TM 1-1520-237-PMD	PM	6.17	0.2
40 Hr Output Shaft Inspection	TM 1-1520-237-23	PM	ch 1 sec 7-10.2	0.4
120 Hr DS Inspection	TM 1-1520-237-23	-18	ch 1 sec 7-11.1	3.4
120 Hr Clean Engine Compressor	TM 1-2840-248-23	-18	1.158 thru 1.161	1.6
350 Hr	TM 1-1520-237-PMI	PM	6.37, 6.43	5.9
700 Hr	TM 1-1520-237-PMI	PM	6.37 - 6.48	12.4

It is evident that the most time intensive inspection occurs every 700 hours and it requires 12.4 maintenance man-hours (MMH). 12.4 MMH is the h_{max} . We assume the probability of detecting a DS during this inspection is $P_L(700) = P_C$. We assume that the amount of MMH expended during an inspection, h , is an indication of the probability of discovering a DS of $P_L(h)$. We model the probability of detecting a DS for the other inspections as follows:

1. Set $x^{h_{max}} = 1 - P_L(h_{max})$ for the known most MMH-intensive inspection;

2. Solve for $x = (1 - P_L(h_{max}))^{\frac{1}{h_{max}}}$;

3. The probability of detecting a DS during an inspection lasting h hours is

$$P_L(h) = 1 - (1 - P_L(h_{max}))^{\frac{h}{h_{max}}}$$

Using this methodology and Table 8 the following values are computed for $P_L(h)$ at differing maintenance inspection intervals.

Table 9. UH-60 Blackhawk 701C Engine Assembly P_L

Inspection Interval	Maintenance Man-Hours	$P_L(h)$
Baseline*	0.3	0.11
40 Hour	0.4	0.14
120 Hour	5	0.84
350 Hour	5.9	0.89
700 Hour	12.4	0.99
* Baseline is summed total of Pre/PostFlight and Daily inspection times		

This provides realistic models of varying levels of $P_L(h)$ that can be input into the simulation. The generation of the times until DS discovery for both processes is detailed in Section D below.

C. ANALYTICAL VERSUS STOCHASTIC RESULTS

Results obtained from the simulation and the analytical formulas are displayed in Table 10. Examination of the results can determine whether or not the simulation model and the analytical model results are comparable. Since DS arrivals drive all other factors in this simulation it is important to evaluate the number of DS arrivals during the course of 1,250 missions (5,000 flight hours). The expected number of DSs that are generated during 1250 missions is $\gamma 5000^\delta = 11.42$ where $\gamma = 5.4 * 10^{-6}$ and $\delta = 1.71$. The simulation model with 1,000 replications results in a mean number of DSs generated equal to 11.34 with a 95% confidence interval of (11.14, 11.54). Thus the generation of DSs in the analytical model and the simulation are in good statistical agreement.

Results from a simulation of the number of mission aborts during 500 missions are displayed in Table 10. Each simulation has 500 replications. The time until a DS is discovered has a geometric distribution with constant probability of success P_C . The time until a DS causes a mission abort has a geometric distribution with probability of success P_A ; the two times are assumed independent. The mean number of system aborts and the corresponding expected number of system aborts obtained from the analytical model equations (1) and (2) are displayed. As expected the analytical results fall within the 95% confidence interval of the simulation results.

Table 10. Special Case Analytical and Simulation Results

Case	Analytical	Simulation (95% CI)
$P_C=.7, P_A=.1$	5.99	6.02 (5.87, 6.17)
$P_C=.7, P_A=.2$	11.44	11.60 (11.40, 11.80)
$P_L=.3, P_A=.2$	19.50	19.77 (19.49, 20.05)

D. RANDOM NUMBER GENERATION USING CRYSTAL BALL

The add-in Crystal Ball version 5.5 is used as the random number generator (RNG) for this simulation. Crystal Ball version 5.5 is chosen to provide the random numbers for this

simulation because Microsoft Excel 2003's RNG has been shown to have insufficient period length and an incorrect implementation of the Wichmann-Hill Algorithm. (McCullough and Wilson, 2005) Crystal Ball is considered one of the industry's leading edge Monte Carlo simulation add-ins for Excel. It uses a multiplicative congruential generator that has a stream of $2^{31}-1$ pseudo random numbers before repeating. The iteration formula uses the multiplier 62089911. Crystal Ball produces a cycle of random numbers that repeats only after several billion trials. (Decisioneering, 2005)

The times until detection of DSs are generated for the CBM+ process by drawing a random variable from an exponential distribution with a mean of 1 and multiplying that value by $\frac{1}{\theta_C}$ then rounding the value up to the next integer; θ_C is equal to $-\ln(1-P_C)$. This gives the number of downtimes until the DS is discovered. If the downtime is one, the DS is discovered during the downtime immediately following the mission during which it was generated. The generation for $\theta_L(h)$ is based on the maintenance schedule for the component. For example if an arduous inspection occurs every fifty operating hours then that is reflected in an increase in the probability a DS is discovered, $P_L(h)$, and subsequently $\theta_L(h) = -\ln(1-P_L(h))$. The time until detection of a DS for the Legacy process is determined by generating an exponential random variable with mean 1, Y , and determining the smallest n such that $Y \leq \theta_L(h_1) + \dots + \theta_L(h_n)$ where h_n is the MMH of the n th inspection after generation of the DS with h_1 being the MMH for the inspection following the mission the DS is generated in. A common independent exponential random variable with a mean of 1 is used to generate the time until DS discovery for the Legacy process and for the CBM+ process. The operational time until a DS causes a mission abort is generated by drawing an independent random variable from a Weibull distribution. Since the Weibull distribution is a continuous distribution the value is rounded up to the nearest whole number. The time until mission abort and the time until DS discovery are then compared and whichever event occurs first is the event that happens; the other event is ignored. If the two discrete times are equal, the mission is aborted. N_i is the number of DSs that originate in a given mission (i). The simulation is designed so that the N_i is identical for both the Legacy and CBM+ processes. Crystal Ball uses the method of inverse

transformation to generate both the Exponential and Weibull random variables. (Decisioneering, 2005)

V. DATA ANALYSIS

A. VARYING CBM+ SENSOR EFFICIENCY

One of the measures to evaluate a component for selection to the CBM+ process is the level of CBM+ sensor efficiency. In particular how effective must a CBM+ sensor be in discovering DSs to result in a smaller number of aborted missions compared to that of the Legacy process. Varying sensor efficiency is defined as varying the mean probability of successfully discovering a particular DS, P_C , in the simulation. Appendix E contains tables displaying the statistical summaries of the simulation output for the Legacy and CBM+ processes as the CBM+ sensor efficiency mean value is varied from 0.99 to 0.1. The value of P_C for each generated DS is determined by an independent draw from a Beta distribution. Table 11 displays the beta parameter values used in the simulation.

Table 11. P_C Beta Distribution Parameters

$E(X)=P_C$	$VAR(X)$	α_B	β_B
0.99	0.00037711	25	0.25252525
0.90	0.00312741	25	2.77777777
0.80	0.00496124	25	6.25
0.70	0.00571984	25	10.71428571
0.60	0.00562500	25	16.66666666
0.50	0.00490196	25	25
0.40	0.00377953	25	37.5
0.30	0.00249012	25	58.33333333
0.20	0.00126984	25	100
0.10	0.00035857	25	225

The time until a DS causes a mission abort has a Weibull distribution with mean 10 and shape parameter $\alpha_W=1.5$. The number of replications in the simulation is set to 1000. Although P_C is randomized for each DS for the CBM+ process, the values of $P_L(h)$ are not randomized for the Legacy process and therefore the only changes in the Legacy process observed between simulations of different P_C s are due to the variability inherent in the stochastic nature of the simulation. In Appendix E the statistical summaries of the simulation output are displayed and indicate very small standard errors for the estimates of mean number of mission aborts in the following graphs.

Figure 6. Mean Number of Mission Aborts out of 1,250 Missions when time until Mission Aborts has a Weibull distribution with mean 10 and $\alpha_W=1.5$

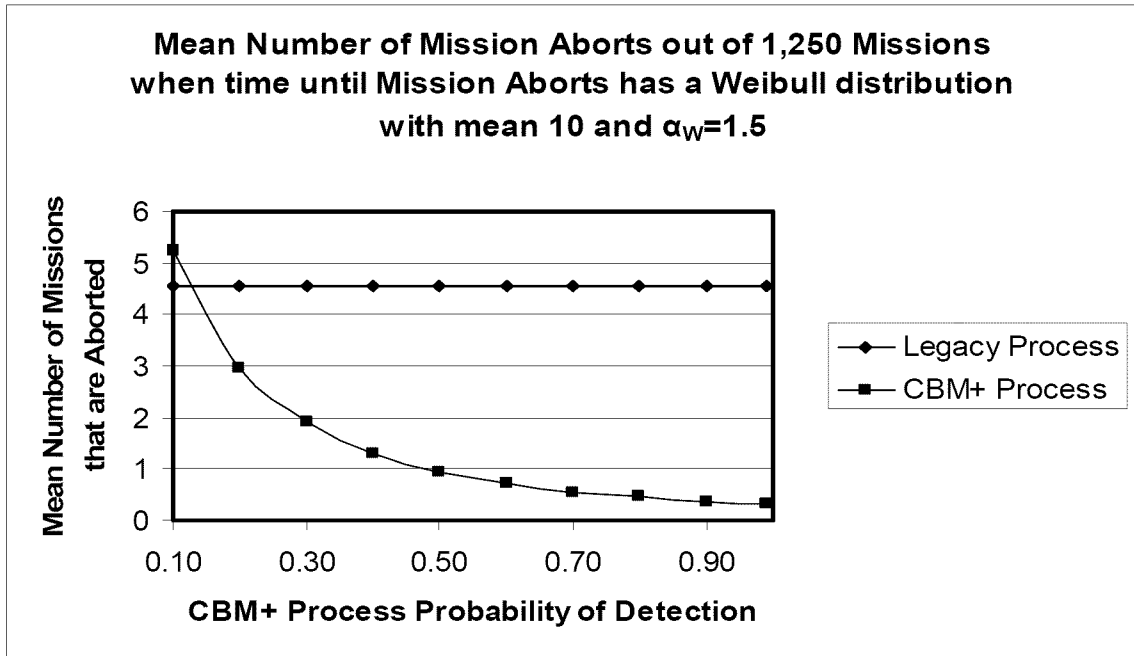
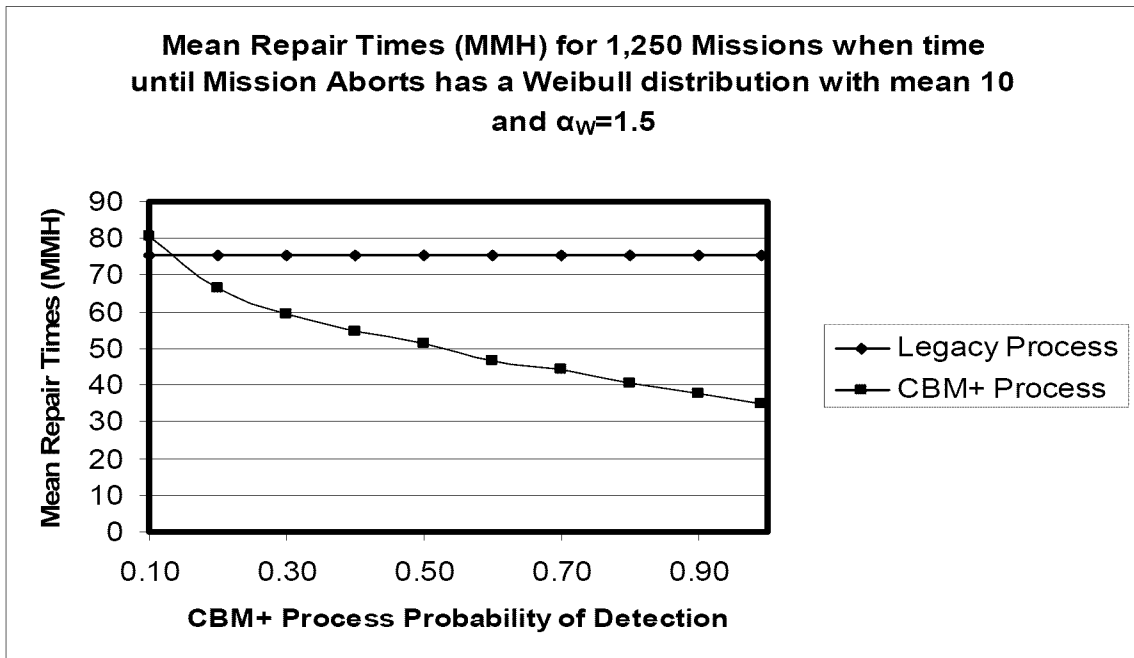


Figure 7. Mean Repair Times for 1,250 Missions when time until Mission Aborts has a Weibull distribution with mean 10 and $\alpha_W=1.5$

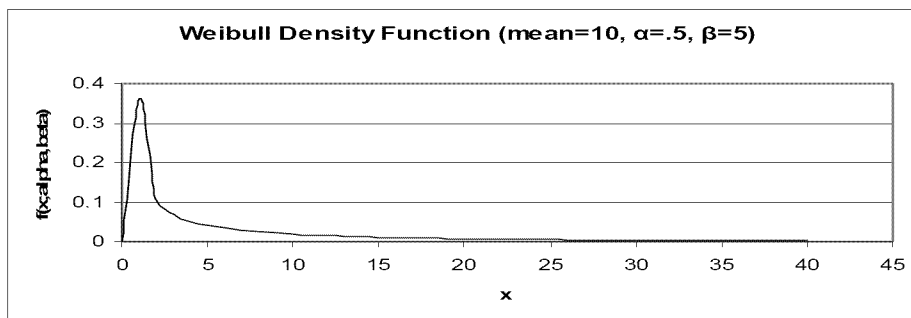


As shown in Figures 6 and 7 the CBM+ Process has a smaller mean number of system aborts and mean repair time than the Legacy Process until the probability of successful discovery of a DS during a downtime for the CBM+ sensor is degraded to approximately 12-15%. This corresponds roughly with the average of $P_L(h_n)$ ($n=1,2,\dots,1,250$) where h_n is the MMH for the Legacy inspection after mission n that is determined using the methodology in Chapter 4; the baseline $P_L(h)$ is determined using the sum of the daily, preflight, and postflight inspection MMH requirements. Since the baseline MMH is the most common MMH requirement, the baseline $P_L(h)$ is approximately equal to the average of $P_L(h)$ s. Abort times depend upon the α_W and β_W Weibull distribution parameters selected for M_A as described in Chapter 4. In the examples listed above the mean value selected for M_A 's Weibull distribution was 10 with shape parameter $\alpha_W=1.5$ and scale $\beta_W=11.07732168$. This means that on average it requires 2.5 missions for an engine's diagnostic symptom to become a mission abort situation; the variance of the time until mission abort is 46.8059. This value was selected as a placeholder and does not indicate an actual estimation of engine abort occurrences. However, it does serve to illustrate a generic abort behavior as P_C is varied as seen in the previous two figures.

B. EXAMINING MISSION ABORT TIME VARIANCES

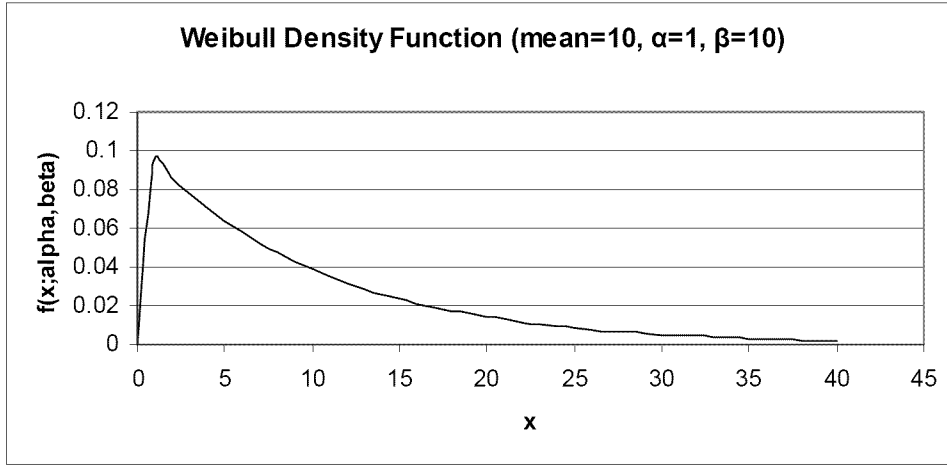
In this section we explore the effect the variance of the time from when a DS is generated until it causes mission abort has on the mean number of mission aborts. The mean time from when a DS is generated until it causes a mission abort is constant for all cases studied in this section. The parameters of the Weibull distribution are varied to obtain different variances. In this section the parameters of the beta distribution used to generate P_C for each DS are $\alpha_B=25$ and $\beta_B=.25$ giving an expected value of P_C equal to 0.99. The density functions of 3 different Weibull distributions are displayed in Figures 8, 9, and 10:

Figure 8. CASE #1 Weibull Density Function (mean=10, $\alpha_W=.5$, $\beta_W=5$)



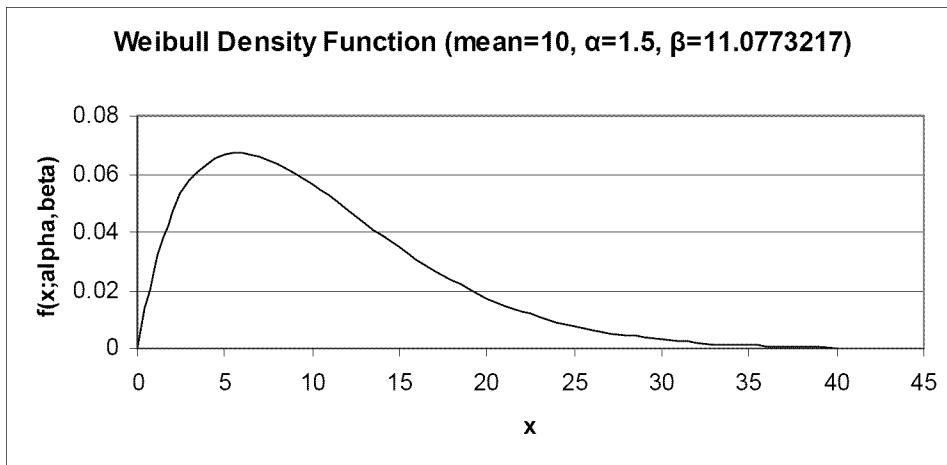
The Weibull distribution whose density function is displayed in Figure 8 has expected value equal to 10 and variance equal to 500.

Figure 9. CASE #2 Weibull Density Function (mean=10, $\alpha_w=1$, $\beta_w=10$)



The Weibull distribution whose density function is displayed in Figure 9 has expected value equal to 10 and variance equal to 100..

Figure 10. CASE #3 Weibull Density Function (mean=10, $\alpha_w=1.5$, $\beta_w=11.08$)



The Weibull distribution whose density function is displayed in Figure 10 has expected value equal to 10 and variance equal to 46.09.

The results of simulations of the two processes utilizing the three different cases of the Weibull distribution of the time from DS generation until it causes mission abort with the mean P_C equal to 0.99 appear below. Summary statistics of the simulation output appearing in

Appendix E indicate very small standard errors for the estimates of the fraction of DSs that cause mission abort. The fraction of DSs that cause mission aborts is defined as the number of DSs that actually cause a mission abort divided by the total number of DSs that occurred during 1,250 missions. This divisor is the sum of the DSs that caused mission aborts and DSs that did not cause mission aborts.

CASE #1 (Weibull with mean equal to 10, variance equal to 500, $\alpha_W=0.5$; $\beta_W=5$)

The fraction of DSs that causes a mission abort in the Legacy process is 0.64; the fraction of DSs that causes a mission abort is 0.37 in the CBM+ process. Recall that if more than one DS can cause a mission to abort, the mission is only aborted once. This means that given these conditions under the Legacy process a DS will result in a mission abort 64% of the time, whereas, under the CBM+ process a DS will result in a mission abort on 37% of the time.

CASE #2 (Weibull with mean equal to 10, variance equal to 100, $\alpha_W=1$; $\beta_W=10$)

The fraction of DSs that causes a mission abort in the Legacy process is 0.47; the fraction of DSs that causes a mission abort is 0.10 in the CBM+ process. Recall that if more than one DS can cause a mission to abort, the mission is only aborted once. This means that given these conditions under the Legacy process a DS will result in a mission abort 47% of the time, whereas, under the CBM+ process a DS will result in a mission abort on 10% of the time.

CASE #3 (Weibull with mean equal to 10, variance equal to 46.09, $\alpha_W=1.5$; $\beta_W=11.08$)

The fraction of DSs that causes a mission abort in the Legacy process is 0.40; the fraction of DSs that causes mission abort is 0.03 in the CBM+ process. Recall that if more than one DS can cause a mission to abort, the mission is only aborted once. This means that given these conditions under the Legacy process a DS will result in a mission abort 40% of the time, whereas, under the CBM+ process a DS will result in a mission abort on 3% of the time.

Thus the number of mission aborts depends on more than just the mean time from when a DS is generated until it causes mission abort. The variance associated with the mission abort arrival time can be equally influential. The CBM+ Process which monitors every mission with a high mean probability P_C of discovering DSs is most effective in preventing mission aborts in all cases but does best when the variance of the time from when a DS is generated until it causes mission abort is small.

C. EXAMINING MISSION ABORT TIME VARIANCES WITH DEGRADED P_C

In this section, the mean probability an existing DS is discovered during a downtime (P_C) is degraded from the value of 0.99 ($\alpha_B=25, \beta_B=.25$) to the smaller values of 0.50 ($\alpha_B=25, \beta_B=25$) and 0.20 ($\alpha_B=25, \beta_B=100$) in order to study the effect of the variance of the time from when a DS is generated until it causes a mission abort with a less effective sensor. The statistical standard errors of the summary statistics of the simulation output are displayed in Appendix E. The results for the Legacy Process remain as stated above since a varying P_C does not affect the Legacy Process. For all cases the Weibull parameters of the time until an undiscovered DS causes a mission abort $\alpha_W=1.5$ and $\beta_W=11.08$ are held constant.

CASE #1 (Weibull with mean equal to 10, variance equal to 500, $\alpha_W=0.5; \beta_W=5$)

This case possesses the largest variance and results in the probability an arriving DS will cause a mission abort for the CBM+ process equal to 0.45 ($P_C=0.50$) / 0.57 ($P_C=0.20$) of the time. This means that given a P_C of 0.50 that a DS will result in a mission abort 45% of the time. Given a P_C of 0.20, a DS will result in a mission abort 57% of the time.

CASE #2 (Weibull with mean equal to 10, variance equal to 100, $\alpha_W=1; \beta_W=10$)

This case possesses the middle variance and results in the probability an arriving DS will cause a mission abort for the CBM+ process equal to 0.17 ($P_C=0.50$) / 0.35 ($P_C=0.20$) of the time. This means that given a P_C of 0.50 that a DS will result in a mission abort 17% of the time. Given a P_C of 0.20, a DS will result in a mission abort 35% of the time.

CASE #3 (Weibull with mean equal to 10, variance equal to 46.09, $\alpha_W=1.5; \beta_W=11.08$)

This case possesses the smallest variance and results in the probability an arriving DS will cause a mission abort for the CBM+ process equal to 0.09 ($P_C=0.50$) / 0.25 ($P_C=0.20$) of the time. This means that given a P_C of 0.50 that a DS will result in a mission abort 9% of the time. Given a P_C of 0.20, a DS will result in a mission abort 25% of the time.

These results of examining P_C at both 0.50 and 0.20 are consistent with the conclusions drawn from examining mission abort arrival time variance when P_C is 0.99. Furthermore, it is concluded that even a very poor performing sensor (i.e. $P_C=0.20$) when compared against the Legacy process reduces the percentage of diagnostic symptoms that can result in mission aborts by an average of 10% regardless of the variance of the time from when a DS is generated until it

can cause a mission abort. When the P_C is at 0.99 the CBM+ Process reduces the percentage of diagnostic symptoms that can result in a mission aborts by an average of 30%-35%. Legacy process performance data used in the comparisons above for these cases is displayed in Appendix E.

D. CBM+ FALSE POSITIVES

It is worthwhile to explore the consequences of the CBM+ sensor indicating a false positive. Since the Army currently uses only passive sensors whose measurements are downloaded at the conclusion of missions a false positive does not impact the mission during which it occurs. However, a false positive will require maintenance personnel to expend maintenance man-hours in order to determine that nothing is wrong with the component. The time required to inspect (repair) and correctly diagnose a diagnostic symptom as a false positive is the same as if it were an actual diagnostic symptom recognized immediately after the mission during which it arrived. This time penalty is a random variable drawn from an exponential distribution with a mean of 3 hours. False positives are assumed to occur according to a Poisson process independent of the other processes. Table 12 displays the mean number of false positive arrivals and their associated mean inspection (repair) times resulting from a simulation with 1,000 replications. The parameters of the simulation are: $\alpha_B=25$, $\beta_B=0.25$ ($P_C=0.99$); $\alpha_W=1.5$, $\beta_W=11.08$ (mean time until mission abort is 10 missions). The total amount of repair expended on false positives that appear during an operational time t is a compound Poisson process.

$$E[\text{total repair time}] = E[\text{number of false positives}] \times E[\text{repair time per false positive}]$$

An expanded version of Table 12 appears in Appendix E annotating standard errors.

Table 12. Simulation Results for mean number of False Positive Arrivals and mean Inspection (Repair) Time resulting from False Positives for 1,250 missions

False Positive Rate	CBM+ PROCESS (NUMBER OF FALSE POSITIVE ARRIVALS)		
0.9999	Σ FP	Mean:	1238.57
0.90	Σ FP	Mean:	1115.29
0.80	Σ FP	Mean:	990.51
0.70	Σ FP	Mean:	866.70
0.60	Σ FP	Mean:	743.41
0.50	Σ FP	Mean:	620.23
0.40	Σ FP	Mean:	495.29
0.30	Σ FP	Mean:	372.07
0.20	Σ FP	Mean:	247.05
0.10	Σ FP	Mean:	124.34
0.0001	Σ FP	Mean:	0.14
False Positive Rate	CBM+ PROCESS (REPAIR TIME INCURRED DUE TO FALSE POSITIVE ARRIVALS)		
0.9999	Σ FP Time	Mean:	3717.41
0.90	Σ FP Time	Mean:	3343.55
0.80	Σ FP Time	Mean:	2969.66
0.70	Σ FP Time	Mean:	2598.47
0.60	Σ FP Time	Mean:	2228.17
0.50	Σ FP Time	Mean:	1861.03
0.40	Σ FP Time	Mean:	1490.28
0.30	Σ FP Time	Mean:	1118.76
0.20	Σ FP Time	Mean:	741.94
0.10	Σ FP Time	Mean:	371.62
0.0001	Σ FP Time	Mean:	0.42

Displayed in Table 13 are the analytical results for the number of false positive arrivals and the resulting inspection (repair) time for 1,250 missions.

Table 13. Analytical Results for mean number of False Positive Arrivals and mean Inspection (Repair) Time resulting from False Positives for 1,250 missions

False Positive Rate	CBM+ PROCESS (NUMBER OF FALSE POSITIVE ARRIVALS)		
0.9999	Σ FP	Mean:	1249.88
0.90	Σ FP	Mean:	1125.00
0.80	Σ FP	Mean:	1000.00
0.70	Σ FP	Mean:	875.00
0.60	Σ FP	Mean:	750.00
0.50	Σ FP	Mean:	625.00
0.40	Σ FP	Mean:	500.00
0.30	Σ FP	Mean:	375.00
0.20	Σ FP	Mean:	250.00
0.10	Σ FP	Mean:	125.00
0.0001	Σ FP	Mean:	0.13
False Positive Rate	CBM+ PROCESS (REPAIR TIME INCURRED DUE TO FALSE POSITIVE ARRIVALS)		
0.9999	Σ FP Time	Mean:	3749.63
0.90	Σ FP Time	Mean:	3375.00
0.80	Σ FP Time	Mean:	3000.00
0.70	Σ FP Time	Mean:	2625.00
0.60	Σ FP Time	Mean:	2250.00
0.50	Σ FP Time	Mean:	1875.00
0.40	Σ FP Time	Mean:	1500.00
0.30	Σ FP Time	Mean:	1125.00
0.20	Σ FP Time	Mean:	750.00
0.10	Σ FP Time	Mean:	375.00
0.0001	Σ FP Time	Mean:	0.38

As expected the simulation results closely match the analytical results and produce a linear relationship as the false positive rate is varied from 0.9999 (false positive arriving every mission) to 0.0001 (false positives very rarely occurring).

Assuming that the Legacy process does not produce a false positive of its own it is useful to note that the Legacy process incurs approximately 75 hours in repair time every 1,250 missions. The Legacy process expected repair time includes all repair times including repair time resulting from mission aborts. Table 14 displays the mean CBM+ Process total repair time (total repair time = diagnostic symptom repair time + false positive repair time) while varying the false positive rate from 0.10 to 0.0001. The mean time until mission abort is 10 missions ($\alpha_W=1.5$, $\beta_W=11.08$). An expanded table including standard errors is displayed in Appendix E.

Table 14. CBM+ Process mean Total Repair Time (including False Positive Repair Time) for 1,250 missions with $\alpha_B= .25$, $\beta_B=.25$

False Positive Rate	CBM+ PROCESS (TOTAL REPAIR TIME=DS REPAIR TIME+FALSE POSITIVE REPAIR TIME)		
	$\Sigma R + \Sigma FP$ Time	Mean:	
0.10	$\Sigma R + \Sigma FP$ Time	Mean:	406.13
0.09	$\Sigma R + \Sigma FP$ Time	Mean:	369.59
0.08	$\Sigma R + \Sigma FP$ Time	Mean:	330.84
0.07	$\Sigma R + \Sigma FP$ Time	Mean:	291.50
0.06	$\Sigma R + \Sigma FP$ Time	Mean:	257.54
0.05	$\Sigma R + \Sigma FP$ Time	Mean:	221.93
0.04	$\Sigma R + \Sigma FP$ Time	Mean:	185.08
0.03	$\Sigma R + \Sigma FP$ Time	Mean:	146.10
0.02	$\Sigma R + \Sigma FP$ Time	Mean:	108.97
0.01	$\Sigma R + \Sigma FP$ Time	Mean:	71.91
0.0001	$\Sigma R + \Sigma FP$ Time	Mean:	36.06

Figure 11 is a graphical display of the total mean repair time of the Legacy and CBM+ Process as the false positive rate is varied from .05 to .0001.

Figure 11. Mean Total Repair Time for 1,250 Missions while varying the False Positive rate from .05 to .0001

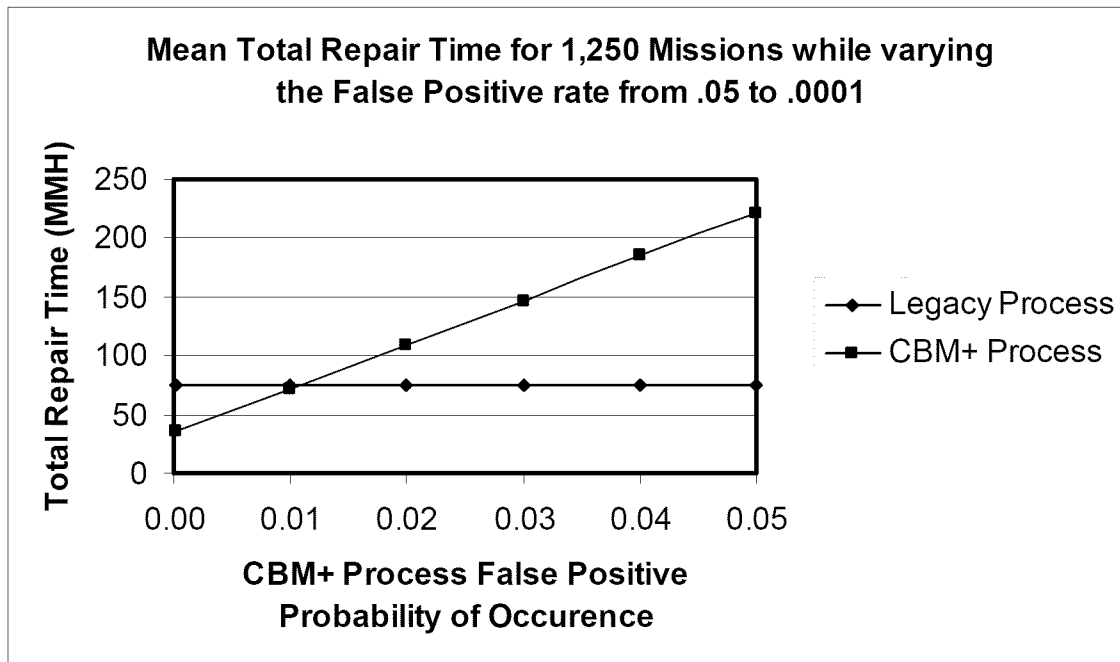


Figure 11 illustrates the importance of limiting the number of false positives that the CBM+ sensor incurs. This simulation was run with a mean probability of DS discovery during a downtime equal to $P_C=0.99$ (a highly accurate sensor) yet when false positive rates begin to increase any advantage in repair time provided by the sensor is quickly lost; the parameters of

the beta distribution for P_C are $\alpha_B=25$ and $\beta_B=.25$. The parameters of the Weibull distribution are $\alpha_W=1.5$ and $\beta_W=11.08$ (mean time until mission abort is 10 missions).

E. LOGISTICAL IMPLICATIONS OF VARYING P_C

It is possible to utilize this simulation to gain insights into the logistical implications of utilizing the CBM+ Process versus the traditional Legacy Process. The following is a general description of the logistics process. An assumption made is that once a DS occurs that the time remaining until mission abort is known; this is very optimistic. Another assumption is that there is only mission per day and that a mission occurs every day. This differs from the current implementation of CBM+ ; once a component shows degraded performance it is removed; the time until failure is not known. For the case of a mean time until a replacement component arrives of 3 days (assuming one mission for every day) the following process is used:

1. A DS is detected.
2. If remaining time until a mission abort is greater than or equal to the time to fly 3 missions the 3 missions will be flown. The following events occur:
 - a. A replacement component is ordered and arrives before there is a mission abort; there is no time with aircraft down waiting for the replacement part (T_{OH}). Since one mission is flown per day, the time until the replacement component arrives is three days. This assumes both the number of missions until mission abort is known and the time until the replacement component arrives is constant and known. This fixed time is an approximate of the prognostics capability of the CBM+ sensor and can be modified as further research is done in this area.
3. If the remaining time until a mission abort is less than the time to fly 3 missions, the aircraft will not fly until the failing component is replaced. A Bernoulli random variable is generated with probability of success P_{OH} (probability component is on hand):
 - a. If a replacement component is on hand, there is no aircraft downtime waiting for the replacement component.
 - b. If component is not on hand an exponential time with mean of 3 is generated to determine T_{OH} (time in days spent awaiting component).

The following charts illustrate two cases. The first case is when a component requires a mean of 3 days to arrive once ordered and the second case is when a component requires a mean

of 10 days to arrive once ordered. Through examining these two situations conclusions can be drawn concerning the effect of a CBM+ sensor on the component ordering time requirements. When a DS is discovered, the number of future missions that can be flown before a mission abort is calculated. One mission is flown per day. Thus the number of additional missions that can be flown is compared to the mean number of days until a replacement component can arrive. If the number of missions that can be flown without a mission abort is less than the mean number of days until a replacement component arrives, then an independent Bernoulli random variable is generated to determine if the replacement component is on hand. If the component is not immediately available then an Exponential distribution is used to determine the amount of time required for component arrival. These random numbers are independent for the Legacy and CBM+ processes. P_{OH} will be used to represent the probability that a replacement component is on hand at the location of the unit requiring the component; when a DS is discovered whether or not a replacement component is at the location is independent from DS to DS. There is no randomization of the probability a replacement component is available. The value of P_{OH} will be varied from .9999 to .0001 in order to compare the mean number of days awaiting replacement components for both the CBM+ system and the Legacy system. The number of missions is 1,250 and there are 1,000 replications. The parameters of the CBM+ process are $\alpha_B=25$ and $\beta_B=.25$. The parameters of the Weibull distribution are $\alpha_W=1.5$, $\beta_W=11.08$ (the mean time until mission abort is 10 missions). Upon the occurrence of a mission abort or if the DS is discovered but it is not at least 3 days before the mission abort were to occur (CASE #1) or ten days before the mission abort were to occur (CASE #2) then a Bernoulli random variable is generated to determine whether or not the component is on hand (P_{OH}) and if the component is not on hand then an exponential distribution with mean 3 days (CASE #1) or 10 days (CASE #2) is used to determine the number of days spent awaiting component (T_{OH}). Summary statistics of the simulation output appear in Appendix E. The standard errors of the mean number of days expended until a replacement component arrives are small and this information is located in Appendix E for all graphs listed in the remainder of Chapter 5.

1. 3 Day Mean Component Ordering Time

The first case examines three different P_C levels for the CBM+ Process. The first P_C level is .99. The mean number of days expended awaiting replacement components as the P_{OH} is varied from .9999 to .0001 are displayed in Figure 12. DSs causing mission aborts are included.

Figure 12. Mean Number of Days Expended Awaiting Replacement Components where $P_C=.99$ and Mean Time until replacement component arrives=3 days

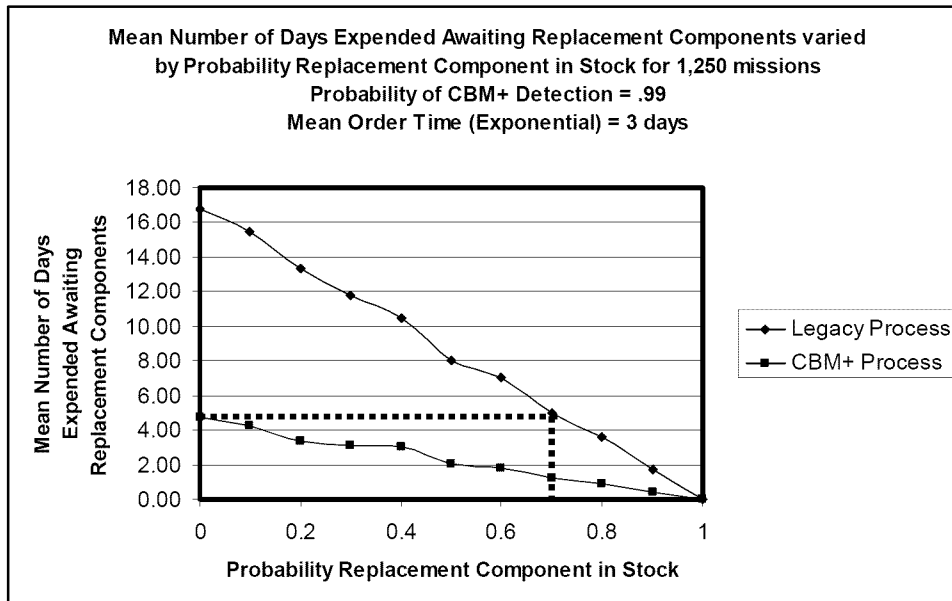


Figure 12 shows that if the remaining time until component failure is known perfectly then utilizing the CBM+ Process and having no the components on hand when P_C is .99 is equivalent to keeping approximately enough of the components on hand under the Legacy Process to have a replacement component immediately available 70% of the time. The reason the mean time expended waiting for replacement components is so different between the two processes is that since the CBM+ process discovers DSs so much earlier on average than the Legacy process, the CBM+ process is able to order the component before the component fails. The Legacy process does not have this advantage since it will either not detect until a mission abort or once a DS is discovered it is too late to order the component before the component fails. Figures 13 and 14 display the mean delay time until replacement components arrive, for P_C equal to 0.50 (respectively 0.20); if the remaining time until component failure is known perfectly, then the result for the case the CBM+ process has no components on hand is the same that for the Legacy process that has enough components at the location to replace 60% (respectively 30%) of the discovered DSs at their time of discovery.

Figure 13. Mean Number of Days Expended Awaiting Replacement Components where $P_C=.50$ and Mean Order Time=3 days

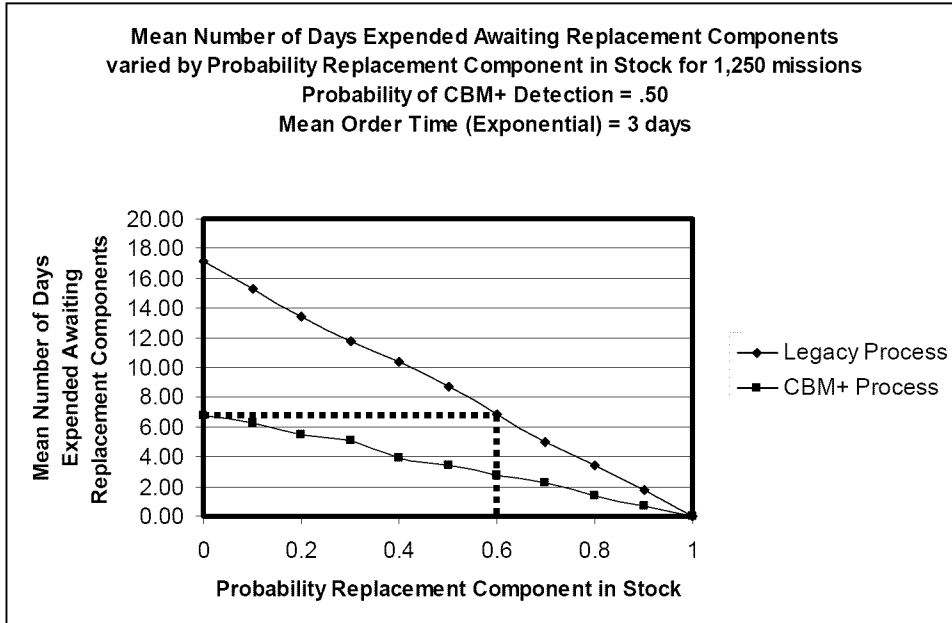
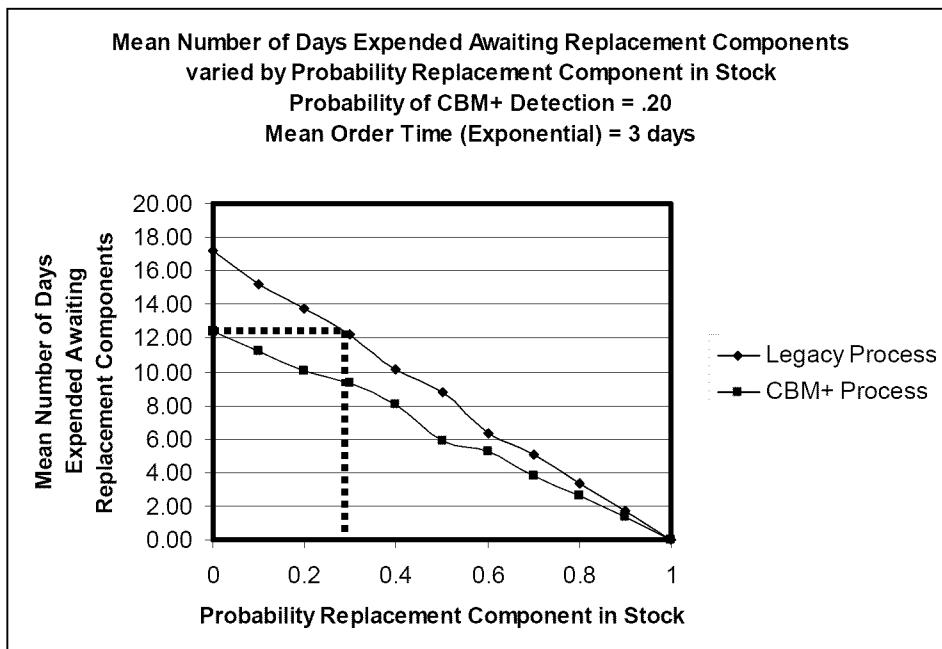


Figure 14. Mean Number of Days Expended Awaiting Replacement Components where $P_C=.20$ and Mean Order Time=3 days



2. 10 Day Mean Component Ordering Time

If the mean time of the exponential ordering time is increased to 10 days this will provide insight into the advantage of utilizing the CBM+ Process for a component that is not as readily available in the Army's logistical system.

A review of Figures 15, 16, and 17 show that if the remaining time to component failure is known when the P_C is .99 / .50 / .20 and no components are kept on hand that the equivalent mean wait time for ordered components is the same for keeping enough on hand under the Legacy Process to have this component available 30% / 20% / 10% of the time respectively. This suggests that if a component is to be chosen for entry in the CBM+ Process it is more beneficial to choose a component that can be shipped faster and not one that requires longer to arrive to the organization requiring the replacement component. The advantage that the CBM+ Process delivers is that it gives the maintainer advance warning that a component will fail in the near future. If the component can be ordered when a diagnostic symptom is recognized and sent to the organization requiring the component before the component causes mission abort then great savings in on hand stockage requirements can be realized; this assumes that the remaining time until mission abort can be predicted with accuracy. If the aircraft is grounded until replacement parts become available then the CBM process is comparable to the Legacy process. However, if the component requires a longer time to arrive then this advantage that the CBM+ Process possesses over the Legacy Process still exists but is diminished.

Figure 15. Mean Number of Days Expended Awaiting Replacement Components where $P_C=.99$ and Mean Order Time=10 days

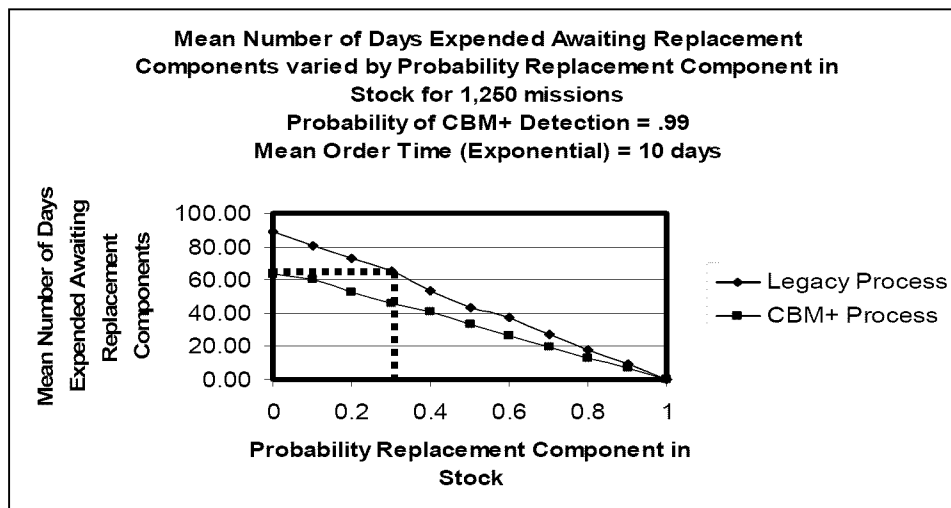


Figure 16. Mean Number of Days Expended Awaiting Replacement Components where $P_C=.50$ and Mean Order Time=10 days

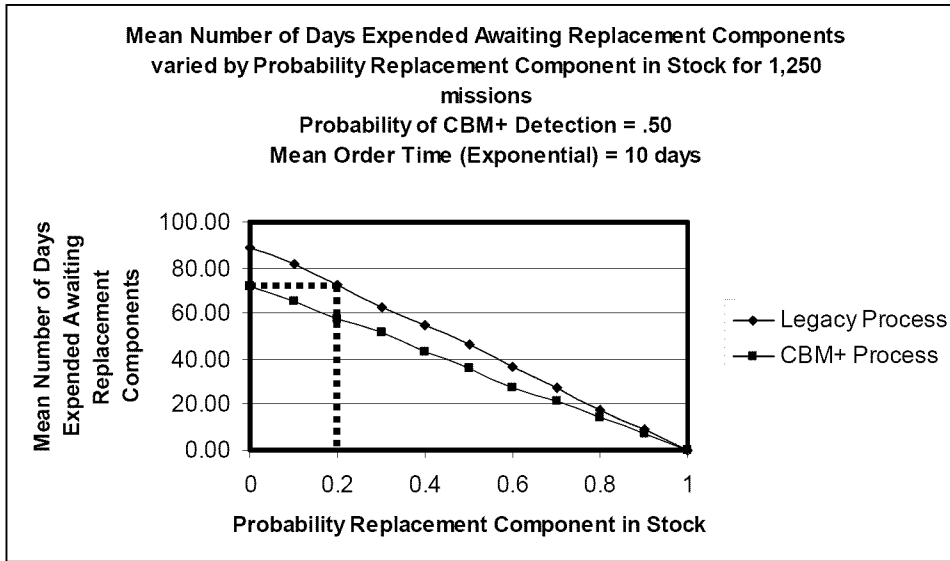
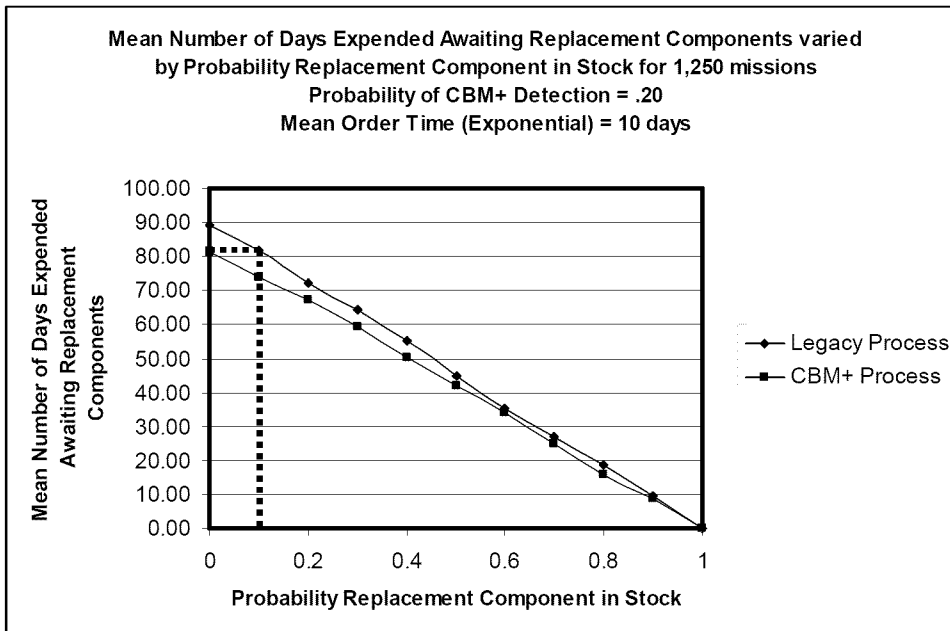


Figure 17. Mean Number of Days Expended Awaiting Replacement Components where $P_C=.20$ and Mean Order Time=10 days



VI. RESULTS AND CONCLUSIONS

A. APPLICATIONS

A model of the Legacy maintenance/repair process and the CBM+ maintenance /repair process has been presented. The model assumes that prior to a component failure, a measurable diagnostic symptom (DS) appears. Once a DS is generated, it remains measurable and can be detected by a CBM+ sensor or by physical inspection (Legacy process). The model output includes the number of missions that are aborted and the repair time incurred by component failures and false positives. By comparing two or more different components it is possible to determine which component will produce more favorable results in terms of mission abort rates and repair time expenditures by introducing it into the CBM+ process. Furthermore, patterns and behaviors can be observed as conditions vary thereby providing insight and information to be used by the decision-maker.

The following factors are influential to the successful introduction of a component in a CBM+ program:

1. Since the CBM+ sensor is continually monitoring a component, the sensor doesn't have to have an extremely high level of probability of detection of diagnostic symptoms; this result assumes that the probability of detection of a DS is independent from mission to mission. It also assumes that once a DS has occurred it remains detectable; that is measurable evidence of the DS is not intermittent. Simply by providing a level of detection for every mission that exceeds the baseline (the daily pre-flight and post-flight inspections) probability of detection provided by the Legacy Process the CBM+ Process will show a substantial increase in the maintainer's ability to recognize and mitigate impending mission aborts. However, this advantage will decrease if the sensor produces false alarms.

2. When selecting a component for entry in the CBM+ Process more than just a comparison of the mean times between the arrival of a diagnostic symptom until development of a mission abort are required. The variance of the mean time until mission abort given that a diagnostic symptom has occurred is equally important. A CBM+ sensor may be less effective if the time from when a DS is generated until it causes a mission abort has a high variance. This finding remains true for degraded levels of mean probability a DS is discovered, P_C . Data

concerning the time from when a DS is generated until component failure would be very informative in judging whether to include a component in the CBM+ process.

3. Whereas a component's CBM+ sensor doesn't need an extremely high probability of detection that a DS has occurred, it is extremely important that false positives be kept to extremely low levels. Otherwise, the advantage of continual inspection using sensors begins to work against the CBM+ Process. If a component whose CBM+ sensor provides a fair number of false positives (i.e. 5% of the missions result in a false positive) the time spent by maintenance personnel confirming that the DS was in fact a false positive quickly overshadows any gains in actual repair times.

To reiterate some factors to consider when considering introducing a component to the CBM+ process from Chapter 3:

1. How often does the component fail during active flight hours?

It is preferable to introduce a component that fails often versus components that rarely fail.

2. What are the consequences of a component failing?

It is preferable to introduce a component that possesses severe consequences for failure versus a component that is inconsequential in its failure.

3. What is the difficulty level of the inspection that would be alleviated by CBM+?

If an inspection is extremely difficult and resource intensive to perform, it would be preferable to have this inspection replaced by CBM+ versus an inspection that is simple and easy to perform.

4. Is a CBM+ sensor feasible for a component?

If measurements cannot be taken to assess the degradation of the component before it fails, i.e. no useful DS, then that component would not be a good CBM+ candidate. Furthermore, the time from when the occurrence of measurable evidence of impending failure until failure should be long enough to detect the impending failure and take maintenance action.

5. What is the reliability of the CBM+ sensor, the difficulty of inspecting the CBM+ sensor, and the effect of the CBM+ sensor on performance of the component being monitored? Is there a CBM+ sensor currently developed for a component? What is the cost of the sensor?

B. RECOMMENDATIONS FOR FUTURE STUDY

Models for the following random variables are selected as placeholders. Collection and analysis of data are needed to provide more appropriate models.

1. M_A : (time from when a DS occurs until it causes a mission abort) A Weibull distribution with a mean of 10 hours was selected. The distributional form is conjectural. Experiments need to be designed and conducted to collect data concerning the time from when a DS is generated by a component until the DS causes the component to fail. It is also important to collect data on the time from when a DS is generated until the sensor detects the DS.

2. R_0 : (initial repair time) An Exponential distribution with a mean of 3 hours was selected. This provided the initial mean repair time incurred upon a DS discovery.

3. R_1 : (subsequent fixed repair time) A fixed value of 3 hours was chosen. This provided for an additional repair time if the DS was not discovered after the first mission in which it arrived. This value was only applied once. For example, R_1 was the same if the DS was discovered after the second mission it appeared or the tenth mission after it appeared.

4. A_0 : (initial repair time resulting from a mission abort) An Exponential distribution with a mean of 5 hours was selected. This provided mean repair time incurred upon a mission abort.

5. A_1 : (subsequent fixed repair time resulting from a mission abort) A fixed value of 5 hours was chosen. This provided for an additional repair time if the DS that caused the mission abort was not discovered after the first mission in which it arrived. This value was only applied once. For example, A_1 was the same if the DS was discovered after the second mission it appeared or the tenth mission after it appeared.

It is also important to conduct a study of the reliability and maintainability of the CBM+ sensors. It is envisioned that CBM+ sensors will eliminate the need for scheduled inspection and maintenance. A sensor may be able to detect the occurrence of a DS; however, if the sensor is experiences failure often and is difficult to inspect and maintain, the effectiveness of the sensor

will be diminished. In addition it is important to study the ability of the logistics process to respond to the sensor measurements. If it takes a long time to analyze sensor measurements and/or obtain replacement components, then the attractiveness of introducing a component into CBM is lessened. The cost of the sensor also needs to be considered.

EXHIBIT 2, APPENDIX A AH-64/UH-60 701C ENGINE DATA

SN	EI_SN	MODEL	Date	REP_NUM	CEN	LIFE	TSN	F_TYPE	FCODE	Failure	FAMILY	PREV_FC
GEE761067	9126370	MH-60K	5/17/2001	1	0	944	944	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	
GEE761067	8926194	MH-60K	2/19/2002	2	0	231	1178	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	537
GEE761067	9426547	MH-60L	1/8/2003	3	0	246	1426	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	537
GEE761067	9026285	MH-60L	3/9/2004	4	0	285	1712	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	537
GEE761067	9026285	MH-60L	8/5/2005	4	0	372	2085	C1_REMOVAL	374	INTERNAL FAILURE	Assembly	537
GEE761158	9026295	UH-60L	10/11/2001	1	0	1873	1873	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	
GEE761158	9226426	UH-60L	9/26/2002	2	0	256	2129	C1_REMOVAL	374	INTERNAL FAILURE	Assembly	537
GEE761158	8900227	AH-64A	3/15/2003	3	0	245	2374	C1_REMOVAL	585	SHEARED	Op/FOD	374
GEE761158	9626689	UH-60L	9/10/2003	4	1	1034	2376	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	585
GEE761259	9126329	UH-60L	2/14/2001	1	0	1573	1573	C1_REMOVAL	790	OUT OF ADJUSTMT,OUT	Tol/Bal	
GEE761259	8900235	AH-64A	3/11/2003	2	0	412	1986	C1_REMOVAL	372	METAL ON MAGNETIC		790
GEE761259		UNKNOWN	2/10/2004	3	0	249	2235	C3C2ACT	20	WORN EXCESSIVELY	Rem	372
GEE761259	9000482	AH-64A	9/15/2004	4	1	339.8	2349	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	0
GEE761705	9705043	AH-64D	2/22/2002	1	0	1729	1729	C1_REMOVAL	705	BEYOND SPECIFIED	Tol/Bal	
GEE761705		UNKNOWN	11/29/2003	2	0	254	1988	C3C2ACT	181	LOW COMPRESSION	Rem	705
GEE761705		UNKNOWN	8/19/2004	3	0	97	2085	C3C2ACT	855	HEAT DAMAGE	Rem	0
GEE761705	5201	AH-64D	8/19/2004	4	1	305.8	2085	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	0
GEE761735	9000294	AH-64A	12/11/2001	1	0	1769	1769	C1_REMOVAL	374	INTERNAL FAILURE	Assembly	
GEE761735	9000294	AH-64A	7/18/2003	2	0	393	2163	C1_REMOVAL	329	STARTING STALL		374
GEE761735		UNKNOWN	2/4/2005	3	0	165	2330	C3C2ACT	230	DIRTY	Rem	329
GEE761735	9926829	UH-60L	2/8/2005	4	1	106.5	2330	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	0
GEE761745	9000306	AH-64A	10/24/2002	1	0	1812	1812	C1_REMOVAL	519	SURGED		
GEE761745		UNKNOWN	8/11/2003	2	0	106	1920	C3C2ACT	537	LOW POWER OR TORQUE	Rem	519
GEE761745		UNKNOWN	1/24/2004	3	0	125	2045	C3C2ACT	230	DIRTY	Rem	0
GEE761745	9326486	UH-60L	3/2/2004	4	0	5	2050	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	0
GEE761745	9326525	UH-60L	2/1/2005	4	0	284	2336	C1_REMOVAL	374	INTERNAL FAILURE	Assembly	537
GEE761745	9626678	UH-60L	9/10/2005	4	1	136.5	2340	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	374
GEE761816	9126373	MH-60K	9/6/2002	1	0	2055	2055	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	
GEE761816	9026293	UH-60L	5/22/2003	2	0	129	2184	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	537
GEE761816	9126363	MH-60L	11/24/2003	3	0	144	2329	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	537
GEE761816	9126360	MH-60L	6/5/2004	4	0	61	2390	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	537
GEE761816	8926184	MH-60L	5/9/2005	4	0	236	2626	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	537
GEE761816	8926184	MH-60L	6/8/2005	4	1	118.7	2626	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	537
GEE762055	9126379	MH-60K	4/22/2002	1	0	2027	2027	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	
GEE762055	9126379	MH-60K	3/24/2003	2	0	239	2267	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	537
GEE762055		UNKNOWN	9/17/2005	3	0	329	2841	C3C2ACT	537	LOW POWER OR TORQUE	Rem	537
GEE762055	305400	AH-64D	1/3/2006	4	1	2838.9	2841	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	0
GEE762287		UNKNOWN	1/8/2001	1	0	1379	1379	C3C2ACT	537	LOW POWER OR TORQUE	Rem	
GEE762287	9826825	UH-60L	8/20/2002	2	0	487	1866	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	0
GEE762287	8926182	UH-60L	9/10/2003	3	0	172	2042	C1_REMOVAL	180	CLOGGED		537
GEE762287	9026294	UH-60L	5/12/2004	4	0	223	2265	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	180
GEE762287	UNKN@L2	UNKNOWN	1/4/2005	4	1	250.6	2267	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	537
GEE762385	9326503	UH-60L	9/25/2002	1	0	1549	1549	C1_REMOVAL	290	FAILS	HeaterBk	
GEE762385	9426583	UH-60L	2/2/2004	2	0	50	1599	C1_REMOVAL	70	BROKEN	Broken	290
GEE762385	9426558	UH-60L	2/18/2005	3	0	346	1945	C1_REMOVAL	307	OIL LEAK		70
GEE762385	9426587	UH-60L	7/27/2005	4	1	283.1	1945	INSTALLED	307	OIL LEAK		307
GEE762436		UNKNOWN	2/16/2001	1	0	1413	1413	C3C2ACT	381	LEAKING (LIQUID)	Rem	

GEE762436		UNKNOWN	10/11/2003	2	0	514	1927	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	0
GEE762436	305368	AH-64D	5/5/2005	3	0	102	2067	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	537
GEE762436	205319	AH-64D	5/17/2005	4	1	241.2	2067	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	537
GEE762440		UNKNOWN	11/13/2002	1	0	1488	1488	C3C2ACT	537	LOW POWER OR TORQUE	Rem	
GEE762440	9226452	UH-60L	10/28/2003	2	0	236	1724	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	0
GEE762440	205295	AH-64D	11/17/2004	3	0	251	1975	C1_REMOVAL	374	INTERNAL FAILURE	Assembly	537
GEE762440	9026250	UH-60L	11/28/2005	4	1	23.9	1978	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	374
GEE762523		UNKNOWN	12/9/2002	1	0	1432	1432	C3C2ACT	537	LOW POWER OR TORQUE	Rem	
GEE762523	9226452	UH-60L	6/6/2003	2	0	124	1556	C1_REMOVAL	181	LOW COMPRESSION	Debond	0
GEE762523	9626685	UH-60L	11/3/2004	3	0	352	1921	C1_REMOVAL	381	LEAKING (LIQUID)	AirLeak	181
GEE762523	9905114	AH-64D	9/15/2005	4	1	209.6	1926	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	381
GEE762606	9426561	UH-60L	9/9/2003	1	0	2115	2115	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	
GEE762606	9426561	UH-60L	12/9/2003	2	0	14	2129	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	537
GEE762606	9526597	UH-60L	3/1/2004	3	0	5	2134	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	537
GEE762606	9426552	UH-60L	7/13/2004	4	1	576.8	2136	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	537
GEE762993		UNKNOWN	11/22/2002	1	0	1082	1082	C3C2ACT	537	LOW POWER OR TORQUE	Rem	
GEE762993		UNKNOWN	10/23/2003	2	0	149	1230	C3C2ACT	181	LOW COMPRESSION	Rem	0
GEE762993	9705046	AH-64D	4/30/2004	3	0	135	1365	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	0
GEE762993	9705046	AH-64D	5/20/2004	4	1	1159.6	1486	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	537
GEE763028	9026269	UH-60L	2/2/2002	1	0	956	956	C1_REMOVAL	307	OIL LEAK		
GEE763028	9626674	UH-60L	10/26/2004	2	0	140	1096	C1_REMOVAL	315	RPM		307
GEE763028	9626682	UH-60L	12/27/2004	3	0	0	1096	C1_REMOVAL	381	LEAKING (LIQUID)	AirLeak	315
GEE763028	9626676	UH-60L	9/23/2005	4	0	374	1470	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	381
GEE763102	9705041	AH-64D	6/29/2005	1	0	0	0	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	
GEE763102	9705041	AH-64D	6/29/2005	2	0	1970	1970	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	537
GEE763102		UNKNOWN	9/11/2005	3	0	2	1972	C3C2ACT	537	LOW POWER OR TORQUE	Rem	537
GEE763102	305347	AH-64D	12/31/2005	4	1	0	1972	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	0
GEE763260	9826805	UH-60L	2/23/2001	1	0	696	696	C1_REMOVAL	374	INTERNAL FAILURE	Assembly	
GEE763260	9826805	UH-60L	2/21/2002	2	0	271	967	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	374
GEE763260	9826805	UH-60L	6/16/2003	3	0	499	1469	C1_REMOVAL	855	HEAT DAMAGE	HeaterBk	537
GEE763260	9426587	UH-60L	10/20/2003	4	0	171	1640	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	855
GEE763260	9605015	AH-64D	1/10/2005	4	1	573.5	1643	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	537
GEE763301	9826823	UH-60L	5/8/2003	1	0	983	983	C1_REMOVAL	290	FAILS	HeaterBk	
GEE763301	9826805	UH-60L	8/30/2003	2	0	163	1146	C1_REMOVAL	20	WORN EXCESSIVELY	Erosion	290
GEE763301	9826826	UH-60L	1/15/2004	3	0	134	1280	C1_REMOVAL	374	INTERNAL FAILURE	Assembly	20
GEE763301	9026294	UH-60L	5/27/2004	4	0	35	1318	C1_REMOVAL	105	LOOSE BOLTS, NUTS,	Assembly	374
GEE763301	8926182	UH-60L	12/30/2004	4	0	58	1376	C1_REMOVAL	381	LEAKING (LIQUID)	AirLeak	105
GEE763301	9526603	UH-60L	4/19/2005	4	1	115	1378	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	381
GEE763383	9426558	UH-60L	3/8/2003	1	0	742	742	C1_REMOVAL	537	LOW POWER OR TORQUE	Other	
GEE763383	9926830	UH-60L	8/25/2004	2	0	513	1255	C1_REMOVAL	513	STALLS, COMPRESSOR		537
GEE763383	9226448	UH-60L	11/16/2004	3	0	1	1256	C1_REMOVAL	513	STALLS, COMPRESSOR		513
GEE763383	9126332	UH-60L	8/10/2005	4	1	104.2	1259	INSTALLED	799	NO DEFECT-SERVICEABLE	NoDefect	513
GEE763401	9426575	UH-60L	12/1/2001	1	0	422	422	C1_REMOVAL	381	LEAKING (LIQUID)	AirLeak	
GEE763401	9426569	UH-60L	3/27/2003	2	0	266	689	C1_REMOVAL	381	LEAKING (LIQUID)	AirLeak	381
GEE763401	9426568	UH-60L	9/11/2003	3	0	3	692	C1_REMOVAL	381	LEAKING (LIQUID)	AirLeak	381
GEE763401	9426577	UH-60L	11/7/2003	4	0	4	696	C1_REMOVAL	307	OIL LEAK		381
GEE763401	9526649	UH-60L	7/14/2005	4	0	108	806	C1_REMOVAL	513	STALLS, COMPRESSOR		307

**EXHIBIT 2, APPENDIX B ESTIMATED INTENSITY FUNCTIONS USING ENGINES
WITH 3 OR MORE OBSERVED FAILURES**

The table and figure in this Appendix are taken from Professor Patricia A. Jacobs' "A Nonhomogeneous Poisson process model (NHPP) for engine data" written 27 March 2006.

Estimated intensity function for engines with at least 3 recorded failures			
Age interval		Number of failures (number of engines)	Estimated failure rate
0	500	2 (21)	0.00019
501	1000	10 (20)	0.001
1001	1500	19 (20)	0.0019
1501	2000	21 (18)	0.0023
2001	2500	16 (9)	0.0036
2501	3000	2 (2)	0.002

EXHIBIT 2, APPENDIX C ESTIMATION OF γ AND δ

Let $\{N(t); t \geq 0\}$ be a NHPP with mean value function $\Lambda(t) = \gamma t^\delta$ having intensity function $\lambda(t) = \gamma \delta t^{\delta-1}$. There are K systems. The k th system has n_k observed times of failure; the i th failure occurs at time t_{ik} . The k th system is observed for a time T_k . Maximum likelihood can be used to estimate the parameters.

The likelihood function is

$$L = \prod_{k=1}^K \prod_{i=1}^{n_k} \lambda(t_{ik}) \exp\{-\Lambda(T_k)\} \quad (\text{A1})$$

Taking logarithms results in the log likelihood

$$\ell(\gamma, \delta) = \ln(\gamma) \sum_{k=1}^K n_k + \ln(\delta) \sum_{k=1}^K n_k + (\delta - 1) \sum_{k=1}^K \sum_{i=1}^{n_k} t_{ik} - \gamma \sum_{k=1}^K T_k^\delta \quad (\text{A2})$$

Partial differentiation of the log-likelihood results in

$$\frac{\partial \ell(\gamma, \delta)}{\partial \gamma} = \frac{1}{\gamma} \sum_{k=1}^K n_k - \sum_{k=1}^K T_k^\delta \quad (\text{A3})$$

Setting the partial derivative equal to 0 and solving results in

$$\gamma = \frac{\sum_{k=1}^K n_k}{\sum_{k=1}^K T_k^\delta} \quad (\text{A4})$$

$$\begin{aligned}
\frac{\partial \ell(\gamma, \delta)}{\partial \delta} &= \frac{1}{\delta} \sum_{k=1}^K n_k + \sum_{k=1}^K \sum_{i=1}^{n_k} t_{ik} - \gamma \sum_{k=1}^K T_k^\delta \ln(T_k) \\
&= \frac{1}{\delta} \sum_{k=1}^K n_k + \sum_{k=1}^K \sum_{i=1}^{n_k} t_{ik} - \frac{\sum_{k=1}^K n_k}{\sum_{k=1}^K T_k^\delta} \sum_{k=1}^K T_k^\delta \ln(T_k)
\end{aligned} \tag{A5}$$

Setting the partial derivative equal to 0 results in an equation that can be solved numerically providing an estimate of δ and γ .

The second partial derivative of the log-likelihood result in

$$\frac{\partial^2 \ell}{\partial \delta \partial \gamma} = \sum_{k=1}^K T_k^\delta \ln(T_k) \tag{A6}$$

$$\frac{\partial^2 \ell}{\partial \gamma^2} = -\frac{1}{\gamma^2} \sum_{k=1}^K n_k \tag{A7}$$

$$\frac{\partial^2 \ell}{\partial \delta^2} = -\frac{1}{\delta^2} \sum_{k=1}^K n_k - \gamma \sum_{k=1}^K T_k^\delta [\ln(T_k)]^2 \tag{A8}$$

The second derivatives can be used to obtain estimates of the asymptotic variance of estimates of γ and δ using Fisher information evaluated at the parameter estimates. (Crowder, 1991)

EXHIBIT 2 APPENDIX D VISUAL BASIC FOR APPLICATIONS CODING

Sub CBM()

' CBM Macro

' Macro recorded 3/31/2006 by Stephen E. Gauthier

' Documentation: LT Jason Kratz (NPS student) provided exceptional
' assistance with this code by proofreading and finding many ways to
' improve upon it's processing speed.

'This keeps workbook from updating every iteration

Application.ScreenUpdating = False

With Application

.Calculation = xlManual

.MaxChange = 0.001

End With

ActiveWorkbook.PrecisionAsDisplayed = False

'This computes Theta L and sets number of missions to 1250

Sheets("Legacy Process").Select

NumberMissions = 1250

NewMissionLength = 0

Worksheets("Legacy Process").Range(Cells(8, 1), Cells(7 + NumberMissions,
1)).ClearContents

Dim ThreeJArray(9) As Double

Dim FourJArray(9) As Double

For j = 1 To 9

ThreeJArray(j) = Worksheets("Legacy Process").Cells(3, j)

FourJArray(j) = Worksheets("Legacy Process").Cells(4, j)

Next j

For i = 1 To NumberMissions

NewMissionLength = NewMissionLength + 4

For j = 1 To 5

```

If ThreeJArray(j) = 0 Then
    Worksheets("Legacy Process").Cells(7 + i, 1) = FourJArray(1)
End If

If ThreeJArray(j) > 0 Then
    multiplier = 0
    multiplier =
Application.WorksheetFunction.RoundDown(NewMissionLength / ThreeJArray(j), 0)
    Worksheets("Legacy Process").Cells(1, 1) = multiplier
End If

If NewMissionLength = multiplier * ThreeJArray(j) Then
    Worksheets("Legacy Process").Cells(7 + i, 1) = FourJArray(j)

ElseIf NewMissionLength - 1 = multiplier * ThreeJArray(j) Then
    Worksheets("Legacy Process").Cells(7 + i, 1) = FourJArray(j)

ElseIf NewMissionLength - 2 = multiplier * ThreeJArray(j) Then
    Worksheets("Legacy Process").Cells(7 + i, 1) = FourJArray(j)

ElseIf NewMissionLength - 3 = multiplier * ThreeJArray(j) Then
    Worksheets("Legacy Process").Cells(7 + i, 1) = FourJArray(j)
End If

Next j

Next i

'This clears Data Worksheet below Row 24 and left of and including Column 36
Worksheets("Data").Select
M = NumberMissions
N = 36
Worksheets("Data").Range(Cells(25, 1), Cells(24 + M, N)).ClearContents

'This sets the number of iterations to perform
Replications = Worksheets("RVs").Cells(1, 2)
For v = 1 To Replications
Calculate

```

```

'This clears N, M, R, and AS Columns of Legacy Process Worksheet
Sheets("Legacy Process").Select
N = 3
Worksheets("Legacy Process").Range(Cells(8, 12), Cells(7 + M, 11 +
N)).ClearContents
Worksheets("Legacy Process").Range(Cells(8, 24), Cells(7 + M, 23 +
N)).ClearContents
Worksheets("Legacy Process").Range(Cells(8, 35), Cells(7 + M, 34 +
N)).ClearContents
Worksheets("Legacy Process").Range(Cells(8, 46), Cells(7 + M, 45 +
N)).ClearContents

```

```

'This computes Sum of Dij and Rij for cases <= and > M
Sheets("Legacy Process").Select
NCount = 0
RTime = 0
N = 7
  For i = 1 To M
    If Worksheets("Legacy Process").Cells(7 + i, 4) > 0 Then
      NewNCount = 0
      NCount = 0
      NewNCount2 = 0
      NCount2 = 0
      NewNCount3 = 0
      NCount3 = 0
      NewNCount4 = 0
      NCount4 = 0
      NewRTime = 0
      RTime = 0
      NewRTime2 = 0
      RTime2 = 0
      NewASTime = 0
      ASTime = 0
      ASTime2 = 0
      NewASTime2 = 0
      temp2 = Worksheets("Legacy Process").Cells(7 + i, 2)
    End If
  Next i

```



```

For j = 1 To N
    temp4 = Worksheets("Legacy Process").Cells(7 + i, 4 + j)
    temp16 = Worksheets("Legacy Process").Cells(7 + i, 16 + j)
    temp27 = Worksheets("Legacy Process").Cells(7 + i, 27 + j)
    temp38 = Worksheets("Legacy Process").Cells(7 + i, 38 + j)

    If temp4 < temp16 Then
        If temp4 > 0 And temp2 + temp4 <= M + 1 Then
            NewNCount = 1
            NCount = NewNCount + NCount
        End If
        If temp4 > 0 And temp2 + temp4 > M + 1 Then
            NewNCount2 = 1
            NCount2 = NewNCount2 + NCount2
        End If
        If temp2 + temp4 <= NumberMissions + 1 Then
            NewRTime = temp27
            RTime = NewRTime + RTime
            NewASTime = temp38
            ASTime = NewASTime + ASTime
        End If
        If temp2 + temp4 > NumberMissions + 1 Then
            NewRTime2 = temp27
            RTime2 = NewRTime2 + RTime2
            NewASTime2 = temp38
            ASTime2 = NewASTime2 + ASTime2
        End If
    Else
        If temp16 > 0 And temp2 + temp16 <= M + 1 Then
            NewNCount3 = 1
            NCount3 = NewNCount3 + NCount3
        End If
        If temp16 > 0 And temp2 + temp16 > M + 1 Then
            NewNCount4 = 1
            NCount4 = NewNCount4 + NCount4
        End If
        If temp2 + temp16 <= NumberMissions + 1 Then

```

```

        NewRTime = temp27
        RTime = NewRTime + RTime
        NewASTime = temp38
        ASTime = NewASTime + ASTime
    End If
    If temp2 + temp16 > NumberMissions + 1 Then
        NewRTime2 = temp27
        RTime2 = NewRTime2 + RTime2
        NewASTime2 = temp38
        ASTime2 = NewASTime2 + ASTime2
    End If
End If

Next j

Worksheets("Legacy Process").Cells(7 + i, 12) = NCount
Worksheets("Legacy Process").Cells(7 + i, 13) = NCount2
Worksheets("Legacy Process").Cells(7 + i, 24) = NCount3
Worksheets("Legacy Process").Cells(7 + i, 25) = NCount4
Worksheets("Legacy Process").Cells(7 + i, 35) = RTime
Worksheets("Legacy Process").Cells(7 + i, 36) = RTime2
Worksheets("Legacy Process").Cells(7 + i, 46) = ASTime
Worksheets("Legacy Process").Cells(7 + i, 47) = ASTime2

End If
Worksheets("Legacy Process").Cells(7 + i, 14) = Worksheets("Legacy
Process").Cells(7 + i, 12) + Worksheets("Legacy Process").Cells(7 + i, 13)
Worksheets("Legacy Process").Cells(7 + i, 26) = Worksheets("Legacy
Process").Cells(7 + i, 24) + Worksheets("Legacy Process").Cells(7 + i, 25)
Worksheets("Legacy Process").Cells(7 + i, 37) = Worksheets("Legacy
Process").Cells(7 + i, 35) + Worksheets("Legacy Process").Cells(7 + i, 36)
Worksheets("Legacy Process").Cells(7 + i, 48) = Worksheets("Legacy
Process").Cells(7 + i, 46) + Worksheets("Legacy Process").Cells(7 + i, 47)
Next i

'This determines if there was an immediate Mission Abort
Sheets("RVs").Select

```

```

For i = 1 To M
    If Application.WorksheetFunction.CountIf(Range(Cells(4 + i, 6), Cells(4
+ i, 12))), "= 1") >= 1 Then
        Sheets("Legacy Process").Select
        Worksheets("Legacy Process").Cells(7 + i, 16) = 1
        Sheets("RVs").Select
    Else
        Worksheets("Legacy Process").Cells(7 + i, 16) = 0
    End If
Next i

```

```

'This produces the summed outputs for the Legacy Spreadsheet
Sheets("Legacy Process").Select
Worksheets("Legacy Process").Cells(1, 15) =
Application.WorksheetFunction.Sum(Range(Cells(8, 12), Cells(7 + M, 12)))
Worksheets("Legacy Process").Cells(2, 15) =
Application.WorksheetFunction.Sum(Range(Cells(8, 13), Cells(7 + M, 13)))
Worksheets("Legacy Process").Cells(3, 15) =
Application.WorksheetFunction.Sum(Range(Cells(8, 14), Cells(7 + M, 14)))
Worksheets("Legacy Process").Cells(4, 15) =
Application.WorksheetFunction.Sum(Range(Cells(8, 24), Cells(7 + M, 24)))
Worksheets("Legacy Process").Cells(5, 15) =
Application.WorksheetFunction.Sum(Range(Cells(8, 25), Cells(7 + M, 25)))
Worksheets("Legacy Process").Cells(6, 15) =
Application.WorksheetFunction.Sum(Range(Cells(8, 26), Cells(7 + M, 26)))
Worksheets("Legacy Process").Cells(1, 18) =
Application.WorksheetFunction.Sum(Range(Cells(8, 35), Cells(7 + M, 35)))
Worksheets("Legacy Process").Cells(2, 18) =
Application.WorksheetFunction.Sum(Range(Cells(8, 36), Cells(7 + M, 36)))
Worksheets("Legacy Process").Cells(3, 18) =
Application.WorksheetFunction.Sum(Range(Cells(8, 37), Cells(7 + M, 37)))
Worksheets("Legacy Process").Cells(4, 18) =
Application.WorksheetFunction.Sum(Range(Cells(8, 46), Cells(7 + M, 46)))
Worksheets("Legacy Process").Cells(5, 18) =
Application.WorksheetFunction.Sum(Range(Cells(8, 47), Cells(7 + M, 47)))
Worksheets("Legacy Process").Cells(6, 18) =
Application.WorksheetFunction.Sum(Range(Cells(8, 48), Cells(7 + M, 48)))

```

```

'This clears Summed D, M, R, and AS Columns of CBM+ Process Worksheet
Sheets("CBM+ Process").Select
N = 3
Worksheets("CBM+ Process").Range(Cells(8, 12), Cells(7 + M, 11 +
N)).ClearContents
Worksheets("CBM+ Process").Range(Cells(8, 24), Cells(7 + M, 23 +
N)).ClearContents
Worksheets("CBM+ Process").Range(Cells(8, 35), Cells(7 + M, 34 +
N)).ClearContents
Worksheets("CBM+ Process").Range(Cells(8, 46), Cells(7 + M, 45 +
N)).ClearContents

```

```

'This computes Sum of Dij and Sum of Rij for cases <= and > M
Sheets("CBM+ Process").Select
NCount = 0
M = NumberMissions
N = 7

```

```

For i = 1 To M
  If Worksheets("CBM+ Process").Cells(7 + i, 4) > 0 Then
    NewNCount = 0
    NCount = 0
    NewNCount2 = 0
    NCount2 = 0
    NewNCount3 = 0
    NCount3 = 0
    NewNCount4 = 0
    NCount4 = 0
    NewRTime = 0
    RTime = 0
    NewRTime2 = 0
    RTime2 = 0
    NewASTime = 0
    ASTime = 0
    ASTime2 = 0
    NewASTime2 = 0
  End If
End For

```

```
temp2 = Worksheets("CBM+ Process").Cells(7 + i, 2)
```

```
For j = 1 To N
```

```
temp4 = Worksheets("CBM+ Process").Cells(7 + i, 4 + j)
```

```
temp16 = Worksheets("CBM+ Process").Cells(7 + i, 16 + j)
```

```
temp27 = Worksheets("CBM+ Process").Cells(7 + i, 27 + j)
```

```
temp38 = Worksheets("CBM+ Process").Cells(7 + i, 38 + j)
```

```
If temp4 < temp16 Then
```

```
    If temp4 > 0 And temp2 + temp4 <= M + 1 Then
```

```
        NewNCount = 1
```

```
        NCount = NewNCount + NCount
```

```
    End If
```

```
    If temp4 > 0 And temp2 + temp4 > M + 1 Then
```

```
        NewNCount2 = 1
```

```
        NCount2 = NewNCount2 + NCount2
```

```
    End If
```

```
    If temp2 + temp4 <= NumberMissions + 1 Then
```

```
        NewRTime = temp27
```

```
        RTime = NewRTime + RTime
```

```
        NewASTime = temp38
```

```
        ASTime = NewASTime + ASTime
```

```
    End If
```

```
    If temp2 + temp4 > NumberMissions + 1 Then
```

```
        NewRTime2 = temp27
```

```
        RTime2 = NewRTime2 + RTime2
```

```
        NewASTime2 = temp38
```

```
        ASTime2 = NewASTime2 + ASTime2
```

```
    End If
```

```
Else
```

```
    If temp16 > 0 And temp2 + temp16 <= M + 1 Then
```

```
        NewNCount3 = 1
```

```
        NCount3 = NewNCount3 + NCount3
```

```
    End If
```

```
    If temp16 > 0 And temp2 + temp16 > M + 1 Then
```

```
        NewNCount4 = 1
```

```
        NCount4 = NewNCount4 + NCount4
```

```
    End If
```

```
If temp2 + temp16 <= NumberMissions + 1 Then
```

```
    NewRTime = temp27
```

```
    RTime = NewRTime + RTime
```

```
    NewASTime = temp38
```

```
    ASTime = NewASTime + ASTime
```

```
End If
```

```
If temp2 + temp16 > NumberMissions + 1 Then
```

```
    NewRTime2 = temp27
```

```
    RTime2 = NewRTime2 + RTime2
```

```
    NewASTime2 = temp38
```

```
    ASTime2 = NewASTime2 + ASTime2
```

```
End If
```

```
End If
```

```
Next j
```

```
Worksheets("CBM+ Process").Cells(7 + i, 12) = NCount
```

```
Worksheets("CBM+ Process").Cells(7 + i, 13) = NCount2
```

```
Worksheets("CBM+ Process").Cells(7 + i, 24) = NCount3
```

```
Worksheets("CBM+ Process").Cells(7 + i, 25) = NCount4
```

```
Worksheets("CBM+ Process").Cells(7 + i, 35) = RTime
```

```
Worksheets("CBM+ Process").Cells(7 + i, 36) = RTime2
```

```
Worksheets("CBM+ Process").Cells(7 + i, 46) = ASTime
```

```
Worksheets("CBM+ Process").Cells(7 + i, 47) = ASTime2
```

```
End If
```

```
Worksheets("CBM+ Process").Cells(7 + i, 14) = Worksheets("CBM+  
Process").Cells(7 + i, 12) + Worksheets("CBM+ Process").Cells(7 + i, 13)
```

```
Worksheets("CBM+ Process").Cells(7 + i, 26) = Worksheets("CBM+  
Process").Cells(7 + i, 24) + Worksheets("CBM+ Process").Cells(7 + i, 25)
```

```
Worksheets("CBM+ Process").Cells(7 + i, 37) = Worksheets("CBM+  
Process").Cells(7 + i, 35) + Worksheets("CBM+ Process").Cells(7 + i, 36)
```

```
Worksheets("CBM+ Process").Cells(7 + i, 48) = Worksheets("CBM+  
Process").Cells(7 + i, 46) + Worksheets("CBM+ Process").Cells(7 + i, 47)
```

```
Worksheets("CBM+ Process").Cells(7 + i, 52) = Worksheets("CBM+  
Process").Cells(7 + i, 37) + Worksheets("CBM+ Process").Cells(7 + i, 51)
```

```
Next i
```

```
'This determines if there was an immediate Mission Abort  
Sheets("RVs").Select
```

```
For i = 1 To M  
    If Application.WorksheetFunction.CountIf(Range(Cells(4 + i, 6), Cells(4  
+ i, 12))), "= 1") >= 1 Then  
        Sheets("CBM+ Process").Select  
        Worksheets("CBM+ Process").Cells(7 + i, 16) = 1  
        Sheets("RVs").Select  
    Else  
        Worksheets("CBM+ Process").Cells(7 + i, 16) = 0  
    End If  
Next i
```

```
'This produces the summed outputs for the CBM+ Spreadsheet  
Sheets("CBM+ Process").Select
```

```
Worksheets("CBM+ Process").Cells(1, 15) =  
Application.WorksheetFunction.Sum(Range(Cells(8, 12), Cells(7 + M, 12)))  
Worksheets("CBM+ Process").Cells(2, 15) =  
Application.WorksheetFunction.Sum(Range(Cells(8, 13), Cells(7 + M, 13)))  
Worksheets("CBM+ Process").Cells(3, 15) =  
Application.WorksheetFunction.Sum(Range(Cells(8, 14), Cells(7 + M, 14)))  
Worksheets("CBM+ Process").Cells(4, 15) =  
Application.WorksheetFunction.Sum(Range(Cells(8, 24), Cells(7 + M, 24)))  
Worksheets("CBM+ Process").Cells(5, 15) =  
Application.WorksheetFunction.Sum(Range(Cells(8, 25), Cells(7 + M, 25)))  
Worksheets("CBM+ Process").Cells(6, 15) =  
Application.WorksheetFunction.Sum(Range(Cells(8, 26), Cells(7 + M, 26)))  
Worksheets("CBM+ Process").Cells(1, 18) =  
Application.WorksheetFunction.Sum(Range(Cells(8, 35), Cells(7 + M, 35)))  
Worksheets("CBM+ Process").Cells(2, 18) =  
Application.WorksheetFunction.Sum(Range(Cells(8, 36), Cells(7 + M, 36)))  
Worksheets("CBM+ Process").Cells(3, 18) =  
Application.WorksheetFunction.Sum(Range(Cells(8, 37), Cells(7 + M, 37)))  
Worksheets("CBM+ Process").Cells(4, 18) =  
Application.WorksheetFunction.Sum(Range(Cells(8, 46), Cells(7 + M, 46)))
```

```

Worksheets("CBM+ Process").Cells(5, 18) =
Application.WorksheetFunction.Sum(Range(Cells(8, 47), Cells(7 + M, 47)))
Worksheets("CBM+ Process").Cells(6, 18) =
Application.WorksheetFunction.Sum(Range(Cells(8, 48), Cells(7 + M, 48)))
Worksheets("CBM+ Process").Cells(1, 21) =
Application.WorksheetFunction.Sum(Range(Cells(8, 50), Cells(7 + M, 50)))
Worksheets("CBM+ Process").Cells(2, 21) =
Application.WorksheetFunction.Sum(Range(Cells(8, 51), Cells(7 + M, 51)))
Worksheets("CBM+ Process").Cells(3, 21) =
Application.WorksheetFunction.Sum(Range(Cells(8, 52), Cells(7 + M, 52)))

```

```

'This transposes data onto Data Worksheet
Sheets("Legacy Process").Select
Range(Cells(1, 15), Cells(6, 15)).Select
Selection.Copy
Sheets("Data").Select
Range(Cells(24 + v, 1), Cells(24 + v, 6)).Select
Selection.PasteSpecial Paste:=xlPasteAll, Operation:=xlNone, SkipBlanks:= _
    False, Transpose:=True

```

```

Sheets("Legacy Process").Select
Range(Cells(1, 18), Cells(6, 18)).Select
Selection.Copy
Sheets("Data").Select
Range(Cells(24 + v, 7), Cells(24 + v, 12)).Select
Selection.PasteSpecial Paste:=xlPasteAll, Operation:=xlNone, SkipBlanks:= _
    False, Transpose:=True

```

```

'This transposes data onto Data Worksheet
Sheets("CBM+ Process").Select
Range(Cells(1, 15), Cells(6, 15)).Select
Selection.Copy
Sheets("Data").Select
Range(Cells(24 + v, 22), Cells(24 + v, 27)).Select
Selection.PasteSpecial Paste:=xlPasteAll, Operation:=xlNone, SkipBlanks:= _
    False, Transpose:=True

```

```

Sheets("CBM+ Process").Select

```



```
Range(Cells(1, 18), Cells(6, 18)).Select
Selection.Copy
Sheets("Data").Select
Range(Cells(24 + v, 28), Cells(24 + v, 33)).Select
Selection.PasteSpecial Paste:=xlPasteAll, Operation:=xlNone, SkipBlanks:= _
    False, Transpose:=True
```

```
Sheets("CBM+ Process").Select
Range(Cells(1, 21), Cells(3, 21)).Select
Selection.Copy
Sheets("Data").Select
Range(Cells(24 + v, 34), Cells(24 + v, 36)).Select
Selection.PasteSpecial Paste:=xlPasteAll, Operation:=xlNone, SkipBlanks:= _
    False, Transpose:=True
```

Next v

'This determines means and CIs

```
Sheets("Data").Select
Worksheets("Data").Cells(2, 3) =
Application.WorksheetFunction.Average(Range(Cells(25, 1), Cells(24 + v, 1)))
Worksheets("Data").Cells(3, 3) =
Application.WorksheetFunction.Average(Range(Cells(25, 2), Cells(24 + v, 2)))
Worksheets("Data").Cells(4, 3) =
Application.WorksheetFunction.Average(Range(Cells(25, 3), Cells(24 + v, 3)))
Worksheets("Data").Cells(5, 3) =
Application.WorksheetFunction.Average(Range(Cells(25, 4), Cells(24 + v, 4)))
Worksheets("Data").Cells(6, 3) =
Application.WorksheetFunction.Average(Range(Cells(25, 5), Cells(24 + v, 5)))
Worksheets("Data").Cells(7, 3) =
Application.WorksheetFunction.Average(Range(Cells(25, 6), Cells(24 + v, 6)))
Worksheets("Data").Cells(8, 3) =
Application.WorksheetFunction.Average(Range(Cells(25, 7), Cells(24 + v, 7)))
Worksheets("Data").Cells(9, 3) =
Application.WorksheetFunction.Average(Range(Cells(25, 8), Cells(24 + v, 8)))
Worksheets("Data").Cells(10, 3) =
Application.WorksheetFunction.Average(Range(Cells(25, 9), Cells(24 + v, 9)))
```

```

Worksheets("Data").Cells(11, 3) =
Application.WorksheetFunction.Average(Range(Cells(25, 10), Cells(24 + v,
10)))
Worksheets("Data").Cells(12, 3) =
Application.WorksheetFunction.Average(Range(Cells(25, 11), Cells(24 + v,
11)))
Worksheets("Data").Cells(13, 3) =
Application.WorksheetFunction.Average(Range(Cells(25, 12), Cells(24 + v,
12)))

Worksheets("Data").Cells(2, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 22), Cells(24 + v,
22)))
Worksheets("Data").Cells(3, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 23), Cells(24 + v,
23)))
Worksheets("Data").Cells(4, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 24), Cells(24 + v,
24)))
Worksheets("Data").Cells(5, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 25), Cells(24 + v,
25)))
Worksheets("Data").Cells(6, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 26), Cells(24 + v,
26)))
Worksheets("Data").Cells(7, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 27), Cells(24 + v,
27)))
Worksheets("Data").Cells(8, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 28), Cells(24 + v,
28)))
Worksheets("Data").Cells(9, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 29), Cells(24 + v,
29)))
Worksheets("Data").Cells(10, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 30), Cells(24 + v,
30)))

```

```

Worksheets("Data").Cells(11, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 31), Cells(24 + v,
31)))
Worksheets("Data").Cells(12, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 32), Cells(24 + v,
32)))
Worksheets("Data").Cells(13, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 33), Cells(24 + v,
33)))
Worksheets("Data").Cells(14, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 34), Cells(24 + v,
34)))
Worksheets("Data").Cells(15, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 35), Cells(24 + v,
35)))
Worksheets("Data").Cells(16, 11) =
Application.WorksheetFunction.Average(Range(Cells(25, 36), Cells(24 + v,
36)))

```

```

If Worksheets("Data").Cells(2, 3) > 0 Then
    Worksheets("Data").Cells(2, 5) =
Application.WorksheetFunction.StDev(Range(Cells(25, 1), Cells(24 + v, 1)))
    Else: Worksheets("Data").Cells(2, 5) = 0
End If

```

```

If Worksheets("Data").Cells(3, 3) > 0 Then
    Worksheets("Data").Cells(3, 5) =
Application.WorksheetFunction.StDev(Range(Cells(25, 2), Cells(24 + v, 2)))
    Else: Worksheets("Data").Cells(3, 5) = 0
End If

```

```

If Worksheets("Data").Cells(4, 3) > 0 Then
    Worksheets("Data").Cells(4, 5) =
Application.WorksheetFunction.StDev(Range(Cells(25, 3), Cells(24 + v, 3)))
    Else: Worksheets("Data").Cells(4, 5) = 0
End If

```

```
If Worksheets("Data").Cells(5, 3) > 0 Then
    Worksheets("Data").Cells(5, 5) =
Application.WorksheetFunction.StDev(Range(Cells(25, 4), Cells(24 + v, 4)))
    Else: Worksheets("Data").Cells(5, 5) = 0
End If
```

```
If Worksheets("Data").Cells(6, 3) > 0 Then
    Worksheets("Data").Cells(6, 5) =
Application.WorksheetFunction.StDev(Range(Cells(25, 5), Cells(24 + v, 5)))
    Else: Worksheets("Data").Cells(6, 5) = 0
End If
```

```
If Worksheets("Data").Cells(7, 3) > 0 Then
    Worksheets("Data").Cells(7, 5) =
Application.WorksheetFunction.StDev(Range(Cells(25, 6), Cells(24 + v, 6)))
    Else: Worksheets("Data").Cells(7, 5) = 0
End If
```

```
If Worksheets("Data").Cells(8, 3) > 0 Then
    Worksheets("Data").Cells(8, 5) =
Application.WorksheetFunction.StDev(Range(Cells(25, 7), Cells(24 + v, 7)))
    Else: Worksheets("Data").Cells(8, 5) = 0
End If
```

```
If Worksheets("Data").Cells(9, 3) > 0 Then
    Worksheets("Data").Cells(9, 5) =
Application.WorksheetFunction.StDev(Range(Cells(25, 8), Cells(24 + v, 8)))
    Else: Worksheets("Data").Cells(9, 5) = 0
End If
```

```
If Worksheets("Data").Cells(10, 3) > 0 Then
    Worksheets("Data").Cells(10, 5) =
Application.WorksheetFunction.StDev(Range(Cells(25, 9), Cells(24 + v, 9)))
    Else: Worksheets("Data").Cells(10, 5) = 0
End If
```

```
If Worksheets("Data").Cells(11, 3) > 0 Then
```

```

Worksheets("Data").Cells(11, 5) =
Application.WorksheetFunction.StDev(Range(Cells(25, 10), Cells(24 + v, 10)))
Else: Worksheets("Data").Cells(11, 5) = 0
End If

If Worksheets("Data").Cells(12, 3) > 0 Then
Worksheets("Data").Cells(12, 5) =
Application.WorksheetFunction.StDev(Range(Cells(25, 11), Cells(24 + v, 11)))
Else: Worksheets("Data").Cells(12, 5) = 0
End If

If Worksheets("Data").Cells(13, 3) > 0 Then
Worksheets("Data").Cells(13, 5) =
Application.WorksheetFunction.StDev(Range(Cells(25, 12), Cells(24 + v, 12)))
Else: Worksheets("Data").Cells(13, 5) = 0
End If

If Worksheets("Data").Cells(2, 11) > 0 Then
Worksheets("Data").Cells(2, 13) =
Application.WorksheetFunction.StDev(Range(Cells(25, 22), Cells(24 + v, 22)))
Else: Worksheets("Data").Cells(2, 13) = 0
End If

If Worksheets("Data").Cells(3, 11) > 0 Then
Worksheets("Data").Cells(3, 13) =
Application.WorksheetFunction.StDev(Range(Cells(25, 23), Cells(24 + v, 23)))
Else: Worksheets("Data").Cells(3, 13) = 0
End If

If Worksheets("Data").Cells(4, 11) > 0 Then
Worksheets("Data").Cells(4, 13) =
Application.WorksheetFunction.StDev(Range(Cells(25, 24), Cells(24 + v, 24)))
Else: Worksheets("Data").Cells(4, 13) = 0
End If

If Worksheets("Data").Cells(5, 11) > 0 Then

```

```
Worksheets("Data").Cells(5, 13) =  
Application.WorksheetFunction.StDev(Range(Cells(25, 25), Cells(24 + v, 25)))  
Else: Worksheets("Data").Cells(5, 13) = 0  
End If
```

```
If Worksheets("Data").Cells(6, 11) > 0 Then  
Worksheets("Data").Cells(6, 13) =  
Application.WorksheetFunction.StDev(Range(Cells(25, 26), Cells(24 + v, 26)))  
Else: Worksheets("Data").Cells(6, 13) = 0  
End If
```

```
If Worksheets("Data").Cells(7, 11) > 0 Then  
Worksheets("Data").Cells(7, 13) =  
Application.WorksheetFunction.StDev(Range(Cells(25, 27), Cells(24 + v, 27)))  
Else: Worksheets("Data").Cells(7, 13) = 0  
End If
```

```
If Worksheets("Data").Cells(8, 11) > 0 Then  
Worksheets("Data").Cells(8, 13) =  
Application.WorksheetFunction.StDev(Range(Cells(25, 28), Cells(24 + v, 28)))  
Else: Worksheets("Data").Cells(8, 13) = 0  
End If
```

```
If Worksheets("Data").Cells(9, 11) > 0 Then  
Worksheets("Data").Cells(9, 13) =  
Application.WorksheetFunction.StDev(Range(Cells(25, 29), Cells(24 + v, 29)))  
Else: Worksheets("Data").Cells(9, 13) = 0  
End If
```

```
If Worksheets("Data").Cells(10, 11) > 0 Then  
Worksheets("Data").Cells(10, 13) =  
Application.WorksheetFunction.StDev(Range(Cells(25, 30), Cells(24 + v, 30)))  
Else: Worksheets("Data").Cells(10, 13) = 0  
End If
```

```
If Worksheets("Data").Cells(11, 11) > 0 Then  
Worksheets("Data").Cells(11, 13) =  
Application.WorksheetFunction.StDev(Range(Cells(25, 31), Cells(24 + v, 31)))
```

```

        Else: Worksheets("Data").Cells(11, 13) = 0
    End If

    If Worksheets("Data").Cells(12, 11) > 0 Then
        Worksheets("Data").Cells(12, 13) =
    Application.WorksheetFunction.StDev(Range(Cells(25, 32), Cells(24 + v, 32)))
        Else: Worksheets("Data").Cells(12, 13) = 0
    End If

    If Worksheets("Data").Cells(13, 11) > 0 Then
        Worksheets("Data").Cells(13, 13) =
    Application.WorksheetFunction.StDev(Range(Cells(25, 33), Cells(24 + v, 33)))
        Else: Worksheets("Data").Cells(13, 13) = 0
    End If

    If Worksheets("Data").Cells(14, 11) > 0 Then
        Worksheets("Data").Cells(14, 13) =
    Application.WorksheetFunction.StDev(Range(Cells(25, 34), Cells(24 + v, 34)))
        Else: Worksheets("Data").Cells(14, 13) = 0
    End If

    If Worksheets("Data").Cells(15, 11) > 0 Then
        Worksheets("Data").Cells(15, 13) =
    Application.WorksheetFunction.StDev(Range(Cells(25, 35), Cells(24 + v, 35)))
        Else: Worksheets("Data").Cells(15, 13) = 0
    End If

    If Worksheets("Data").Cells(16, 11) > 0 Then
        Worksheets("Data").Cells(16, 13) =
    Application.WorksheetFunction.StDev(Range(Cells(25, 36), Cells(24 + v, 36)))
        Else: Worksheets("Data").Cells(16, 13) = 0
    End If

    If Worksheets("Data").Cells(2, 5) > 0 Then
        Worksheets("Data").Cells(2, 7) =
    Application.WorksheetFunction.Max(Worksheets("Data").Cells(2, 3) -
    Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(2,
    5), (v - 1)), 0)

```

```
Worksheets("Data").Cells(2, 8) = Worksheets("Data").Cells(2, 3) +  
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(2,  
5), v - 1)  
Else  
Worksheets("Data").Cells(2, 7) = 0  
Worksheets("Data").Cells(2, 8) = 0  
End If
```

```
If Worksheets("Data").Cells(3, 5) > 0 Then  
Worksheets("Data").Cells(3, 7) =  
Application.WorksheetFunction.Max(Worksheets("Data").Cells(3, 3) -  
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(3,  
5), (v - 1)), 0)  
Worksheets("Data").Cells(3, 8) = Worksheets("Data").Cells(3, 3) +  
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(3,  
5), v - 1)  
Else  
Worksheets("Data").Cells(3, 7) = 0  
Worksheets("Data").Cells(3, 8) = 0  
End If
```

```
If Worksheets("Data").Cells(4, 5) > 0 Then  
Worksheets("Data").Cells(4, 7) =  
Application.WorksheetFunction.Max(Worksheets("Data").Cells(4, 3) -  
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(4,  
5), (v - 1)), 0)  
Worksheets("Data").Cells(4, 8) = Worksheets("Data").Cells(4, 3) +  
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(4,  
5), v - 1)  
Else  
Worksheets("Data").Cells(4, 7) = 0  
Worksheets("Data").Cells(4, 8) = 0  
End If
```

```
If Worksheets("Data").Cells(5, 5) > 0 Then  
Worksheets("Data").Cells(5, 7) =  
Application.WorksheetFunction.Max(Worksheets("Data").Cells(5, 3) -
```



```
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(5, 5), (v - 1)), 0)
```

```
Worksheets("Data").Cells(5, 8) = Worksheets("Data").Cells(5, 3) +  
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(5, 5), v - 1)
```

```
Else
```

```
Worksheets("Data").Cells(5, 7) = 0
```

```
Worksheets("Data").Cells(5, 8) = 0
```

```
End If
```

```
If Worksheets("Data").Cells(6, 5) > 0 Then
```

```
Worksheets("Data").Cells(6, 7) =
```

```
Application.WorksheetFunction.Max(Worksheets("Data").Cells(6, 3) -  
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(6, 5), (v - 1)), 0)
```

```
Worksheets("Data").Cells(6, 8) = Worksheets("Data").Cells(6, 3) +  
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(6, 5), v - 1)
```

```
Else
```

```
Worksheets("Data").Cells(6, 7) = 0
```

```
Worksheets("Data").Cells(6, 8) = 0
```

```
End If
```

```
If Worksheets("Data").Cells(7, 5) > 0 Then
```

```
Worksheets("Data").Cells(7, 7) =
```

```
Application.WorksheetFunction.Max(Worksheets("Data").Cells(7, 3) -  
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(7, 5), (v - 1)), 0)
```

```
Worksheets("Data").Cells(7, 8) = Worksheets("Data").Cells(7, 3) +  
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(7, 5), v - 1)
```

```
Else
```

```
Worksheets("Data").Cells(7, 7) = 0
```

```
Worksheets("Data").Cells(7, 8) = 0
```

```
End If
```

```
If Worksheets("Data").Cells(8, 5) > 0 Then
```

```

Worksheets("Data").Cells(8, 7) =
Application.WorksheetFunction.Max(Worksheets("Data").Cells(8, 3) -
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(8,
5), (v - 1)), 0)
Worksheets("Data").Cells(8, 8) = Worksheets("Data").Cells(8, 3) +
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(8,
5), v - 1)
Else
Worksheets("Data").Cells(8, 7) = 0
Worksheets("Data").Cells(8, 8) = 0
End If

```

```

If Worksheets("Data").Cells(9, 5) > 0 Then
Worksheets("Data").Cells(9, 7) =
Application.WorksheetFunction.Max(Worksheets("Data").Cells(9, 3) -
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(9,
5), (v - 1)), 0)
Worksheets("Data").Cells(9, 8) = Worksheets("Data").Cells(9, 3) +
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(9,
5), v - 1)
Else
Worksheets("Data").Cells(9, 7) = 0
Worksheets("Data").Cells(9, 8) = 0
End If

```

```

If Worksheets("Data").Cells(10, 5) > 0 Then
Worksheets("Data").Cells(10, 7) =
Application.WorksheetFunction.Max(Worksheets("Data").Cells(10, 3) -
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(10,
5), (v - 1)), 0)
Worksheets("Data").Cells(10, 8) = Worksheets("Data").Cells(10, 3) +
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(10,
5), v - 1)
Else
Worksheets("Data").Cells(10, 7) = 0
Worksheets("Data").Cells(10, 8) = 0
End If

```

```

If Worksheets("Data").Cells(11, 5) > 0 Then
    Worksheets("Data").Cells(11, 7) =
Application.WorksheetFunction.Max(Worksheets("Data").Cells(11, 3) -
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(11,
5), (v - 1)), 0)
    Worksheets("Data").Cells(11, 8) = Worksheets("Data").Cells(11, 3) +
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(11,
5), v - 1)
    Else
        Worksheets("Data").Cells(11, 7) = 0
        Worksheets("Data").Cells(11, 8) = 0
End If

```

```

If Worksheets("Data").Cells(12, 5) > 0 Then
    Worksheets("Data").Cells(12, 7) =
Application.WorksheetFunction.Max(Worksheets("Data").Cells(12, 3) -
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(12,
5), (v - 1)), 0)
    Worksheets("Data").Cells(12, 8) = Worksheets("Data").Cells(12, 3) +
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(12,
5), v - 1)
    Else
        Worksheets("Data").Cells(12, 7) = 0
        Worksheets("Data").Cells(12, 8) = 0
End If

```

```

If Worksheets("Data").Cells(13, 5) > 0 Then
    Worksheets("Data").Cells(13, 7) =
Application.WorksheetFunction.Max(Worksheets("Data").Cells(13, 3) -
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(13,
5), (v - 1)), 0)
    Worksheets("Data").Cells(13, 8) = Worksheets("Data").Cells(13, 3) +
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(13,
5), v - 1)
    Else
        Worksheets("Data").Cells(13, 7) = 0
        Worksheets("Data").Cells(13, 8) = 0

```

End If

If Worksheets("Data").Cells(2, 13) > 0 Then

Worksheets("Data").Cells(2, 15) =

Application.WorksheetFunction.Max(Worksheets("Data").Cells(2, 11) -
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(2,
13), (v - 1)), 0)

Worksheets("Data").Cells(2, 16) = Worksheets("Data").Cells(2, 11) +
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(2,
13), v - 1)

Else

Worksheets("Data").Cells(2, 15) = 0

Worksheets("Data").Cells(2, 16) = 0

End If

If Worksheets("Data").Cells(3, 13) > 0 Then

Worksheets("Data").Cells(3, 15) =

Application.WorksheetFunction.Max(Worksheets("Data").Cells(3, 11) -
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(3,
13), (v - 1)), 0)

Worksheets("Data").Cells(3, 16) = Worksheets("Data").Cells(3, 11) +
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(3,
13), v - 1)

Else

Worksheets("Data").Cells(3, 15) = 0

Worksheets("Data").Cells(3, 16) = 0

End If

If Worksheets("Data").Cells(4, 13) > 0 Then

Worksheets("Data").Cells(4, 15) =

Application.WorksheetFunction.Max(Worksheets("Data").Cells(4, 11) -
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(4,
13), (v - 1)), 0)

Worksheets("Data").Cells(4, 16) = Worksheets("Data").Cells(4, 11) +
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(4,
13), v - 1)

Else

Worksheets("Data").Cells(4, 15) = 0

```

        Worksheets("Data").Cells(4, 16) = 0
    End If

    If Worksheets("Data").Cells(5, 13) > 0 Then
        Worksheets("Data").Cells(5, 15) =
        Application.WorksheetFunction.Max(Worksheets("Data").Cells(5, 11) -
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(5,
        13), (v - 1)), 0)
        Worksheets("Data").Cells(5, 16) = Worksheets("Data").Cells(5, 11) +
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(5,
        13), v - 1)
    Else
        Worksheets("Data").Cells(5, 15) = 0
        Worksheets("Data").Cells(5, 16) = 0
    End If

    If Worksheets("Data").Cells(6, 13) > 0 Then
        Worksheets("Data").Cells(6, 15) =
        Application.WorksheetFunction.Max(Worksheets("Data").Cells(6, 11) -
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(6,
        13), (v - 1)), 0)
        Worksheets("Data").Cells(6, 16) = Worksheets("Data").Cells(6, 11) +
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(6,
        13), v - 1)
    Else
        Worksheets("Data").Cells(6, 15) = 0
        Worksheets("Data").Cells(6, 16) = 0
    End If

    If Worksheets("Data").Cells(7, 13) > 0 Then
        Worksheets("Data").Cells(7, 15) =
        Application.WorksheetFunction.Max(Worksheets("Data").Cells(7, 11) -
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(7,
        13), (v - 1)), 0)
        Worksheets("Data").Cells(7, 16) = Worksheets("Data").Cells(7, 11) +
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(7,
        13), v - 1)
    Else
        Worksheets("Data").Cells(7, 15) = 0
    
```

```

        Worksheets("Data").Cells(7, 16) = 0
    End If

    If Worksheets("Data").Cells(8, 13) > 0 Then
        Worksheets("Data").Cells(8, 15) =
        Application.WorksheetFunction.Max(Worksheets("Data").Cells(8, 11) -
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(8,
        13), (v - 1)), 0)
        Worksheets("Data").Cells(8, 16) = Worksheets("Data").Cells(8, 11) +
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(8,
        13), v - 1)
    Else
        Worksheets("Data").Cells(8, 15) = 0
        Worksheets("Data").Cells(8, 16) = 0
    End If

    If Worksheets("Data").Cells(9, 13) > 0 Then
        Worksheets("Data").Cells(9, 15) =
        Application.WorksheetFunction.Max(Worksheets("Data").Cells(9, 11) -
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(9,
        13), (v - 1)), 0)
        Worksheets("Data").Cells(9, 16) = Worksheets("Data").Cells(9, 11) +
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(9,
        13), v - 1)
    Else
        Worksheets("Data").Cells(9, 15) = 0
        Worksheets("Data").Cells(9, 16) = 0
    End If

    If Worksheets("Data").Cells(10, 13) > 0 Then
        Worksheets("Data").Cells(10, 15) =
        Application.WorksheetFunction.Max(Worksheets("Data").Cells(10, 11) -
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(10,
        13), (v - 1)), 0)
        Worksheets("Data").Cells(10, 16) = Worksheets("Data").Cells(10, 11) +
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(10,
        13), v - 1)
    Else

```

```

        Worksheets("Data").Cells(10, 15) = 0
        Worksheets("Data").Cells(10, 16) = 0
    End If

    If Worksheets("Data").Cells(11, 13) > 0 Then
        Worksheets("Data").Cells(11, 15) =
        Application.WorksheetFunction.Max(Worksheets("Data").Cells(11, 11) -
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(11,
        13), (v - 1)), 0)
        Worksheets("Data").Cells(11, 16) = Worksheets("Data").Cells(11, 11) +
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(11,
        13), v - 1)
    Else
        Worksheets("Data").Cells(11, 15) = 0
        Worksheets("Data").Cells(11, 16) = 0
    End If

    If Worksheets("Data").Cells(12, 13) > 0 Then
        Worksheets("Data").Cells(12, 15) =
        Application.WorksheetFunction.Max(Worksheets("Data").Cells(12, 11) -
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(12,
        13), (v - 1)), 0)
        Worksheets("Data").Cells(12, 16) = Worksheets("Data").Cells(12, 11) +
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(12,
        13), v - 1)
    Else
        Worksheets("Data").Cells(12, 15) = 0
        Worksheets("Data").Cells(12, 16) = 0
    End If

    If Worksheets("Data").Cells(13, 13) > 0 Then
        Worksheets("Data").Cells(13, 15) =
        Application.WorksheetFunction.Max(Worksheets("Data").Cells(13, 11) -
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(13,
        13), (v - 1)), 0)
        Worksheets("Data").Cells(13, 16) = Worksheets("Data").Cells(13, 11) +
        Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(13,
        13), v - 1)
    End If

```

```

Else
    Worksheets("Data").Cells(13, 15) = 0
    Worksheets("Data").Cells(13, 16) = 0
End If

If Worksheets("Data").Cells(14, 13) > 0 Then
    Worksheets("Data").Cells(14, 15) =
Application.WorksheetFunction.Max(Worksheets("Data").Cells(14, 11) -
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(14,
13), (v - 1)), 0)
    Worksheets("Data").Cells(14, 16) = Worksheets("Data").Cells(14, 11) +
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(14,
13), v - 1)
Else
    Worksheets("Data").Cells(14, 15) = 0
    Worksheets("Data").Cells(14, 16) = 0
End If

If Worksheets("Data").Cells(15, 13) > 0 Then
    Worksheets("Data").Cells(15, 15) =
Application.WorksheetFunction.Max(Worksheets("Data").Cells(15, 11) -
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(15,
13), (v - 1)), 0)
    Worksheets("Data").Cells(15, 16) = Worksheets("Data").Cells(15, 11) +
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(15,
13), v - 1)
Else
    Worksheets("Data").Cells(15, 15) = 0
    Worksheets("Data").Cells(15, 16) = 0
End If

If Worksheets("Data").Cells(16, 13) > 0 Then
    Worksheets("Data").Cells(16, 15) =
Application.WorksheetFunction.Max(Worksheets("Data").Cells(16, 11) -
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(16,
13), (v - 1)), 0)

```



```
Worksheets("Data").Cells(16, 16) = Worksheets("Data").Cells(16, 11) +  
Application.WorksheetFunction.Confidence(0.05, Worksheets("Data").Cells(16,  
13), v - 1)
```

```
Else
```

```
Worksheets("Data").Cells(16, 15) = 0
```

```
Worksheets("Data").Cells(16, 16) = 0
```

```
End Sub
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EXHIBIT 2 APPENDIX E STATISTICAL RESULTS FOR VARYING P_C

All table listed below were computed using 1,000 replications of the simulation.

Table A1 displays statistical summaries of the output from simulation of the number of mission aborts occurring as a result of 1,250 missions (5,000 flight hours) while varying P_C . The parameters of the beta distribution are as per Table 11; the parameters of the Weibull distribution are $\alpha_W=1.5$ and $\beta_W=11.08$. This is data for Figure 6.

Table A1

P_C	LEGACY PROCESS						CBM+ PROCESS					
	Σ Aborts	Mean:	SD:	95% CI:			Σ Aborts	Mean:	SD:	95% CI:		
0.10	Σ Aborts	Mean: 4.70	SD: 2.14	95% CI: 4.57	4.83		Σ Aborts	Mean: 5.25	SD: 2.27	95% CI: 5.11	5.39	
0.20	Σ Aborts	Mean: 4.53	SD: 2.11	95% CI: 4.40	4.66		Σ Aborts	Mean: 2.95	SD: 1.64	95% CI: 2.85	3.06	
0.30	Σ Aborts	Mean: 4.57	SD: 2.07	95% CI: 4.44	4.70		Σ Aborts	Mean: 1.91	SD: 1.40	95% CI: 1.83	2.00	
0.40	Σ Aborts	Mean: 4.49	SD: 2.09	95% CI: 4.36	4.62		Σ Aborts	Mean: 1.32	SD: 1.11	95% CI: 1.25	1.39	
0.50	Σ Aborts	Mean: 4.45	SD: 2.15	95% CI: 4.32	4.58		Σ Aborts	Mean: 0.93	SD: 0.97	95% CI: 0.87	0.99	
0.60	Σ Aborts	Mean: 4.55	SD: 2.13	95% CI: 4.42	4.68		Σ Aborts	Mean: 0.73	SD: 0.87	95% CI: 0.67	0.78	
0.70	Σ Aborts	Mean: 4.56	SD: 2.06	95% CI: 4.44	4.69		Σ Aborts	Mean: 0.53	SD: 0.74	95% CI: 0.48	0.57	
0.80	Σ Aborts	Mean: 4.52	SD: 2.08	95% CI: 4.39	4.65		Σ Aborts	Mean: 0.46	SD: 0.68	95% CI: 0.42	0.50	
0.90	Σ Aborts	Mean: 4.51	SD: 2.08	95% CI: 4.38	4.64		Σ Aborts	Mean: 0.36	SD: 0.61	95% CI: 0.32	0.40	
0.99	Σ Aborts	Mean: 4.53	SD: 2.14	95% CI: 4.40	4.66		Σ Aborts	Mean: 0.32	SD: 0.58	95% CI: 0.28	0.35	

Table A2 displays the statistical summaries of the output from simulation of the repair times occurring as a result of 1,250 missions (5,000 flight hours) while varying P_C . The parameters of the beta distribution are as per Table 11; the parameters of the Weibull distribution are $\alpha_W=1.5$ and $\beta_W=11.08$. This is data for Figure 7.

Table A2

P_C	LEGACY PROCESS						CBM+ PROCESS					
	Σ R	Mean:	SD:	95% CI:			Σ R	Mean:	SD:	95% CI:		
0.10	Σ R	Mean: 76.13	SD: 27.36	95% CI: 74.44	77.83		Σ R	Mean: 80.75	SD: 29.17	95% CI: 78.94	82.55	
0.20	Σ R	Mean: 75.06	SD: 26.71	95% CI: 73.40	76.71		Σ R	Mean: 66.58	SD: 23.92	95% CI: 65.10	68.07	
0.30	Σ R	Mean: 75.94	SD: 27.24	95% CI: 74.25	77.63		Σ R	Mean: 59.27	SD: 23.04	95% CI: 57.84	60.70	
0.40	Σ R	Mean: 74.65	SD: 27.13	95% CI: 72.97	76.33		Σ R	Mean: 54.83	SD: 20.85	95% CI: 53.54	56.13	
0.50	Σ R	Mean: 75.29	SD: 26.56	95% CI: 73.65	76.94		Σ R	Mean: 51.40	SD: 19.09	95% CI: 50.22	52.58	
0.60	Σ R	Mean: 75.02	SD: 27.49	95% CI: 73.32	76.73		Σ R	Mean: 46.68	SD: 18.23	95% CI: 45.55	47.81	
0.70	Σ R	Mean: 76.24	SD: 26.60	95% CI: 74.59	77.89		Σ R	Mean: 44.07	SD: 17.29	95% CI: 42.99	45.14	
0.80	Σ R	Mean: 75.84	SD: 28.04	95% CI: 74.10	77.58		Σ R	Mean: 40.75	SD: 16.05	95% CI: 39.75	41.74	
0.90	Σ R	Mean: 74.73	SD: 27.10	95% CI: 73.05	76.41		Σ R	Mean: 37.64	SD: 15.80	95% CI: 36.66	38.62	
0.99	Σ R	Mean: 75.38	SD: 27.58	95% CI: 73.67	77.09		Σ R	Mean: 34.83	SD: 14.53	95% CI: 33.93	35.73	

Table A3 displays the statistical summaries of the simulation output for the number of diagnostic symptoms recognized, number of mission aborts, repair time as a result of 1,250 missions (5,000 flight hours) while varying the variance of the Weibull distribution determining M_A for the case with mean $P_C=0.99$. The beta distribution has parameters $\alpha_B=25$ and $\beta_B=.25$. The parameters of the Weibull distribution when $\alpha_W=0.5$ then $\beta_W=5$, when $\alpha_W=1$ then $\beta_W=10$, and when $\alpha_W=1.5$ then $\beta_W=11.08$. This is data for Figures 8, 9, and 10.

Table A3

α	LEGACY PROCESS						CBM+ PROCESS									
0.50	Σ DSs	Mean:	4.08	SD:	1.98	95% CI:	3.96	4.20	Σ DSs	Mean:	7.26	SD:	2.64	95% CI:	7.10	7.42
0.50	Σ Aborts	Mean:	7.35	SD:	2.76	95% CI:	7.18	7.52	Σ Aborts	Mean:	4.17	SD:	2.07	95% CI:	4.04	4.30
0.50	Σ R	Mean:	70.13	SD:	26.62	95% CI:	68.48	71.78	Σ R	Mean:	42.64	SD:	18.51	95% CI:	41.49	43.79
1.00	Σ DSs	Mean:	6.08	SD:	2.48	95% CI:	5.92	6.23	Σ DSs	Mean:	10.40	SD:	3.28	95% CI:	10.19	10.60
1.00	Σ Aborts	Mean:	5.44	SD:	2.25	95% CI:	5.30	5.58	Σ Aborts	Mean:	1.12	SD:	1.03	95% CI:	1.05	1.18
1.00	Σ R	Mean:	75.86	SD:	27.82	95% CI:	74.14	77.59	Σ R	Mean:	36.54	SD:	16.35	95% CI:	35.53	37.56
1.50	Σ DSs	Mean:	6.79	SD:	2.66	95% CI:	6.62	6.95	Σ DSs	Mean:	11.03	SD:	3.36	95% CI:	10.82	11.24
1.50	Σ Aborts	Mean:	4.52	SD:	2.12	95% CI:	4.39	4.65	Σ Aborts	Mean:	0.28	SD:	0.51	95% CI:	0.24	0.31
1.50	Σ R	Mean:	74.81	SD:	27.39	95% CI:	73.11	76.50	Σ R	Mean:	34.78	SD:	14.80	95% CI:	33.87	35.70

Tables A4 and A5 display the statistical summaries for the simulation output of the number of diagnostic symptoms recognized, number of mission aborts, repair time as a result of 1,250 missions (5,000 flight hours) while varying the variance of the Weibull distribution having mean 10 determining M_A for the cases where mean $P_C=0.50$ and mean $P_C=0.20$; the parameters of the beta distribution are $\alpha_B=25$ $\beta_B=25$ (when $P_C=0.50$) and $\alpha_B=25$ $\beta_B=100$ (when $P_C=0.20$). This is data for Figures 8, 9, and 10.

Table A4 ($P_C=0.50$)

α	LEGACY PROCESS						CBM+ PROCESS									
0.5	Σ DSs	Mean:	4.19	SD:	2.02	95% CI:	4.06	4.31	Σ DSs	Mean:	6.39	SD:	2.54	95% CI:	6.23	6.55
0.5	Σ Aborts	Mean:	7.32	SD:	2.70	95% CI:	7.15	7.49	Σ Aborts	Mean:	5.12	SD:	2.28	95% CI:	4.97	5.26
0.5	Σ R	Mean:	70.71	SD:	26.44	95% CI:	69.07	72.34	Σ R	Mean:	53.00	SD:	21.19	95% CI:	51.69	54.31
1	Σ DSs	Mean:	5.99	SD:	2.44	95% CI:	5.83	6.14	Σ DSs	Mean:	9.30	SD:	3.12	95% CI:	9.11	9.49
1	Σ Aborts	Mean:	5.28	SD:	2.34	95% CI:	5.13	5.42	Σ Aborts	Mean:	1.96	SD:	1.45	95% CI:	1.87	2.05
1	Σ R	Mean:	74.59	SD:	28.77	95% CI:	72.80	76.37	Σ R	Mean:	51.20	SD:	20.26	95% CI:	49.94	52.45
1.5	Σ DSs	Mean:	6.72	SD:	2.50	95% CI:	6.57	6.87	Σ DSs	Mean:	10.35	SD:	3.10	95% CI:	10.16	10.54
1.5	Σ Aborts	Mean:	4.62	SD:	2.10	95% CI:	4.49	4.75	Σ Aborts	Mean:	1.00	SD:	0.98	95% CI:	0.93	1.06
1.5	Σ R	Mean:	75.54	SD:	26.39	95% CI:	73.91	77.18	Σ R	Mean:	50.22	SD:	18.71	95% CI:	49.06	51.38

Table A5 ($P_C=0.20$)

α	LEGACY PROCESS						CBM+ PROCESS									
0.5	Σ DSs	Mean:	4.06	SD:	1.98	95% CI:	3.94	4.18	Σ DSs	Mean:	4.88	SD:	2.27	95% CI:	4.74	5.02
0.5	Σ Aborts	Mean:	7.26	SD:	2.62	95% CI:	7.09	7.42	Σ Aborts	Mean:	6.44	SD:	2.45	95% CI:	6.29	6.59
0.5	Σ R	Mean:	70.19	SD:	26.71	95% CI:	68.54	71.85	Σ R	Mean:	63.61	SD:	24.94	95% CI:	62.06	65.15
1	Σ DSs	Mean:	6.10	SD:	2.47	95% CI:	5.95	6.25	Σ DSs	Mean:	7.56	SD:	2.72	95% CI:	7.39	7.72
1	Σ Aborts	Mean:	5.40	SD:	2.39	95% CI:	5.25	5.54	Σ Aborts	Mean:	3.94	SD:	2.09	95% CI:	3.81	4.07
1	Σ R	Mean:	75.93	SD:	28.37	95% CI:	74.17	77.68	Σ R	Mean:	68.00	SD:	25.51	95% CI:	66.42	69.58
1.5	Σ DSs	Mean:	7.04	SD:	2.59	95% CI:	6.88	7.20	Σ DSs	Mean:	8.67	SD:	2.95	95% CI:	8.49	8.85
1.5	Σ Aborts	Mean:	4.54	SD:	2.19	95% CI:	4.41	4.68	Σ Aborts	Mean:	2.91	SD:	1.72	95% CI:	2.80	3.01
1.5	Σ R	Mean:	75.81	SD:	27.79	95% CI:	74.08	77.53	Σ R	Mean:	68.02	SD:	25.21	95% CI:	66.45	69.58

Table A6 displays the statistical summaries of simulation output for the number of false positives and the repair (inspection) times as a result of 1,250 missions (5,000 flight hours) while varying the false positive arrival rate; the parameters of the beta distribution are $\alpha_B=25$ and $\beta_B=.25$; the parameters of the Weibull distribution are $\alpha_W=1.5$ and $\beta_W=11.08$. This is an expanded version of Table 12.

Table A6

False Positive Rate	CBM+ PROCESS (NUMBER OF FALSE POSITIVE ARRIVALS)						
	Σ FP	Mean:	SD:	95% CI:			
0.9999	Σ FP	Mean: 1238.57	SD: 3.31	95% CI: 1238.36		1238.78	
0.90	Σ FP	Mean: 1115.29	SD: 11.18	95% CI: 1114.59		1115.98	
0.80	Σ FP	Mean: 990.51	SD: 14.47	95% CI: 989.61		991.41	
0.70	Σ FP	Mean: 866.70	SD: 16.58	95% CI: 865.67		867.73	
0.60	Σ FP	Mean: 743.41	SD: 17.13	95% CI: 742.34		744.47	
0.50	Σ FP	Mean: 620.23	SD: 17.69	95% CI: 619.14		621.33	
0.40	Σ FP	Mean: 495.29	SD: 16.85	95% CI: 494.25		496.34	
0.30	Σ FP	Mean: 372.07	SD: 16.24	95% CI: 371.06		373.08	
0.20	Σ FP	Mean: 247.05	SD: 14.09	95% CI: 246.18		247.92	
0.10	Σ FP	Mean: 124.34	SD: 10.44	95% CI: 123.69		124.98	
0.0001	Σ FP	Mean: 0.14	SD: 0.36	95% CI: 0.11		0.16	

False Positive Rate	CBM+ PROCESS (REPAIR TIME INCURRED DUE TO FALSE POSITIVE ARRIVALS)						
	Σ FP Time	Mean:	SD:	95% CI:			
0.9999	Σ FP Time	Mean: 3717.41	SD: 105.16	95% CI: 3710.89		3723.93	
0.90	Σ FP Time	Mean: 3343.55	SD: 106.54	95% CI: 3336.95		3350.15	
0.80	Σ FP Time	Mean: 2969.66	SD: 104.41	95% CI: 2963.19		2976.13	
0.70	Σ FP Time	Mean: 2598.47	SD: 104.49	95% CI: 2591.99		2604.94	
0.60	Σ FP Time	Mean: 2228.17	SD: 98.01	95% CI: 2222.10		2234.25	
0.50	Σ FP Time	Mean: 1861.03	SD: 89.15	95% CI: 1855.50		1866.55	
0.40	Σ FP Time	Mean: 1490.28	SD: 85.40	95% CI: 1484.98		1495.57	
0.30	Σ FP Time	Mean: 1118.76	SD: 74.55	95% CI: 1114.14		1123.38	
0.20	Σ FP Time	Mean: 741.94	SD: 62.68	95% CI: 738.05		745.82	
0.10	Σ FP Time	Mean: 371.62	SD: 47.00	95% CI: 368.71		374.54	
0.0001	Σ FP Time	Mean: 0.42	SD: 1.64	95% CI: 0.32		0.52	

Table A7 displays the statistical summaries of the output of simulations for the total repair time (total repair time = diagnostic symptom repair time + false positive repair time) as a result of 1,250 missions (5,000 flight hours) while varying the false positive arrival rate. The parameters of the beta distribution are $\alpha_B=25$ and $\beta_B=.25$; the parameters of the Weibull distribution are $\alpha_W=1.5$ and $\beta_W=11.08$. This is an expanded version of Table 14.

Table A7

False Positive Rate	CBM+ PROCESS (TOTAL REPAIR TIME=DS REPAIR TIME+FALSE POSITIVE REPAIR TIME)						
	$\Sigma R+\Sigma$ FP Time	Mean:	SD:	95% CI:			
0.10	$\Sigma R+\Sigma$ FP Time	Mean: 406.13	SD: 48.87	95% CI: 403.11		409.16	
0.09	$\Sigma R+\Sigma$ FP Time	Mean: 369.59	SD: 46.37	95% CI: 366.71		372.46	
0.08	$\Sigma R+\Sigma$ FP Time	Mean: 330.84	SD: 42.89	95% CI: 328.18		333.50	
0.07	$\Sigma R+\Sigma$ FP Time	Mean: 291.50	SD: 42.19	95% CI: 288.89		294.12	
0.06	$\Sigma R+\Sigma$ FP Time	Mean: 257.54	SD: 38.12	95% CI: 255.18		259.91	
0.05	$\Sigma R+\Sigma$ FP Time	Mean: 221.93	SD: 37.29	95% CI: 219.61		224.24	
0.04	$\Sigma R+\Sigma$ FP Time	Mean: 185.08	SD: 32.49	95% CI: 183.06		187.09	
0.03	$\Sigma R+\Sigma$ FP Time	Mean: 146.10	SD: 30.02	95% CI: 144.24		147.96	
0.02	$\Sigma R+\Sigma$ FP Time	Mean: 108.97	SD: 25.81	95% CI: 107.38		110.57	
0.01	$\Sigma R+\Sigma$ FP Time	Mean: 71.91	SD: 20.47	95% CI: 70.64		73.17	
0.0001	$\Sigma R+\Sigma$ FP Time	Mean: 36.06	SD: 15.43	95% CI: 35.10		37.02	

Table A8 displays the statistical summaries of simulation output for the time awaiting replacement components as a result of 1,250 missions (5,000 flight hours) while varying P_{OH} when mean P_C is 0.99 and the mean time until the replacement component arrives is 3 days. The parameters of the beta distribution are $\alpha_B=25$ and

$\beta_B=.25$; the parameters of the Weibull distribution are $\alpha_W=1.5$ and $\beta_W=11.08$. The time until a component replacement arrives has an exponential distribution. This is data for Figure 12.

Table A8

P _{ON HAND}	LEGACY PROCESS							CBM+ PROCESS						
	ΣAS	Mean:	SD:	95% CI:	0.00	0.01	ΣAS	Mean:	SD:	95% CI:	0.00	0.00		
0.9999	ΣAS	Mean: 0.00	SD: 0.09	95% CI: 0.00	0.01	ΣAS	Mean: 0.00	SD: 0.00	95% CI: 0.00	0.00	0.00			
0.90	ΣAS	Mean: 1.72	SD: 3.23	95% CI: 1.52	1.92	ΣAS	Mean: 0.45	SD: 1.64	95% CI: 0.35	0.55				
0.80	ΣAS	Mean: 3.57	SD: 4.77	95% CI: 3.28	3.87	ΣAS	Mean: 0.87	SD: 2.27	95% CI: 0.73	1.01				
0.70	ΣAS	Mean: 5.03	SD: 5.59	95% CI: 4.68	5.38	ΣAS	Mean: 1.26	SD: 2.83	95% CI: 1.08	1.44				
0.60	ΣAS	Mean: 7.05	SD: 6.76	95% CI: 6.63	7.47	ΣAS	Mean: 1.83	SD: 3.27	95% CI: 1.63	2.03				
0.50	ΣAS	Mean: 7.99	SD: 7.05	95% CI: 7.56	8.43	ΣAS	Mean: 2.09	SD: 3.40	95% CI: 1.88	2.30				
0.40	ΣAS	Mean: 10.46	SD: 8.02	95% CI: 9.96	10.95	ΣAS	Mean: 3.01	SD: 4.19	95% CI: 2.75	3.27				
0.30	ΣAS	Mean: 11.75	SD: 8.58	95% CI: 11.22	12.28	ΣAS	Mean: 3.15	SD: 4.37	95% CI: 2.88	3.42				
0.20	ΣAS	Mean: 13.37	SD: 9.05	95% CI: 12.81	13.93	ΣAS	Mean: 3.36	SD: 4.12	95% CI: 3.10	3.61				
0.10	ΣAS	Mean: 15.50	SD: 9.47	95% CI: 14.91	16.08	ΣAS	Mean: 4.23	SD: 5.65	95% CI: 3.88	4.58				
0.0001	ΣAS	Mean: 16.77	SD: 10.16	95% CI: 16.14	17.40	ΣAS	Mean: 4.72	SD: 5.57	95% CI: 4.37	5.06				

Table A9 displays the statistical summaries of simulation output for the time awaiting replacement components as a result of 1,250 missions (5,000 flight hours) while varying P_{OH} when mean P_C is 0.50 and the mean time until the replacement component arrives is 3 days. The parameters of the beta distribution are $\alpha_B=25$ and $\beta_B=25$; the parameters of the Weibull distribution are $\alpha_W=1.5$ and $\beta_W=11.08$. The time until a replacement component arrives has an exponential distribution. This is data for Figure 13.

Table A9

P _{ON HAND}	LEGACY PROCESS							CBM+ PROCESS						
	ΣAS	Mean:	SD:	95% CI:	0.00	0.00	ΣAS	Mean:	SD:	95% CI:	0.00	0.00		
0.9999	ΣAS	Mean: 0.00	SD: 0.01	95% CI: 0.00	0.00	ΣAS	Mean: 0.00	SD: 0.00	95% CI: 0.00	0.00				
0.90	ΣAS	Mean: 1.76	SD: 3.47	95% CI: 1.55	1.98	ΣAS	Mean: 0.69	SD: 1.86	95% CI: 0.58	0.81				
0.80	ΣAS	Mean: 3.41	SD: 4.53	95% CI: 3.13	3.69	ΣAS	Mean: 1.38	SD: 2.80	95% CI: 1.21	1.56				
0.70	ΣAS	Mean: 4.98	SD: 5.55	95% CI: 4.64	5.33	ΣAS	Mean: 2.26	SD: 3.80	95% CI: 2.02	2.49				
0.60	ΣAS	Mean: 6.88	SD: 6.32	95% CI: 6.48	7.27	ΣAS	Mean: 2.70	SD: 3.86	95% CI: 2.46	2.94				
0.50	ΣAS	Mean: 8.69	SD: 6.70	95% CI: 8.27	9.10	ΣAS	Mean: 3.43	SD: 4.55	95% CI: 3.15	3.71				
0.40	ΣAS	Mean: 10.38	SD: 8.02	95% CI: 9.89	10.88	ΣAS	Mean: 3.92	SD: 4.66	95% CI: 3.64	4.21				
0.30	ΣAS	Mean: 11.73	SD: 8.35	95% CI: 11.21	12.25	ΣAS	Mean: 5.11	SD: 5.68	95% CI: 4.76	5.46				
0.20	ΣAS	Mean: 13.44	SD: 9.00	95% CI: 12.88	14.00	ΣAS	Mean: 5.50	SD: 5.67	95% CI: 5.15	5.85				
0.10	ΣAS	Mean: 15.31	SD: 9.27	95% CI: 14.73	15.88	ΣAS	Mean: 6.30	SD: 6.12	95% CI: 5.92	6.68				
0.0001	ΣAS	Mean: 17.16	SD: 10.06	95% CI: 16.53	17.78	ΣAS	Mean: 6.77	SD: 6.14	95% CI: 6.39	7.15				

Table A10 displays statistical summaries of simulation output for the time awaiting replacement components as a result of 1,250 missions (5,000 flight hours) while varying P_{OH} when mean P_C is 0.20 and the mean time until the replacement component arrives is 3 days. The parameters of the beta distribution are $\alpha_B=25$ and $\beta_B=100$; the parameters of the Weibull distribution are $\alpha_W=1.5$ and $\beta_W=11.08$. The time until a replacement component arrives has an exponential distribution. This is data for Figure 14.

Table A10

$P_{ON\ HAND}$	LEGACY PROCESS						CBM+ PROCESS					
	ΣAS	Mean:	SD:	95% CI:			ΣAS	Mean:	SD:	95% CI:		
0.9999	ΣAS	Mean: 0.00	SD: 0.00	95% CI: 0.00	0.00	0.00	ΣAS	Mean: 0.00	SD: 0.00	95% CI: 0.00	0.00	0.00
0.90	ΣAS	Mean: 1.69	SD: 3.10	95% CI: 1.50	1.88		ΣAS	Mean: 1.32	SD: 2.91	95% CI: 1.14	1.50	
0.80	ΣAS	Mean: 3.34	SD: 4.51	95% CI: 3.07	3.62		ΣAS	Mean: 2.67	SD: 4.05	95% CI: 2.42	2.92	
0.70	ΣAS	Mean: 5.06	SD: 5.17	95% CI: 4.74	5.38		ΣAS	Mean: 3.81	SD: 4.92	95% CI: 3.51	4.12	
0.60	ΣAS	Mean: 6.37	SD: 6.04	95% CI: 6.00	6.75		ΣAS	Mean: 5.25	SD: 5.43	95% CI: 4.91	5.58	
0.50	ΣAS	Mean: 8.78	SD: 7.08	95% CI: 8.34	9.22		ΣAS	Mean: 5.92	SD: 5.74	95% CI: 5.57	6.28	
0.40	ΣAS	Mean: 10.14	SD: 8.04	95% CI: 9.64	10.64		ΣAS	Mean: 8.03	SD: 7.25	95% CI: 7.58	8.48	
0.30	ΣAS	Mean: 12.23	SD: 8.40	95% CI: 11.71	12.75		ΣAS	Mean: 9.31	SD: 7.65	95% CI: 8.84	9.79	
0.20	ΣAS	Mean: 13.77	SD: 9.34	95% CI: 13.19	14.34		ΣAS	Mean: 10.08	SD: 7.37	95% CI: 9.62	10.53	
0.10	ΣAS	Mean: 15.16	SD: 9.55	95% CI: 14.57	15.75		ΣAS	Mean: 11.21	SD: 8.33	95% CI: 10.69	11.73	
0.0001	ΣAS	Mean: 17.16	SD: 10.53	95% CI: 16.51	17.81		ΣAS	Mean: 12.42	SD: 8.69	95% CI: 11.88	12.96	

Table A11 displays the statistical summaries of simulation output for the time awaiting replacement components as a result of 1,250 missions (5,000 flight hours) while varying P_{OH} when P_C is 0.99 and the mean time until the replacement component arrives is 10 days. The parameters of the beta distribution are $\alpha_B=25$ and $\beta_B=.25$; the parameters of the Weibull distribution are $\alpha_W=1.5$ and $\beta_W=11.08$. The time until a replacement component arrives has an exponential distribution. This is data for Figure 15.

Table A11

$P_{ON\ HAND}$	LEGACY PROCESS						CBM+ PROCESS					
	ΣAS	Mean:	SD:	95% CI:			ΣAS	Mean:	SD:	95% CI:		
0.9999	ΣAS	Mean: 0.00	SD: 0.12	95% CI: 0.00	0.01		ΣAS	Mean: 0.00	SD: 0.00	95% CI: 0.00	0.00	0.00
0.90	ΣAS	Mean: 9.44	SD: 13.44	95% CI: 8.60	10.27		ΣAS	Mean: 6.67	SD: 11.20	95% CI: 5.98	7.36	
0.80	ΣAS	Mean: 17.45	SD: 19.30	95% CI: 16.25	18.64		ΣAS	Mean: 12.49	SD: 14.44	95% CI: 11.59	13.38	
0.70	ΣAS	Mean: 27.42	SD: 23.59	95% CI: 25.95	28.88		ΣAS	Mean: 19.50	SD: 18.93	95% CI: 18.33	20.67	
0.60	ΣAS	Mean: 36.92	SD: 27.18	95% CI: 35.23	38.60		ΣAS	Mean: 25.90	SD: 23.77	95% CI: 24.43	27.37	
0.50	ΣAS	Mean: 42.93	SD: 29.17	95% CI: 41.12	44.74		ΣAS	Mean: 33.20	SD: 25.91	95% CI: 31.60	34.81	
0.40	ΣAS	Mean: 53.36	SD: 33.14	95% CI: 51.30	55.41		ΣAS	Mean: 40.31	SD: 29.13	95% CI: 38.51	42.12	
0.30	ΣAS	Mean: 64.97	SD: 36.21	95% CI: 62.72	67.21		ΣAS	Mean: 46.02	SD: 31.59	95% CI: 44.06	47.98	
0.20	ΣAS	Mean: 73.09	SD: 38.88	95% CI: 70.68	75.50		ΣAS	Mean: 52.48	SD: 31.03	95% CI: 50.55	54.40	
0.10	ΣAS	Mean: 80.22	SD: 40.80	95% CI: 77.69	82.75		ΣAS	Mean: 60.02	SD: 34.32	95% CI: 57.90	62.15	
0.0001	ΣAS	Mean: 88.67	SD: 41.58	95% CI: 86.09	91.25		ΣAS	Mean: 63.91	SD: 34.87	95% CI: 61.75	66.07	

Table A12 displays the statistical summaries of simulation output for the time awaiting replacement components as a result of 1,250 missions (5,000 flight hours) while varying P_{OH} when P_C is 0.50 and the mean time until the replacement component arrives is 10 days. The parameters of the beta distribution are $\alpha_B=25$ and $\beta_B=25$; the parameters of the Weibull distribution are $\alpha_W=1.5$ and $\beta_W=11.08$. The time until a replacement component arrives has an exponential distribution. This is data for Figure 16.

Table A12

$P_{ON\ HAND}$	LEGACY PROCESS						CBM+ PROCESS					
	ΣAS	Mean:	SD:	95% CI:			ΣAS	Mean:	SD:	95% CI:		
0.9999	ΣAS	Mean: 0.01	SD: 0.13	95% CI: 0.00	0.01		ΣAS	Mean: 0.00	SD: 0.00	95% CI: 0.00	0.00	0.00
0.90	ΣAS	Mean: 9.48	SD: 13.96	95% CI: 8.61	10.34		ΣAS	Mean: 7.47	SD: 12.05	95% CI: 6.73	8.22	
0.80	ΣAS	Mean: 17.40	SD: 17.80	95% CI: 16.30	18.50		ΣAS	Mean: 14.60	SD: 17.07	95% CI: 13.54	15.66	
0.70	ΣAS	Mean: 27.14	SD: 24.12	95% CI: 25.65	28.63		ΣAS	Mean: 21.73	SD: 21.52	95% CI: 20.39	23.06	
0.60	ΣAS	Mean: 36.32	SD: 26.46	95% CI: 34.68	37.96		ΣAS	Mean: 27.52	SD: 23.12	95% CI: 26.08	28.95	
0.50	ΣAS	Mean: 46.22	SD: 30.29	95% CI: 44.34	48.10		ΣAS	Mean: 35.94	SD: 25.66	95% CI: 34.35	37.53	
0.40	ΣAS	Mean: 54.79	SD: 33.17	95% CI: 52.73	56.85		ΣAS	Mean: 43.21	SD: 30.15	95% CI: 41.35	45.08	
0.30	ΣAS	Mean: 63.01	SD: 35.55	95% CI: 60.80	65.21		ΣAS	Mean: 51.58	SD: 31.18	95% CI: 49.65	53.51	
0.20	ΣAS	Mean: 72.70	SD: 38.17	95% CI: 70.34	75.07		ΣAS	Mean: 57.41	SD: 33.00	95% CI: 55.37	59.46	
0.10	ΣAS	Mean: 81.96	SD: 39.36	95% CI: 79.52	84.40		ΣAS	Mean: 65.56	SD: 36.87	95% CI: 63.28	67.85	
0.0001	ΣAS	Mean: 89.19	SD: 42.49	95% CI: 86.56	91.83		ΣAS	Mean: 71.63	SD: 38.87	95% CI: 69.22	74.04	

Table A13 displays the statistical summaries of simulation output for the time awaiting replacement components as a result of 1,250 missions (5,000 flight hours) while varying P_{OH} when P_C is 0.20 and the mean

time until the replacement component arrives is 10 days. The parameters of the beta distribution are $\alpha_B=25$ and $\beta_B=100$; the parameters of the Weibull distribution are $\alpha_W=1.5$ and $\beta_W=11.08$. The time until a replacement component arrives has an exponential distribution. This is data for Figure 17.

Table A13

P ON HAND	LEGACY PROCESS						CBM+ PROCESS					
	ΣAS	Mean:	SD:	95% CI:			ΣAS	Mean:	SD:	95% CI:		
0.9999	ΣAS	Mean: 0.00	SD: 0.04	95% CI: 0.00	0.00		ΣAS	Mean: 0.00	SD: 0.00	95% CI: 0.00	0.00	0.00
0.90	ΣAS	Mean: 9.34	SD: 13.18	95% CI: 8.53	10.16		ΣAS	Mean: 8.54	SD: 12.64	95% CI: 7.76	9.33	
0.80	ΣAS	Mean: 18.52	SD: 20.35	95% CI: 17.25	19.78		ΣAS	Mean: 15.59	SD: 17.45	95% CI: 14.51	16.67	
0.70	ΣAS	Mean: 27.17	SD: 23.59	95% CI: 25.70	28.63		ΣAS	Mean: 24.82	SD: 22.59	95% CI: 23.42	26.22	
0.60	ΣAS	Mean: 35.22	SD: 26.04	95% CI: 33.60	36.83		ΣAS	Mean: 33.89	SD: 26.58	95% CI: 32.24	35.54	
0.50	ΣAS	Mean: 44.64	SD: 29.66	95% CI: 42.80	46.47		ΣAS	Mean: 41.84	SD: 29.17	95% CI: 40.03	43.64	
0.40	ΣAS	Mean: 55.17	SD: 33.73	95% CI: 53.08	57.26		ΣAS	Mean: 50.15	SD: 31.35	95% CI: 48.21	52.10	
0.30	ΣAS	Mean: 64.12	SD: 35.57	95% CI: 61.92	66.33		ΣAS	Mean: 59.46	SD: 34.52	95% CI: 57.32	61.60	
0.20	ΣAS	Mean: 72.38	SD: 37.69	95% CI: 70.04	74.71		ΣAS	Mean: 67.09	SD: 37.19	95% CI: 64.78	69.39	
0.10	ΣAS	Mean: 81.59	SD: 40.41	95% CI: 79.09	84.10		ΣAS	Mean: 73.96	SD: 36.69	95% CI: 71.68	76.23	
0.0001	ΣAS	Mean: 89.03	SD: 41.85	95% CI: 86.44	91.62		ΣAS	Mean: 81.51	SD: 40.35	95% CI: 79.01	84.01	

REFERENCES

- AMCOM, [https://redstoneappsrv1.redstone.army.mil/cbm/cbm_home], January 2006.
- Bickel, Peter J., Doksum, Kjell A., *Mathematical Statistics: Basic Ideas and Selected Topics*, Holden-Day Inc., 1977.
- Brown, Robert, *Condition Based Maintenance (CBM) Proof of Principle*, 30 June 2005.
- Crowder, M. J., Kimber A. C., Smith R. L., Sweeting T. J., *Statistical Analysis of Reliability Data*, Chapman & Hall, New York 1991.
- Decisioneering Incorporated, *Crystal Ball 7.2 Reference Manual*, 2005.
- Department of the Army, *Army Aviation Condition Based Maintenance Plus (CBM+) Plan*, 29 NOV 2004.
- Department of the Army, *TM 1-1520-237-10 OPERATOR'S MANUAL FOR UH-60A HELICOPTER, UH-60L HELICOPTER, EH-60A HELICOPTER*, 1 May 2003.
- Department of the Army, *TM 1-1520-240-10 OPERATOR'S MANUAL FOR ARMY CH-47D HELICOPTER*, 31 January 2003.
- Department of the Army, *TM 1-1520-251-10 OPERATOR'S MANUAL FOR HELICOPTER, ATTACK, AH-64D LONGBOW APACHE*, 29 March 2002.
- Department of Defense, [http://akss.dau.mil/dag/Guidebook/IG_c5.2.1.2.asp], May 2006.
- Department of Defense, *Defense Acquisition Handbook*, 20 December 2004.
- Department of Defense Instruction 5000.2, *Operation of the Defense Acquisition System*, 12 May 2003.
- Gaver, Donald P. Jr, Jacobs, Patricia. A, *A Nonhomogeneous Poisson Process Model for CBM*, Working paper, 29 March 2006.
- Hughes, Wayne P., *Military Modeling for Decision Making*, Third Edition, The Military Operations Research Society Inc., 1997.
- Jacobs, Patricia A., *A Nonhomogeneous Poisson process model (NHPP) for engine data*, Working paper, 27 March 2006.

McCullough, B.D., Wilson B., *On the accuracy of statistical procedures in Microsoft Excel 2003*, Computational Statistics & Data Analysis (CSDA), Volume 49, 2005.

Mobley, R. Keith, *An Introduction to Predictive Maintenance*, First Edition, Van Nostrand Reinhold, 1990.

Moubray, John, *Reliability-centered Maintenance*, Second Edition, Industrial Press Inc., 1997.

Pew, Richard W., Mavor, Anne S., *Modeling Human and Organizational Behavior-Applications to Military Simulations*, First Edition, National Academy Press, 1998.

Ragsdale, Cliff T., *Spreadsheet Modeling & Decision Analysis: A Practical Introduction to Management Science*, Fourth Edition, Thomson South-Western, 2004.


Ross, Sheldon M., *Introduction to Probability Models*, Eighth Edition, Academic Press, 2003.

Wright, Johnny, *Emerging Results Using IMD-HUMS in a Black Hawk Assault Battalion*, 2005.


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Exhibit 3: Driving Toward Greater Mutual Understanding




Condition-Based Maintenance (CBM) For U.S. Army Aviation: A Component Selection Methodology






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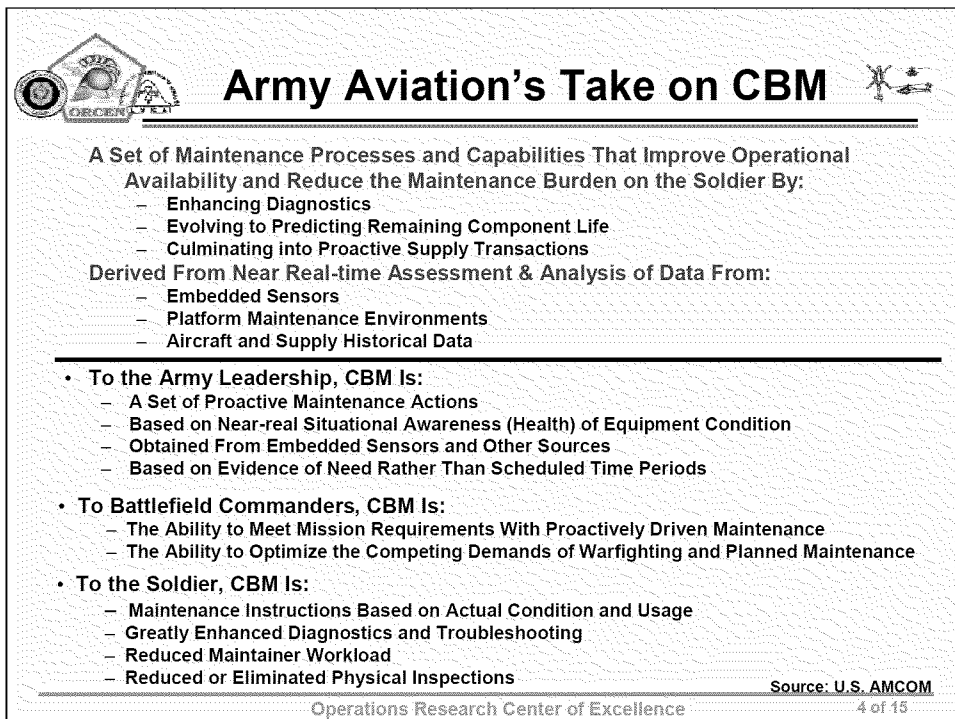
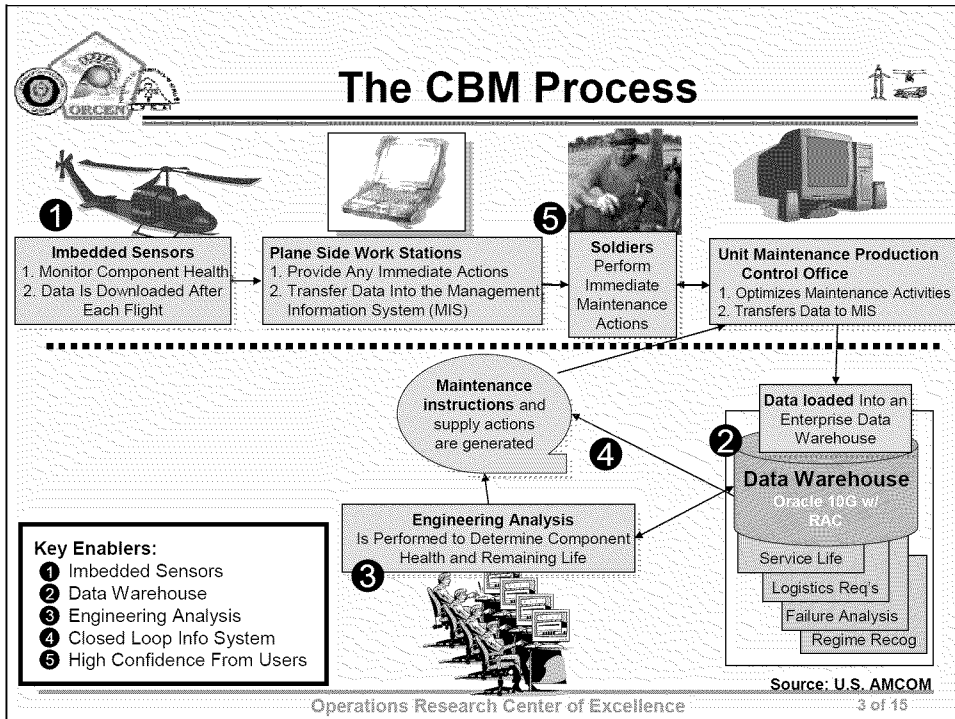
MAJ Ernest Wong
Department of Systems Engineering
United States Military Academy



Types of Maintenance Paradigms

- **Run-to-Failure Maintenance**
 - Corrective Maintenance 
 - “Driveway Diagnostics”
 - Reactive
- **Time-Phased Maintenance**
 - Preventative Maintenance 
 - Calendar-Based
 - Proactive
- **Condition-Based Maintenance**
 - Predictive Prognostics 
 - Non-Invasive

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Army Aviation's CBM Vision



- Decrease the Maintenance Burden on the Soldier
- Increase Platform Availability and Readiness
- Reduce Operations & Support Costs

CURRENT

Maintenance Intensive

- Inspections
- Phases
- TBOs
- Reactive
- Unscheduled

TRANSITION

- CBM Proof Of Principle Feasibility Demonstration
- Selected Components
- Gradual Extension Between Inspections/Maintenance Actions
- Install Diagnostic/Prognostics Equipment on Platforms
- Develop Enablers

END STATE

Maintenance Efficient

- Automated Inspection
 - Continual Monitoring
 - Reduced Maintenance Inspections
- Predictive & Proactive
- Progressive Improvement
- Fully integrated LCM
- Business Process Change
- Proactive Supply

Source: U.S. AMCOM

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5 of 15



Timeline for CBM Implementation



- **Phase 1 – Concept Development – FY 05-07**
 - Proof of Principle – Engineering Analysis, July 2005
 - Cross Functional Data Warehouse Development for Analysis
 - Development of Diagnostics/Prognostic Algorithms
 - Assess DOTMLPF Impacts & Potential Business Process Improvements
 - Interoperability/Interfaces With GCSS-A, CLOE, PME, LMP, PLM+
- **Phase 2 – Implementation – FY 08-15**
 - Battalion and/or Brigade Pilot Implementation
 - Modify Business Processes: Forecasting, Other Supply Chain Initiatives
 - Identify/Implement Training/Doctrine/Publication Changes
 - Implementation of CBM on Aircraft With DSCs
 - Examine New Technologies
- **Phase 3 – Operations & Process Improvements – FY 16+**
 - Sustain CBM Operations
 - Continuous Analysis of Data
 - Refinement of Prognostic Capability
 - Reassess DOTMLPF and Business Processes

PREPARE

WALK

RUN

Source: U.S. AMCOM

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6 of 15



Realized Benefits of CBM



Aviation Engineering Directorate Published Airworthiness Releases
(as of 16JUN05) affecting approximately 100 aircraft

SYSTEM	ITEM	BENEFITS
AH-64	M/R Swashplate	Eliminates 50 hr bearing inspection (btw 1750 and 2250 hrs). Eliminates maintenance operational check (approximately 1 hr). MMH saved per inspection: 7.4 hrs. Downtime saved per aircraft: 5.9 hrs.
AH-64	APU Clutch	Eliminates vibration checks at installation and phase. Extends APU mount inspection from 250 hrs to 500 hrs. MMH saved per inspection: 28.0 hrs. Downtime saved per aircraft: 9.0 hrs.
AH-64	Aft Hanger Bearing	Safety improvement w/ continuous diagnostic monitoring. Extends TBO from 2500 hrs to 2750 hrs. MMH saved per inspection: 4.4 hrs. Downtime saved per aircraft: 2.2 hrs.
AH-64	Fwd Hanger Bearing	Safety improvement w/ continuous diagnostic monitoring. Extends TBO from 2500 hrs to 2750 hrs. MMH saved per inspection: 4.4 hrs. Downtime saved per aircraft: 2.2 hrs.
UH-60	Oil Cooler Axial Fan Bearing	Eliminates 120 hr inspection w/ continuous diagnostic monitoring. Extends TBO from 2500 hrs to 3000 hrs.
UH-60	Engine Output Drive Shaft	Eliminates AVA installation requirement for 120 hr inspection. Replace w/ continuous diagnostic monitoring. MMH saved per inspection: 3.3 hrs. Downtime saved per aircraft: 1.8 hrs.



Source: U.S. AMCOM

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7 of 15



Maintenance Paradigm Attributes



- 1. Component contribution to vehicle's critical functions.** How will this component's degradation impact the mission? How will it impact safety? How much downtime must the vehicle endure in order for the component to be repaired or replaced? What is the likelihood of catastrophic failure associated with this part?
- 2. Component overall cost.** This is more than just the simple cost accounting figure for the component—also included are costs associated with the time it takes to replace the part, shortage costs, and inventory costs.
- 3. Complexity of the component.** Will it be feasible to determine the condition of a particular component? Is it reasonable to expect that this part's condition can be isolated from extraneous noise?
- 4. Technological capability to monitor component condition** (vibrations, temperature, electronics, etc.). Is there a history of monitoring and assessing the particular component or a similar component's status? Is the monitoring likely to result in data that generates enough fidelity to determine component degradation?



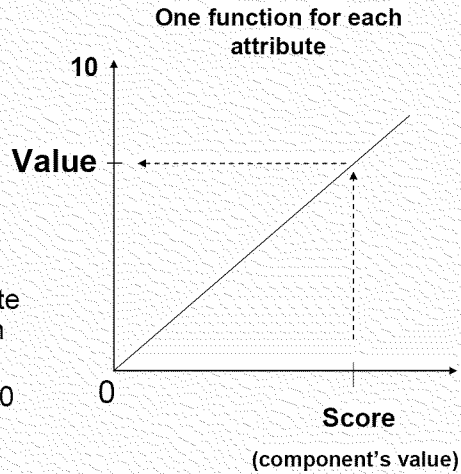
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8 of 15

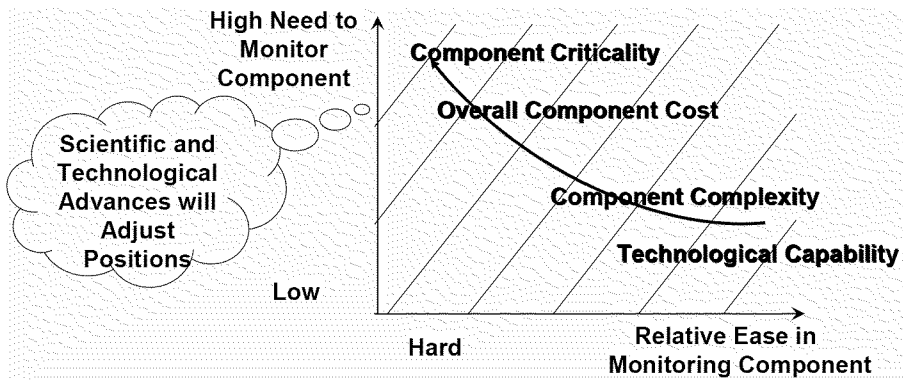


Maintenance Paradigm Calculation

- **Process steps include**
 - Select A_i
 - Select w_i
 - Assign A_i to attributes 1-4
- **To calculate MP**
 - Find the score for an attribute
 - Convert the score to a value
 - Sum the weight of each attribute multiplied by the value for each attribute
 - $MP_i = \sum_i w_i V(A_i)$, max MP of 10



MP Attribute Relative Importance

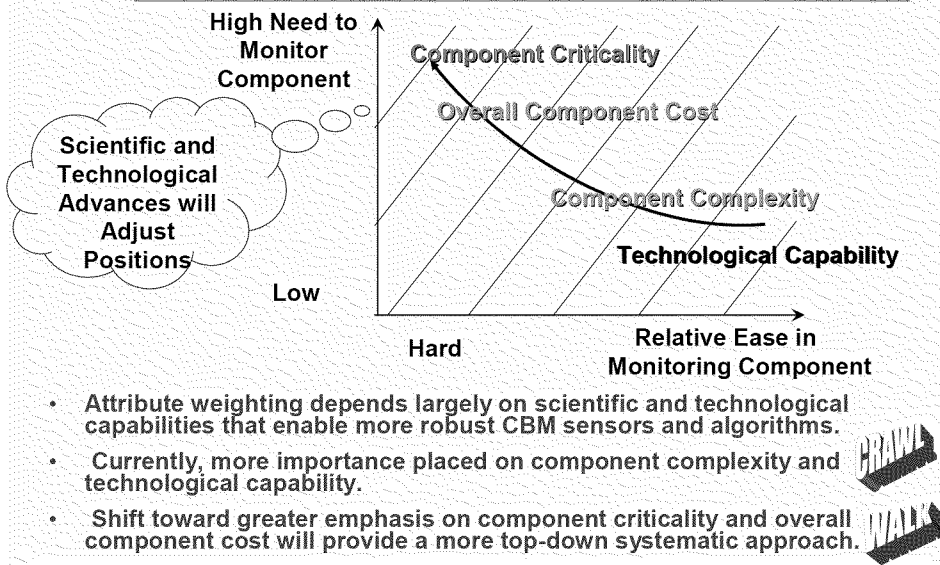


<i>Easy to Monitor</i>	<i>Hard</i>	<i>Difficult</i>
Bearings	Engines	Struts & Dampeners
Drive Shafts	Hydraulic Modules	Pitch Housings
Dynamic Components	Electronic Units	Fatigue Life Limited Parts

--From U.S. AMCOM Pamphlet OCT05

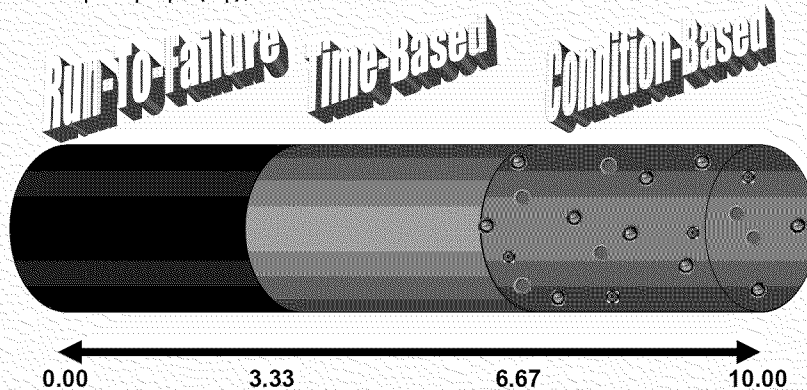


MP Attribute Relative Importance



MP Component Categorization

$$MP_i = \sum_i w_i V(A_i), \text{ max MP of 10}$$



Maintenance Paradigm (MP) Value

- Derived/Ancillary
- Platform/Core
- Breakthrough



Further Research



- **Developers and First Users**
 - NASA
 - DOD
- **Mainstream Adopters**
 - Auto Manufacturers
 - Commercial Aviation
 - Utilities and Power Plants
 - Hospitals and Medical Device Manufacturers
- **New Innovators**
 - Electronics
 - Networks
 - Materials
 - Environment & Ecology
 - Sports Medicine
 - NASCAR



Viability of This Methodology



- **U.S. Army Aviation**
 - UH-60
 - AH-64
 - CH-47
- **Future Combat System (FCS)**
- **Joint Strike Fighter**





Acknowledgements



- Mr. Robert Brown, AMCOM G-3 CBM-Lead
- Aviation and Engineering Directorate, AMRDEC
- Westar Corporation
- MAJ Paul Ewing, Jr., COL William Tarantino, and Dr. Gregory Parnell (2005). "Use of Decision Analysis in the Army Base Realignment and Closure (BRAC) 2005 Military Value Analysis," presented at INFORMS 2005 Annual Conference, San Francisco, CA on 14 NOV 2005.
- Dr. Robert Carlson. Course entitled "New Product Development," taken at Stanford University, 2001.

Exhibit 4: Researching Common Areas of Interest

White Paper
Operations Research Center of Excellence
Department of Systems Engineering
United States Military Academy
West Point, NY 10996

27 February 2006
Major Ernest Wong
U.S. Army
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Defining Appropriate Metrics for Operating Within a Condition-Based Maintenance Paradigm

“The victorious army first realizes the conditions for victory, and then seeks to engage in battle. The vanquished army fights first and then seeks victory.”

--Sun Tsu, *The Art of War*

Executive Summary

Without clear objectives, it is oftentimes difficult to make good decisions. To come up with clear objectives, organizations must first determine what is important and then figure out a way to assess and evaluate how well they are able to perform with respect to what is important [7]. As the familiar saying goes, “What gets measured, gets done.” Metrics, therefore, play a critical role in organizational performance, and leaders today are very concerned about exactly what is measured [5]. Regardless of the type, size, or function of the organization, good metrics help to drive systemic improvement and are usually [1]:

- Few in number to allow concentration on those vital key variables
- Linked to key business drivers to promote organizational success
- Composed of a mix of past, present, and future to achieve a holistic perspective
- Based around needs of customers, shareholders, and key stakeholders
- Driven from the top and permeated throughout all levels of the organization
- Composed of multiple indices to give a better overall assessment
- Flexible and adaptable to changes in environment and strategy
- Based on targets or goals established through research rather than arbitrary numbers

Most organizations spend countless hours collecting and interpreting data intended to enhance business performance and productivity. Yet a large portion of this time amounts to

nothing more than wasted effort when the wrong measurements are analyzed. As a result, organizations tend to create unnecessary procedures, squander resources, and detract from their objectives when this happens. Of greater consequence, however, is that wrong metrics oftentimes lead organizations to inaccurate decision-making which, in turn, translates into poor choices. This paper examines how organizations can ensure that they are focused on a set of appropriate metrics that are linked to critical success factors, such as:

- Higher quality manufacturing through reduced costly mistakes
- Reduced risk and improved safety
- Increased operational efficiency and usage
- Extended equipment life and reduced lifecycle costs
- Increased savings in personnel training costs
- Improved employee satisfaction
- Increased confidence in major decisions

Developing appropriate metrics to evaluate the performance of the condition-based maintenance (CBM) paradigm for U.S. Army aviation is critical not just as a means to assess the progress of the program, but also as a means to help continually improve upon the CBM vision of achieving optimal operational readiness of the aviation fleet. DoD Directive 5000.1 articulates some of the critical success factors for CBM [4]:

- Predict equipment failures based on real-time or near real-time assessments of equipment condition obtained from embedded sensors
- Reduce maintenance down time
- Increase operational readiness by repairing or replacing system components based on actual condition of components rather than on a scheduled or time-phased basis

Accordingly, metrics developed for CBM must relate to factors such as these. A good way to help ensure that the metrics are meaningful is to make sure the chosen measurements are SMART--specific, measurable, aligned, realistic, and time-bound [6].

Introduction—A Shift to More Meaningful Metrics

For every objective, there ought to be at least one quantifiable metric and a target value for that metric. Once the objective-level target for a metric has been reached, the organization

knows that a particular objective has been achieved. Unfortunately, most organizations try to measure too many things, measure the wrong things, use measures that no longer have relevance, or use measures that are ambiguous and give managers and workers little control [6]. When this occurs, a great deal of organizational time, energy, and resources are wasted.

Michael Dell, CEO of Dell Computers, has stated, “To motivate an employee to think like an owner, you have to give her metrics she can embrace” [3]. SMART metrics—those that are specific, measurable, aligned to key objectives, realistic, and time-bound (attainable within a certain time period)—are a key element of a performance management system that helps link employees to the success of the organization (Fig. 1).

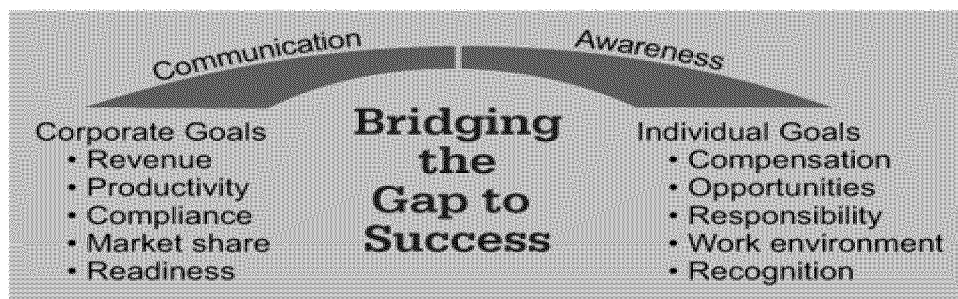


Figure 1: Aligning Organizational and Individual Goals [6]

However, most traditional performance management systems provide “lagging” rather than “leading” indicators. They tend to be more like rearview mirrors that explain how goals were or were not met based on past performance rather than being more like steering wheels that enable organizations to adjust to changing conditions [5]. In today’s more measure-based, goals-driven, performance management culture, improved metrics must be developed to better align efforts, implement strategies, and focus on results (Fig. 2). Organizations that make a concerted effort to shift to metrics that are multidimensional, permit mid-course steering, create value, display line of sight to action, enhance strategy, facilitate management across multiple functions, and assist in the management of output value are much more likely to find themselves to be the leaders in this new century. The shift to more meaningful metrics will lead to the advancement of purposeful organizations that succeed at effectively and efficiently getting things done right.

THE OLD METRICS	THE NEW METRICS
Primarily financial	Multidimensional
After the fact	Mid-course steering
Control and report	Align effort, create value
Not actionable	Line of sight to action
Earnings & taxes	Implement strategy
Within functional areas	Manage across functions
Manage input costs	Manage output value

Figure 2: A Shift to More Meaningful Metrics [5]

A Process for Linking Meaningful Metrics to Organizational Objectives

Dr. Bob Frost has developed a three-step methodology for helping develop meaningful metrics and performance indicators [5]:

- Step 1: The organization examines its business strategy and stakeholders to find crucial Performance Topics.
- Step 2: The organization determines where and how it must succeed on each topic, spelling out the where's and how's as a set of Critical Success Factors.
- Step 3: The organization considers each Critical Success Factor and defines specific Performance Indicators that will track success on it.

This three-step process works from the general to the specific—from Performance Topic to Critical Success Factors to specific Performance Indicators (Fig. 3). Taking the time to link performance indicators to performance topics helps to ensure the chosen metrics will be meaningful and provide value to the organization. Raytheon Corporation's Emery Powell

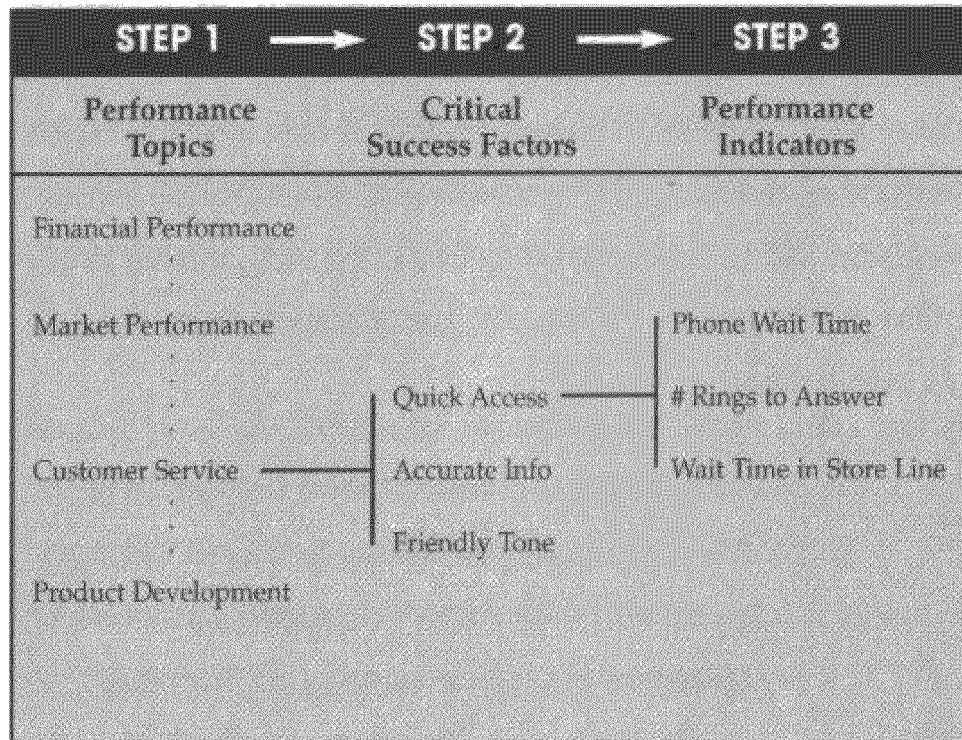


Figure 3: Sample of Frost’s 3-Step Process for Developing Meaningful Performance Indicators [5]

perhaps summarizes it best when he stated, “A strategy without metrics is just a wish. And metrics that are not aligned with strategy are a waste of time.”

Meaningful Performance Metrics for CBM

The CBM vision of achieving optimal operational readiness of the U.S. Army’s aviation fleet already has a set of clearly articulated Critical Success Factors. According to DoD Directive 5000.1, critical to the success of the CBM paradigm is its ability to [4]:

- Predict equipment failures based on real-time or near real-time assessments of equipment condition obtained from embedded sensors
- Reduce maintenance down time
- Increase operational readiness by repairing or replacing system components based on actual condition of components rather than on a scheduled or time-phased basis

As such, performance indicators and metrics developed for CBM ought to align with Critical Success Factors such as these (Fig. 4).

Performance Topics	Critical Success Factors	Suggested Performance Metrics (leading)	Old Performance Metrics (lagging)
Operational Readiness of Aviation Fleet	Predict equipment failures based on real-time or near-real time assessments of equipment condition	Operational readiness rate of unit aircraft	Operational readiness rate of unit aircraft
	Repair or replace system components based on actual condition of components	Percentage of fleet in the Green/Yellow/Red health indicators (by aircraft type, location, etc.)	Operational readiness rate of unit aircraft
Safety of Fleet	Predict equipment failures based on real-time or near-real time assessments of equipment condition	# of new (or more refined) prognostics directed at aircraft safety	# of accidents/qtr
		Differential in published maintenance schedule with prognostics-determined maintenance regimen	# of accidents/qtr
	Isolate and identify component or part defects	NSN or vendor of components that fail at statistically significantly higher rates than average	Fault determination through accident investigation report
Value to Warfighter	Reduce maintenance down time	# of hours of unscheduled maintenance circumvented by planned maintenance	# of hours of maintenance down time
		# of hours of physical inspections replaced or eliminated through CBM monitoring	# of hours of maintenance down time
	Improve Warfighting Capability	Optimal # of stand-by aircraft needed to back-fill a mission	# of stand-by aircraft needed to back-fill a mission

Figure 4: A Sample 3-Step Metrics Development Chart for CBM

Performance Topics	Critical Success Factors	Suggested Performance Metrics (leading)	Old Performance Metrics (lagging)
Cost-Savings & Cost-Avoidance Performance	Predict equipment failures based on real-time or near-real time assessments of equipment condition	Change in number, volume, weight, cost, etc. of supply parts inventory	Cost of repair parts
	Repair or replace system components based on actual condition of components	Optimal lead time determined for acquiring, repairing, and/or replacing a system component	On-time satisfaction of maintenance schedule
		Differential in published maintenance schedule with prognostics-determined maintenance regimen	On-time satisfaction of maintenance schedule

Figure 4 (cont.): A Sample 3-Step Metrics Development Chart for CBM

Conclusions—CBM as a Viable Strategy-Based Performance Management System

To improve, according to one Webster’s definition, means to “enhance in value or quality.” This definition implies that value and quality are already present. The CBM paradigm aims to improve upon the merits of the more widely-accepted preventative and schedule-based maintenance paradigm. Today’s enabling technologies permit CBM to define maintenance actions based on actual conditions obtained from non-invasive tests and predictive prognostics rather than relying on specified intervals which may be too conservative—creating unnecessary maintenance--or too aggressive—resulting in undue risk. Because the CBM paradigm approaches maintenance in a more objective fashion, it follows that CBM should be an ideal strategy-based performance management system that analytically targets continual improvement (Fig. 5). However, success for CBM depends largely on the performance measures chosen to

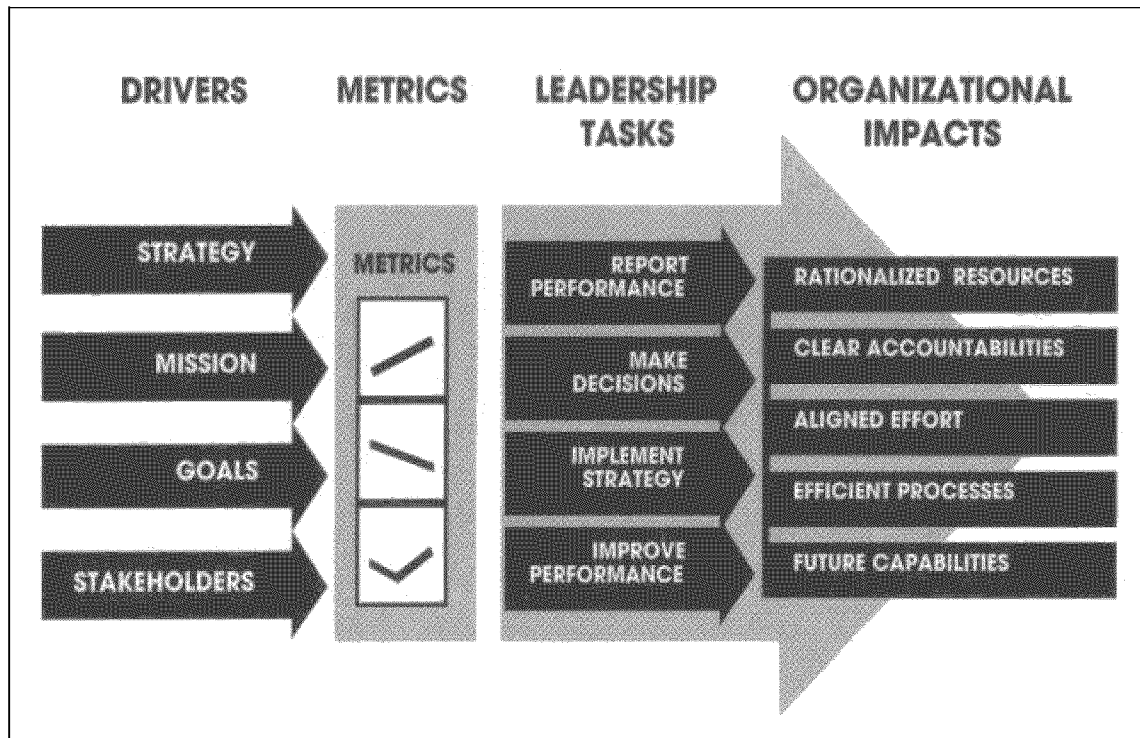


Figure 5: Strategy-Based Performance Management Design [5]

gauge the program’s progress. Perhaps more importantly, continual improvement within CBM itself depends largely on the development and selection of performance indicators that are SMART—specific, measurable, aligned to key objectives, realistic, and time-bound.

Jim O’Brien, University of Kentucky Associate Basketball Coach, once remarked, “Excellence is the unlimited ability to improve the quality of what you have to offer.” CBM has the potential to not only enhance, but also revolutionize the way the Army does maintenance. Although still in its infant stages, CBM is already demonstrating viable progress in predicting equipment failure based on actual conditions, reducing unnecessary maintenance, and increasing the Army aviation fleet’s warfighting reliability and readiness. With the appropriate metrics, CBM has the potential to facilitate real-time communications that is required of highly effective and efficient organizations (Fig. 6). With the right metrics, CBM has the opportunity to align process improvement with long-term vision in order to make our Army a much more lethal

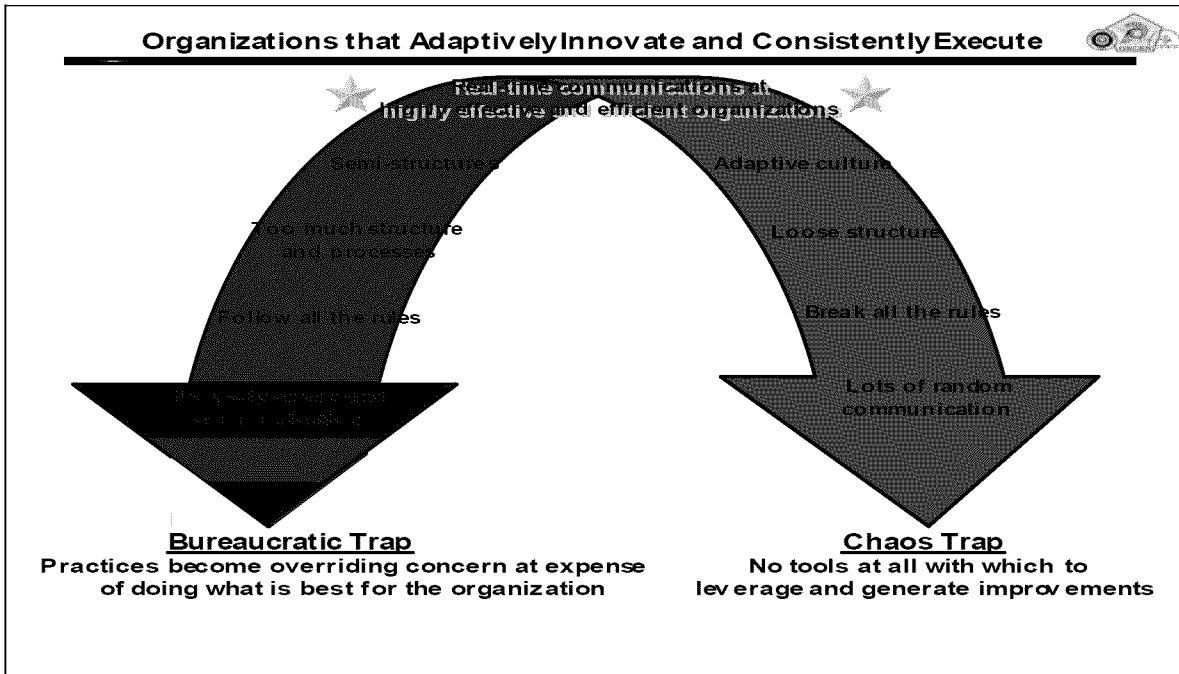


Figure 6: Avoiding Both the Bureaucratic and Chaos Trap [2]

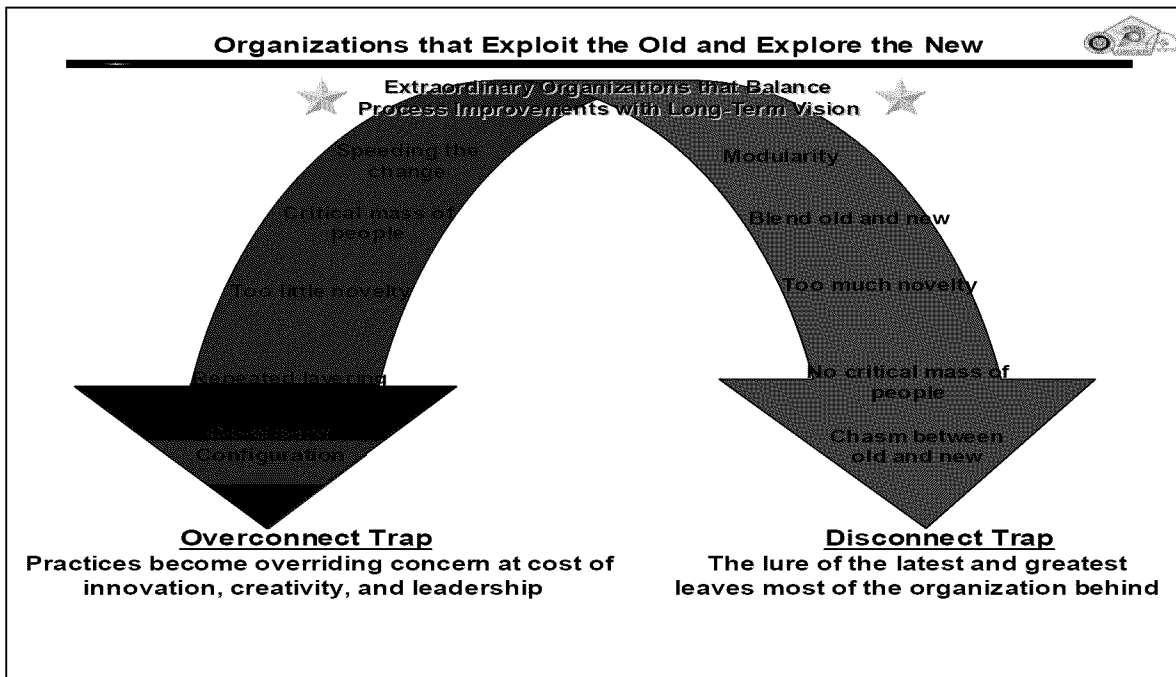


Figure 7: Avoiding Both the Overconnect and Disconnect Trap [2]

fighting force (Fig. 7). Ideal for this new century, CBM is a strategy-based performance management system that aims to achieve organizational excellence.

References

- [1] Brown, M. (1996). *Keeping Score: Using the Right Metrics to Drive World-Class Performance*. New York, NY: Productivity Press.
- [2] Brown, S., and Eisenhardt, K. (1998). *Competing on the Edge of Chaos, Strategy as Structured Chaos*. Boston: Harvard Business School Press.
- [3] Dell, M., and Fredman, C. (1999). *Direct from Dell: Strategies that Revolutionized an Industry*. New York, NY: HarperCollins Publishing.
- [4] Department of Defense. (2003). Directive No. 5000.1 dated May 12, 2003. Retrieved on 11 August 2005 from <http://www.dtic.mil/whs/directives/corres/pdf2/d50001p.pdf>.
- [5] Frost, B. (2000). *Measuring Performance: Using the New Metrics to Deploy Strategy and Improve Performance*. Dallas, TX: Measurement International.
- [6] Moore, C. (August 2005). Measuring Success: “Capturing the Right Metrics”, in *Workforce Performance Solutions*. Retrieved on 26 February 2006 from http://www.wpsmag.com/content/templates/wps_article.asp?articleid=312&zoneid=19
- [7] United States Military Academy, Department of Systems Engineering (Eds.). (2004). *Readings for Systems Engineering & Engineering Management*. Mason, OH: Thomson Customer Publishing.

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REPORT DOCUMENTATION PAGE – SF298

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1. REPORT DATE (DD-MM-YYYY) 23-06-2006		2. REPORT TYPE Technical Report		3. DATES COVERED (From - To) 01-06-2005 23-06-2006	
4. TITLE AND SUBTITLE Condition-Based Maintenance (CBM): A Working Partnership between Government, Industry, and Academia				5a. CONTRACT NUMBER	
				5b. GRANT NUMBER	
				5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S) MAJ Ernest Y. Wong MAJ Stephen E. Gauthier LTC Simon R. Goerger				5d. PROJECT NUMBER DSE-R-0614	
				5e. TASK NUMBER	
				5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Operations Research Center of Excellence Dept. of Systems Engineering United States Military Academy 646 Swift Rd. West Point, NY 10996				8. PERFORMING ORGANIZATION REPORT NUMBER DSE-TR-0614	
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) U.S. Army Aviation & Missile Redstone Arsenal Huntsville, AL 35898				10. SPONSOR/MONITOR'S ACRONYM(S)	
				11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION / AVAILABILITY STATEMENT Distribution A: Approved for public release; distribution is unlimited.					
13. SUPPLEMENTARY NOTES					
14. ABSTRACT While a large number of partnerships form as defensive measures in response to fierce global competition, distress over future uncertainties, and a lack of alternative methods to ensure continued survival, synergistic partnerships are characterized as being cooperative learning experiences that benefit all the parties involved. The best partnerships are those that develop into strategic alliances helping to capture and create value that would otherwise have been difficult to realize if not for the mutually shared goals and resources of the partnership. In this paper, we discuss how government, industry, and academia are able to converge upon a new maintenance paradigm aimed at benefiting our nation's military forces. In particular, representatives from all three domains are working together to determine how condition-based maintenance (CBM) can best serve U.S. Army aviation and bolster our soldiers engaged in the war against terrorism. Described as is a set of maintenance processes and capabilities aimed at improving U.S. Army aviation fleet's operational readiness and reducing soldiers' maintenance burden, CBM leverages advanced technologies to help generate enhanced diagnostics for key components on-board a select number of AH-64 Apache, UH-60 Blackhawk, and CH-47 Chinook helicopters. The near real-time assessment of data from the embedded sensors seeks to provide the U.S. Army with a more effective and efficient way to conduct maintenance based on need rather than scheduled periods, the capability to perform supply chain actions in a more proactive manner, and the ability to optimize the competing demands of war fighting and planned maintenance. In short, CBM attempts to improve the way the U.S. Army approaches maintenance, transforming it from the industrial age of the 20 th Century into the information age of this new century. We believe that through the successful partnering of government, industry, and academia, we will be able to exemplify how CBM is demonstrating business transformation for the U.S. Army.					
15. SUBJECT TERMS Condition Based Maintenance					
16. SECURITY CLASSIFICATION OF: Unclassified			17. LIMITATION OF ABSTRACT None	18. NUMBER OF PAGES 146	19a. NAME OF RESPONSIBLE PERSON MAJ Ernest Y. Wong
a. REPORT Unclassified	b. ABSTRACT Unclassified	c. THIS PAGE Unclassified			19b. TELEPHONE NUMBER (include area code) 845-938-4756