Skip all front matter: Jump to Page 1

Research Report

Methods for Identifying Part Quality Issues and Estimating Their Cost with an Application Using the UH-60

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Preface

The U.S. Army does not currently have tools to leverage empirical demand and usage data to identify existing or emerging problems with part or process quality. Instead, it relies on Product Quality Deficiency Reports (PQDRs) and subject matter experts (SMEs) from various organizations to monitor and react to part quality problems. Because of the scope of the Army's operations (large range of weapon systems, suppliers, and parts) and the lack of information on the total cost of part deficiencies, this approach tends toward a narrow focus either on very expensive parts, such as transmissions, rotor blades, and engines, or on safety-critical items. The current approach is labor intensive, and it does not prioritize corrective action based on what the part deficiency is costing.

The Army asked RAND Arroyo Center to develop a method that uses readily available data sources to detect potential part quality problems and to estimate the potential cost of the problem to the Army.

This report on the cost of poor part quality presents the results of the first year of a RAND Arroyo Center study sponsored by U.S. Army Materiel Command (AMC) and the Deputy Chief of Staff, G-4. We explore the feasibility of using readily available demand and end item maintenance history to identify potential part or process quality issues and estimate their associated incremental cost. Because of the availability of flight hour data, we focus our study on aviation.

This research was sponsored by U.S. Army Materiel Command (AMC) and the Deputy Chief of Staff G-4 and conducted within RAND Arroyo Center's Military Logistics Program. RAND Arroyo Center, part of the RAND Corporation, is a federally funded research and development center sponsored by the United States Army.

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Contents

Appendix

Figures

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Tables

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Summary

This report presents research sponsored by U.S. Army Materiel Command (AMC) and the Deputy Chief of Staff, G-4 to explore the feasibility of using readily available demand and end item maintenance history to identify potential issues with part or process quality and estimate their associated incremental costs.

Currently, the Army relies on Product Quality Deficiency Reports (PQDRs) and subject matter experts (SMEs) from various organizations to monitor and react to part quality problems. Because of the scope of the Army's operations (and accordingly its large range of weapon systems, suppliers, and parts) and the lack of information on the total cost of part deficiencies, which include repair and maintenance, inventory, and disposal costs in addition to the procurement cost, this approach tends to focus either on very expensive parts, such as transmissions, rotor blades, and engines, or on safety-critical items. It does not tend to focus on less-expensive items, which may be total cost drivers.

The purpose of this analysis is threefold:

- First, we identify three part usage patterns that could indicate emerging or existing part or process quality problems.
- Second, we develop and test two methods to evaluate the performance of thousands of parts and identify potential emerging or existing issues. The methods rely on well-understood statistical tests to identify reduced reliability and to group parts for comparison.
- Finally, we develop a cost model incorporating estimates of increased maintenance and inventory costs.

This approach identifies parts for further analysis based on the estimated total system cost of poor quality, allowing the Army to focus on high-marginal-cost items regardless of a part's unit price. This approach is similar to others such as control charts and Weibull analysis, in which a tool identifies potential problems leading to root cause analysis and corrective action.

A case study using the UH-60M demonstrates the potential for this methodology. The value of this approach is its power to analyze the performance of thousands of parts, and by assigning a cost, to prioritize a list of parts with the highest potential return on investment.

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Glossary

AMC	Army Materiel Command
AMCOM	Aviation and Missile Command
AMRDEC	Aviation and Missile Research Development and Engineering Center
AWCF	Army Working Capital Fund
CATI	Category I PQDR Deficiency
CCAD	Corpus Christi Army Depot
CECOM	Communications and Electronics Command
CH-47	Chinook Cargo Helicopter
COQ	Cost of Quality
CSI	Critical Safety Items
CSL	Customer Service Level
CTASC	Corps/Theater Automatic Data Processing Service Center
DCMA	Defense Contract Management Agency
DLA	Defense Logistics Agency
DoD	Department of Defense
EDA	Equipment Downtime Analyzer
FSC	Federal Stock Class
JM&L	Joint Munitions and Lethality Command
LCMC	Life Cycle Management Commands
LIW	Logistics Information Warehouse
MTBF	Mean Time Between Failure
NSN	National Stock Number
OEM	Original Equipment Manufacturer
PQDR	Product Quality Deficiency Report
RAM	Reliability and Maintainability
SME	Subject Matter Expert

SSA	Supply Support Activities
TACOM	Track and Automotive Command
UH-60	Black Hawk Utility Helicopter (A–M models)
ULLS-A (E)	Unit Level Logistics System–Aviation Enhanced
WPU	Weekly Production Update

1. Introduction: Managing the Cost of Poor Quality

Over the next 10 years, the Department of Defense (DoD) will be asked to reduce its projected spending by more than $450 billion. Finding a way to implement these cuts is a critical challenge facing the Department of Defense. In his first major policy address, Secretary of Defense Leon Panetta (Panetta, 2011) said:

> In this fiscal environment, every program, every contract and every facility will be scrutinized for savings, savings that won't reduce readiness or our ability to perform essential missions . . . These cuts will need to be carefully targeted . . . to avoid a hollow force, to ensure that we maintain a robust industrial base, and to protect the new military capabilities we need to sustain our military strength.

This research can help the U.S. Army maintain equipment readiness levels in an austere budget environment by controlling the incremental maintenance and inventory costs, as well as the increased equipment downtime, created by poor quality processes and parts.

The Relationship Between Quality, Cost, and Readiness

There are a variety of reasons why a part may fail before its expected life limit, including manufacturing defects, poor part design, misuse, or incorrect maintenance. These factors contribute to increased costs for operations, many of which are very difficult to quantify or are unknown and unknowable.[1] For example:

- How much does it cost when a part fails prematurely in the field, or when a production line is stopped or slowed due to poor-quality parts?
- What costs are generated when parts are incorrectly diagnosed due to outdated diagnostic software?
- How much can be gained through improved design of parts?
- What is the impact of part quality deficiencies on equipment readiness?[2]

Currently, the Army does not have a way to quantify these costs and therefore does not have a way to prioritize quality improvement actions based on their potential cost

[1] Unknown and unknowable costs related to poor part quality include decreased availability of a system or reduced confidence in a system's operational reliability.

[2] Equipment readiness is measured by the product of the time required to order and repair an item and the failure rate (Peltz et al., 2002)

avoidance. Instead, as we shall discuss in Chapter 2, current quality management efforts are heavily dependent on Product Quality Deficiency Reports (PQDRs) or on resource-intensive analysis of maintenance logbooks. Because the current approaches do not attempt to capture costs beyond an item's unit price, they tend to focus resources on expensive parts.

We broaden this perspective by estimating costs of additional depot repair workload generated by increased failures and inventory required to maintain readiness, thereby allowing for a different—and, we propose, better—prioritization of quality improvement efforts.

Background

The U.S. Army Materiel Command (AMC) manages weapon system procurement and maintenance for the Army. The AMC mission includes procurement of spare parts for field and depot level maintenance, modifications and modernization of existing parts, and recapitalization of equipment. AMC procures millions of parts and services from thousands of suppliers each year, including major suppliers such as organic maintenance and overhaul depots like the Corpus Christi Army Depot (CCAD), the Defense Logistics Agency (DLA), and original equipment manufacturers (OEMs). In turn, these major suppliers procure parts and services from many sub-tier suppliers, with no visibility of the sub-tier suppliers by the Army. It is not uncommon to have multiple suppliers for the same part, or changes in suppliers as contracts expire and new contracts are awarded. The volume of supply, lack of visibility, multiple suppliers, and changes in suppliers are among the challenges to instituting a systematic part quality management process. For the Army, the cost of a poor-quality part entering the system manifests itself in one of three ways:

- A part causes a failure, which compromises safety (parts of this type are categorized as critical safety items (CSI).
- A part causes a failure that results in a weapon system being taken out of service temporarily, reducing readiness and perhaps compromising the ability to fulfill a mission objective/
- (3) Costs rise because of incremental increases in maintenance and inventory level needed to assure readiness, or increased inspection and removals to insure safety.

The first two cost categories are the direct result of poor part quality and include tangible costs, such as the cost of a crashed helicopter, and intangible costs, such as decreased confidence among warfighters in the systems on which they rely. The third category is the cost of mitigating the effects of the first two by investing in buffer stocks and inspections.

AMC asked RAND Arroyo Center to develop a method that would allow the Army to identify the costs incurred due to poor-quality parts and help it identify which suppliers could be disproportionally contributing to maintenance costs.

In the course of this research, it became evident that in addition to the manufacturing quality of the part, other quality factors contribute to the overall cost of maintaining a desired level of readiness. It is therefore necessary to look beyond manufacturing or repair as a root cause for part quality defects and costs.

Study Objective and Approach

The objective of this research is to develop a methodology that can be used to systematically examine a large number of parts, identify parts with potential quality deficiencies, and quantify the costs of those deficiencies. This methodology will be used to identify and prioritize corrective actions and quality improvement initiatives. There is a breadth of potential users—from depot subject matter experts, to program offices, and to item managers responsible for maintaining a supplier base. These initiatives could include, but are not limited to:

1. improving technical manuals and training to reduce user-induced failures;
2. working with suppliers to reduce manufacturing or repair defects;
3. identifying opportunities to increase reliability by redesigning a part; and
4. prioritizing quality improvement initiatives for problematic parts.

This methodology can also be used to communicate quality problems from the field and produce actionable data for HQ AMC.

Our approach is to use readily available part supply and maintenance data, as well as statistically based tests, to identify parts that are exhibiting decreasing reliability or are less reliable than similar parts. We then estimate the additional maintenance and inventory costs incurred by the Army because of the identified quality deficiency. The costs are based on a six-month projection of current reliability and can be used to prioritize and monitor quality improvement initiatives.

This report presents the development and application of Arroyo's Cost of Poor Quality estimation process to Army Aviation. We present a case study using the UH-60M, the Black Hawk Mike model.

Organization of the Document

The remainder of this document is organized in five additional chapters:

- Chapter 2 describes the Army's current system for identifying and managing part quality deficiencies.
- Chapter 3 provides a background on the cost of quality.

- Chapter 4 describes our methodology for identifying part quality problems and for assigning costs for part quality deficiencies.
- Chapter 5 presents a case study using the UH-60M model.
- Chapter 6 presents conclusions and recommendations.

2. How Does the Army Currently Monitor Part Quality Problems?

There are various organizations responsible in one way or another for assuring Army parts quality.

- The RDECOM organizations such as Aviation and Missile Research Development and Engineering Center (AMRDEC), which provide engineering support to program offices and conducts supplier audits.
- AMC/G-4 Continuous Process Improvement (CPI) is a recently established group responsible for setting policy on quality for AMC and driving continuous improvement throughout the command.
- The Defense Contract Management Agency (DCMA) is responsible for overseeing contract requirements and assuring that items conform to specifications.
- The Life Cycle Management Centers (LCMCs) are responsible for managing maintenance activities, including logistics, materiel and supply chain management, and strategic sourcing.

These organizations have limited tools to assess part quality. To date, Product Quality Deficiency Reports (PQDRs) and logbook data are used for the task. Below we describe these data sources and how the listed organizations apply PQDR data to measuring quality.

Product Quality Deficiency Reports

The primary method used to identify and track part quality problems in the field is the PQDR. A PQDR is to be filed on any item with "any defect, nonconforming condition, or premature equipment failure indicating deficiencies in design, specification, material, manufacturing, and workmanship or for deficiencies in major weapon systems, secondary/consumable/repairable items, spare and repair parts, Gov-owned products, and Gov-furnished property" (Product Quality Deficiency Report Process, 2008). The PQDR process is a DoD standard used by all services (DLA, 1993).

PQDRs are classified according to their level of severity. Category I (CATI) PQDRs are deficiencies which may:

- lead to death, injury, severe illness;
- cause major damage to a weapon system; or
- critically restrict combat readiness capabilities.

Category II PQDRs encompass all deficiencies that are not Category I. Once discovered, CATI PQDRs must be reported by the originating organization to the PQDR screening point within 24 hours. The screening point validates the PQDR and, if valid, enters the report into the PQDR data system and forwards it to the action point. For CATI PQDRs, the screening point has 24 hours to process the report and forward it to the action point for further investigation. If severe, CATI PQDRs can lead to grounding or other severe restrictions on the use of a weapon system until the root cause of the deficiency is uncovered.

In addition to quickly communicating potentially critical quality problems, PQDRs serve another important function. If a part fails in the field, the customer will receive a credit for the part if the failure was determined to be a valid product quality deficiency. Therefore, there is an incentive for units to file PQDRs for both safety and financial reasons.

In theory, a part that fails in the field for other than normal wear will generate a PQDR. In practice, there is no mechanism to ensure that all deficiencies are captured. Interviews with subject matter experts (RAND, 2011) indicate that PQDRs are not used to report all instances of deficiencies. Several reasons were given for this:

1. The PQDR process can be time consuming, and if the deficiency is not a CATI, there is little incentive for a unit to file a report unless the part is expensive and the unit wants a credit.
2. When the deficiency is well known, i.e., other PQDRs have been filed and are under investigation, the originating unit may be asked not to file an additional PQDR.

Because of this, PQDR reporting is biased toward deficiencies for more expensive items, or for safety-critical items. Table 2.1 shows how the distribution of PQDRs filed in 2010 for Army Aviation National Stock Numbers (NSNs) tended to be more representative of NSNs valued at $40,000 or more. Column 1 of Table 2.1 categorizes NSNs by unit price; Column 2 and Column 3 show the count and the percent of the total of all critical NSNs[3] for all weapon systems as recorded in the Equipment Downtime Analyzer (EDA) data from 2004 to 2010. Over 89 percent of the parts identified as critical are valued under $1,000. The distribution changes slightly as we limit our selection to parts used by Army Aviation, Column 4.[4] Column 7 shows the percentage distribution by price category of aviation NSNs that also received a PQDR. The takeaway is that only 2 percent of the NSNs used to maintain aviation assets were valued at $40,000 or more, and they

[3] "Critical" means that the NSN appeared on a job order for the repair of an end item that was down for maintenance for more than one day.

[4] NSNs used on repair of UH-60, OH-58, CH-47, AH-64.

generated 16 percent of the PQDRs. While less expensive NSNs generate PQDRs, they do so disproportionately to the number of NSNs in the price category. While the price of the parts on a weapon system varies greatly, the cost of having a piece of equipment out of service is the same regardless of the price of the part downing the equipment. The bias toward more expensive parts limits opportunities for cost avoidance and improvement of reliability.

Table 2.1. Distribution of PQDRs by Price Category

Price	Number of NSNs Critical (All systems)	Percent (All systems)*	Number of NSNs Critical (Aviation)	Percent Aviation*	Number NSNs with PQDRs (2010, Army Aviation)	Percent PQDR Army Aviation 2010
0-100	90006	66%	11312	58%	202	13%
101-1000	30957	23%	4346	22%	310	19%
1001-10K	11661	9%	2749	14%	535	33%
10K-20K	1316	1%	399	2%	151	9%
20K-30K	564	0%	202	1%	83	5%
30K - 40K	320	0%	127	1%	62	4%
>40K	994	1%	393	2%	264	16%

Analysis by Subject Matter Experts

PQDRs are not the only means used to report part quality problems. Program Managers within the Program Executive Office monitor part problems reported from the field and work with suppliers and field maintainers to troubleshoot part reliability issues. Interviews conducted with the Reliability and Maintainability (RAM) Office for the UH-60 program indicated that the program offices use subject matter expertise and strong ties to the maintenance community to analyze and identify potential problems. Subject matter experts (SMEs) and supporting offices read thousands of maintenance logs, looking for indications of emerging or ongoing part quality issues.[5] Multiple entries in the electronic maintenance logs, across the entire fleet of aircraft, are used to highlight

[5] The logbook entries are a series of free-form narratives that capture the mechanic's description of the maintenance action. The logbook data does not use any codes that can be queried, so manual interpretation of the individual entries is needed to analyze this data source. The technical, shorthand nature of the reporting requires knowledgeable interpreters, such as former crew chiefs, to translate the narratives into meaningful data for analysis. Accordingly, only 10 percent of maintenance logs are reviewed and scored, i.e., cleansed enough for analysis (RAND research interview with AMRDEC, 2011).

potential problems. SMEs then contact field and depot maintenance offices to investigate possible causes for an increased occurrence of maintenance issues.

Although it is effective, this process has a couple of drawbacks. First, it is very labor intensive. The Unit Level Logistics System Aviation Enhanced (ULLS-A(E)) electronic logbook is used by field level mechanics to record all maintenance activities performed on an aircraft. Table 2.2 shows a sample from a list of ULLS-A(E) logbook entries. The information is not tracked by serial number or NSN, which requires SMEs to use the narrative fields to identify the type of component being discussed and the cause of its failure. In its raw state, the ULLS-A(E) data is not designed to facilitate the type of data analysis leading to the detection of a trend.

Table 2.2. Sample ULLS-A(E) Data Entry

Fault Detected	Action
STAB FAILED DURING HYD LEAK TEST AND TAIL ROTOR SERVO CHECK. ADDITIONALLY, APU GEN FAILED DURING SECOND TRY.	REPLACED GCU.
#1 GEN FAILED IN FLIGHT. AN ATTEMPT WAS MADE TO RESET THE GENERATOR THAT DID NOT WORK. UPON LANDING AND SHUT DOWN THE #1 GEN CAUTION WENT OUT AND THE GEN CAME BACK ON LINE.	REPLACED #1 GCU S/N 1493FM
MOC REQ'D FOR THE REPLACEMENT OF #1 GCU	MOC OK
MOC REQ'D FOR REPLACEMENT OF APU GCU	MOC OK
#2 GEN LIGHT WILL NOT GO OFF WITH GEN SWITCH IN ON POSITION	INSTALLED #2 GCU
STAB FAILS DURING HYD LEAK TEST AND TAIL ROTOR SERVO CHECK.	REPLACED GCU WITH GCU SERIAL # 2539F.

Second, SMEs are located within program offices and devote their attention to one weapon system. Therefore, they are apt to miss quality problems that cross weapon systems, such as when a part is used on a CH-47 as well as a UH-60. Because the UH-60 is flown at a higher rate than the CH-47, parts may start exhibiting problems on the UH-60 fleet first, resulting in the possibility that the CH-47 Program Office would not be aware of this early indication of potential problems. Our methodology overcomes this issue by systematically examining similar parts across weapon systems.

Communicating to Top Management

The PQDR reports and quality monitoring by SMEs do not by themselves constitute a quality management process. In order to prioritize problems and direct resources, top management needs a standardized method for receiving reports on quality issues from the field. The current process used by AMC to monitor part quality problems in the field is a

Weekly Production Update (WPU) presented by the Life Cycle Management Commands (LCMCs). Each LCMC (TACOM, AMCOM, CECOM, and JM&L COM)[6] takes turns presenting briefs to senior AMC management on key business processes (one report every six weeks.) The report on quality problems is focused on PQDRs: specifically, senior AMC managers are briefed on the top five open PQDRs, by dollar value and by age. Figure 2.1 shows an example from a recent WPU report presented by AMCOM.

Figure 2.1. AMCOM Quality Report Presented at Weekly Production Update

TOP 5 Items with PQDRs by Value ($M)

RCN# (*Oldest PQDR)	Nomenclature	I/E	SOS	NIIN	CAT	Qty Def	Unit Cost	Total # PQDRs	End Item	Value ($M)	Age* (Days)
W25N7V-10-0167/68	Engine, A/C Turboshaft	I	AMC	015031701	I/II	17	706862	17	UH-60/ AH-64	11.73	279
077272-10-0021	Engine, A/C Turboshaft	E	AMC	014585361	II	3	941364	3	CH-47	2.824	286
WT4XBL-10-0006/7	Cold Section Module	E	AMC	012844013	II	7	329553	7	UH-60/ AH-64	2.286	143
W81JMJ-10-0011	Transmission, Mechanical	E	AMC	015209744	I/II	5	401667	5	AH-64D	1.19	166
W81HL5-10-0014	Transmission, Mechanical	E	AMC	015209742	I/II	4	401667	4	AH-64D	1.581	145

TOP 5 PQDRs by Age (Days)

RCN#	Nomenclature	I/E	SOS	NIIN	CAT	Qty Def	Unit Cost	End Item	Value ($M)	Age (Days)
W45N7V-09-0274	Spring, Helical	I	SMS	011291953	II	42	24.16	CH-47D	.0010	577
W25G1Q-10-0071	Charger, Battery	I	AMC	113377422	II	3	14,712	AGPU	.044	395
W90HXE-10-0003	Accumulator, Hydraulic	I	AMC	012224316	II	3	9,326	UH-60A	.028	385
W45N7V-10-0015	Altimeter, Encoder	I	AMC	011769314	II	2	4,912	UH-60L	.010	379
W912U7-10-0003	Nozzle, Turbine Engine	I	AMC	014537890	II	1	24,752	CH-47F	.025	377

The WPU report provides a snapshot in time of top quality drivers. Including a report on the top five PQDRs (in terms of both value and days open) is meant to increase the visibility of unresolved issues.[7] However, because there is no trend data, it is hard to determine whether quality issues are improving or worsening. The top five by dollar value is determined by multiplying the current price of the item by the number of defects reported in the PQDRs. Therefore, it will generate a list of the most expensive NSNs or less expensive items that have had a very large number of quality deficiencies. This list will not include items that did not receive PQDRs, and it will exclude chronic problems

[6] Tank and Automotive LCMC, Aviation and Missile LCMC, Communications-Electronics LCMC, and the Joint Munitions and Lethality LCMC.

[7] The expectation is that by discussing the PQDR during the WPU, action will be taken fix the problem. If the same PQDR shows up in successive WPUs, the LCMC commander is asked to explain why. When the PQDR is closed, it drops off the WPU report.

that do not reach the top dollar value criteria at that point in time. Similarly, the top five by days list is meant to help management identify PQDRs that have not been closed, i.e., a determination on the cause of the quality deficiency has not been completed.

The Continuous Process Improvement (CPI) Division recognizes some of the shortcomings of the current process. They plan to expand the reporting of PQDRs and require more rigor in the WPU reporting. We propose that the Army move toward an enterprise view of quality issues and broaden the scope of "quality deficiencies" beyond PQDRs. Since one of the most effective ways to focus attention on a problem is to attach a dollar value to the cost generated, our approach incorporates a cost estimating function, along with two complementary methods for identifying part quality issues.

3. Estimating the Cost of Quality

Introduction to the Cost of Quality

The term "cost of quality" (COQ) is somewhat contentious. Some have interpreted it to mean the costs of quality improvement programs. However, a generally accepted definition of the COQ is "the sum of conformance plus nonconformance costs, where cost of conformance is the price paid for prevention of poor quality, and cost of non-conformance is the cost of poor quality caused by product and service failure" (Schiffauerova, 2006).

The cost of conformance can include

- operations and process validation,
- quality system audits, and
- maintenance of equipment.

The cost of nonconformance can include

- customer dissatisfaction leading to lost sales (and revenue),
- compromised employee morale due to persistent quality issues,
- increased scrap and rework costs because of defective raw materials, manufacturing defects, or inadequate maintenance procedures, and
- expedited shipping costs due to poor order fulfillment, etc.[8]

The literature on COQ refers to the difficulty of estimating these costs (Campanella, 1999). In part, this difficulty arises because accounting and financial systems are not designed to capture these types of costs. However, the literature and case studies emphasize the importance of estimating the cost of quality as a means of driving change throughout an organization and for helping management prioritize and select quality improvement activities. For example, by tracking the cost of quality, CRC Industries was able to reduce "failure dollars"[9] from 0.70 percent of sales to 0.21 percent of sales over a nine-year period. They did this by collecting data on four categories of failure dollars:

- **Internal quality incidents**: costs related to correcting product defects.
- **Scrap/waste.** includes material scrapped due to defects.

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[8] See Appendix B of *Principles of Quality Costs* (Campanella, 1999).

[9] Failure dollars are the money spent because products and services did not meet customer requirements.

- **Customer complaints/recalls:** all costs involved in resolving a customer complaint or recall, including claims, shipping costs, and labor costs.
- **Product destroyed in field/warranty:** the cost of deductions CRC distributors take for product returned by customers. (Donovan, 2006)

The point illustrated by the CRC case, and supported by the COQ literature, is that tracking and improving a limited number of the many potential COQ categories can greatly reduce overall operating costs.

Estimating the Cost of Poor Part Quality from the Army Perspective

By estimating the cost of poor part quality and incorporating it into the metrics reported by the LCMCs, the PMs, and AMRDEC and by prioritizing Lean Six Sigma activities based on projected cost savings, AMC can (1) send a message to the subordinate commands that measureable cost reductions must be achieved; (2) link poor quality and reduced reliability to cost, emphasizing the importance of improving quality to the overall objective of reducing costs, and (3) properly prioritize and allocate scarce resources where they have the greatest impact on cost. The Army faces a daunting challenge of systematically identifying parts or processes that have a quality issue and associating a cost to this quality issue for proper prioritization and allocation of resources.

Potential for Reducing the Costs of Poor Part Quality

Unlike CRC, the Army does not generate revenue in the conventional meaning of the word. Instead, the DoD, under the provisions of Title 10, established the Army Working Capital Fund (AWCF) to provide inventories of supplies and industrial activities that provide common services, such as repair, manufacturing, or remanufacturing. The AWCF pays for inventory and depot repair under a revolving fund concept whose goal is to break even by returning any monetary gains to appropriated fund customers through lower rates or collecting any monetary losses from customers through higher rates (Department of the Army, 2011). The Army is also provided Operating and Maintenance funding (OMA) to support sustainment and preparation for combat operations. Poor-quality parts represent an additional draw on both AWCF and OMA funds.

In calendar year 2010, the Army issued more than $8.2 billion in materiel from supply support activities (SSAs) to support organizational and intermediate level repair and maintenance of equipment. In addition to organization and intermediate level maintenance and repair, gross sales from depot operations exceed $6.1 billion in 2010 (Department of the Army, 2011).

Realizing the potential for cost savings through improved operational efficiency, the Army has initiated a variety of programs, including Lean Six Sigma, which have been credited for hard savings, cost avoidance, and increased capacity valued at $300 million per year since FY 2007 (Department of the Army, 2011). While these initiatives yielded results, there is still more that can be done to identify and manage the sources of quality deficiencies.

As discussed in Chapter 2, the current methods used to report quality issues are not automated and are, instead, highly dependent upon SMEs. It is preferable that SME time be spent fixing rather than identifying/detecting quality problems. SMEs are essential to identifying root causes and solutions. However, their time is limited, and a process that helps to identify and prioritize SME efforts would enhance their effectiveness as well as improve efficiency.

Our approach focuses on identifying parts that are failing[10] more frequently than in the past, or are failing more often than similar parts. By identifying parts with unusual failure rates and estimating the costs associated with the increased failures, we begin to prioritize corrective action activities. In the remainder of this and the following chapter, we describe a method that could be used by the Army to identify and prioritize part quality problems, which will in turn enhance efforts that reduce the cost of quality associated with poorly performing parts. This methodology can be efficiently applied to a large number of parts to create a list of cost drivers.

What Do We Mean by the "Cost of Poor Quality"?

There are many factors that contribute to the cost of poor quality. PQDRs are primarily used to identify manufacturing defects. However, the underlying cause of a defect is often complex. Consider these examples:

- A seal used on a transmission assembly was manufactured by a new supplier who interpreted the technical drawings incorrectly, producing a rounded seal rather than a flat one, thus generating a PQDR. However, the true cause of the defect was not manufacturing, but a technical drawing that did not specify the shape of the seal.
- A part is sent for repair from an organizational unit to an intermediate repair facility, where no fault is found. This happens several times, until a field team from the intermediate facility discovers that the organizational level maintainers did not have the proper software loaded on their test equipment, therefore generating false failures.
- An engine exits the overhaul line and enters final test and is tested multiple times on a test stand. Each time the repair technician removes the engine and initiates repairs until the engine passes inspection. The "rework" of the engine ties up test

[10] We assume that a part is removed from a weapon system because it is no longer functioning as required. A part failure could be the result of normal wear, improper maintenance, or manufacturing defects, or in some cases the part may not have had a fault but was replaced due to incorrect diagnosis.

equipment, expends additional labor and material, and increases the repair cycle time, yet this data is not captured.
- A part that is supposed to last 1500 hours is failing at 800 hours, increasing the inventory requirement and the maintenance burden.

These are only some examples of many—often hidden—costs due to poor quality documentation, equipment, training, or parts. The cumulative effect of these costs not only deteriorates mission readiness, but can undermine confidence in and morale of the operators and maintainers.

One of the most commonly used models for categorizing cost of quality is the Prevention, Appraisal, and Failure (P-A-F) model. Table 3.1 applies the P-A-F model to some of the processes identified in the course of our interviews with AMC headquarters, field, and depot maintenance personnel. Our definition of quality encompasses all of these elements. However, it is neither possible, nor necessary, to capture all of these costs. As described in the CRC case study, what is needed is a starting point that can provide a measure of relative magnitude. SMEs can then use this information to conduct root cause analysis and measure the results of corrective actions.

Table 3.1. Army Prevention, Appraisal, and Failure Cost

Prevention	Appraisal	Failure Costs
Phase inspection	Supplier visits	PQDR system
Supplier visits	Test equipment	Increased inventory
Quality system administrative expenses	DCMA receiving inspection	Maintenance actions
Time limited service life	Qualification of suppliers	Non-mission-capable equipment
Tech data maintenance	Laboratory support	Supplier corrective action
Manufacturing quality reviews		Rework
Design quality reviews		Repair
		Scrap

Cost Equations

We estimate the costs of quality associated with increased inventory and maintenance actions. The other costs listed above, such as rework, scrap, PQDR system, supplier visits, Defense Contract Management Agency (DCMA) inspections, etc., are not considered, but could be added if data becomes available.

Chapter 4 describes our method for identifying part quality problems and the cost equations used to prioritize parts that should be considered for root cause analysis.

4. Methods for Identifying Parts and Estimating the Cost of Quality

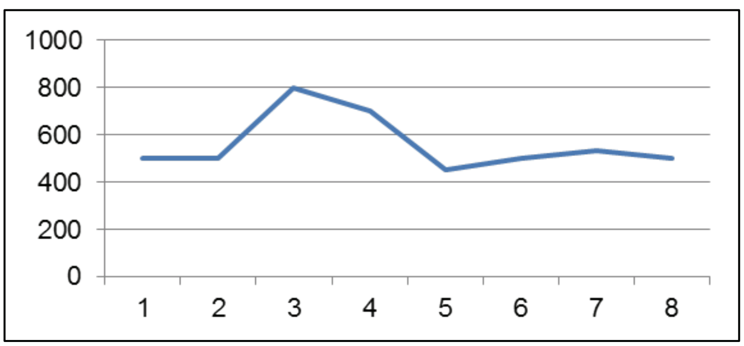
In this chapter we summarize our approach to detecting potential part quality problems and quantify the incremental cost incurred due to increased maintenance actions and inventory required to meet readiness goals.

Three Types of Poor Part Quality Usage Patterns Defined

We define three types of part use patterns that may indicate there is a problem with the quality of a part or an underlying (and perhaps hidden) process deficiency.

Patterns of Type A exhibit a temporary increase in part usage.[11] Figure 4.1 illustrates this behavior with a temporary increase in part usage (y-axis) for a brief period of time (x-axis).

Figure 4.1. Type A Poor Part Quality Behavior

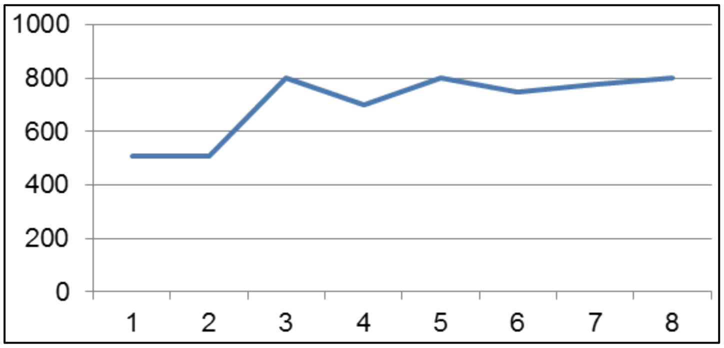


After the temporary increase, the usage rate returns to its previous level. This type of behavior might occur if a supplier produces a bad batch and subsequently corrects the quality problem. It might also occur if the fleet is temporarily exposed to adverse conditions, such as a sandstorm or extreme heat, both of which subside with time, returning the system to its previous state.

Patterns of Type B exhibit a noticeable shift in part use that is sustained over time (see Figure 4.2). For example, a change in a maintenance practice may result in an increased rate of removals, generating an increase in the number of parts used.

[11] In this subsection we use the term "usage" to capture the replacement rate at which parts are being "consumed" within the fleet.

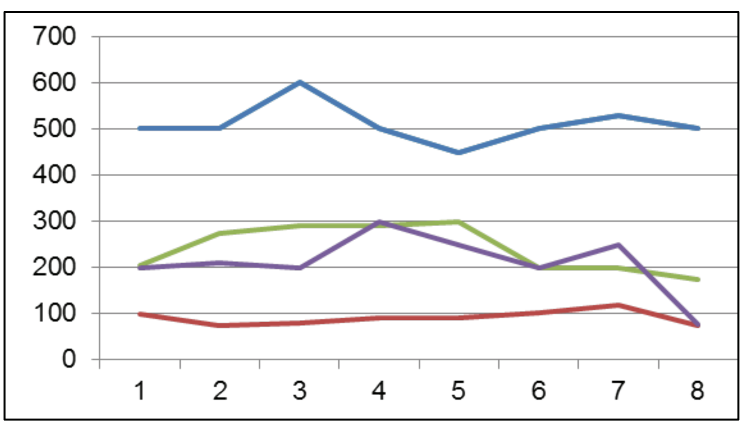
Figure 4.2. Type B Poor Part Quality Behavior



The purpose of our methodology is to detect the onset of a Type A or Type B part quality issue. This early identification of an emerging part quality issue does not allow us to determine whether the issue is Type A or B. Only monitoring the issue after its first detection will reveal its type.

Type C compares the usage rates of parts with similar form, fit, and function. In this case, one or more parts grouped together exhibit similar usage patterns, while another part (or group of parts) exhibits a very different usage pattern (see Figure 4.3). A Type C part quality issue may or may not be experiencing a temporary or sustained increase in usage, but its overall usage rate is much greater than similar parts across time.

Figure 4.3. Type C Poor Part Quality Behavior



Methods

To assess the cost of poor part quality, first, methods are required to automatically identify Type A, B or C part quality issues from among the thousands of parts found on a weapon system. Secondly, these methods need to provide quantitative measures useful for calculating the many cost factors associated with the identified quality issue.

There are several time-tested approaches to monitor and identify product quality defects. In manufacturing, control charts are used to monitor process quality. For example, p-charts track the percent of defective parts over time statistically computed with seven rules for detecting special causes of variation. These rules warn operators of out-of-control patterns in the number of defects. These charts are used to identify problems, which then need to be investigated further to identify and correct root causes. Similarly, in the design and reliability engineering fields, tools such as Pareto and Weibull analysis allow practitioners to monitor system performance over time and assess improvements or degradation in time between failures or between repairs.

In the case of control charts, data is usually readily available both in terms of number of units produced and number of defects or defective[12] items found. This is not the case for the Army's part usage data. Reliability models, such as Weibull, are focused on analysis of single components on a case-by-case basis. This approach of assessing part reliability becomes very resource intensive when an entire weapon system is of concern. The result is a limited reliability analysis using only simple measures like Mean Time Between Failure (MTBF) that are unable to decipher poor part quality behaviors in a timely fashion (e.g., Type A and B). Processing the available data as well as automatically monitoring and detecting unusual patterns of performance are predominant challenges that are preventing more thorough and in-depth analysis of all parts used on a weapon system.

In the following subsections we provide an overview of the methods selected to identify Type A, B, and C part quality issues and to estimate costs. For Type A and B part quality issues, we implement the Crow-AMSAA model (Crow, 1974)[13] along with a breakpoint algorithm that directs attention to current part performance. For Type C quality issues, we develop a unique methodology using hierarchical clustering and other statistical techniques. The last subsection introduces the cost model employed to quantify the cost of poor part quality.

Method for Type A and B Part Quality Issues

For Type A and Type B quality issues, we want to detect when the usage rate of a part is no longer stable and begins to increase—i.e., the onset of an emerging part quality issue. The "beta" value[14] from the Crow-AMSAA model quantifies this increase.

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[12] Note that one defective part can have multiple defects or modes of failure.

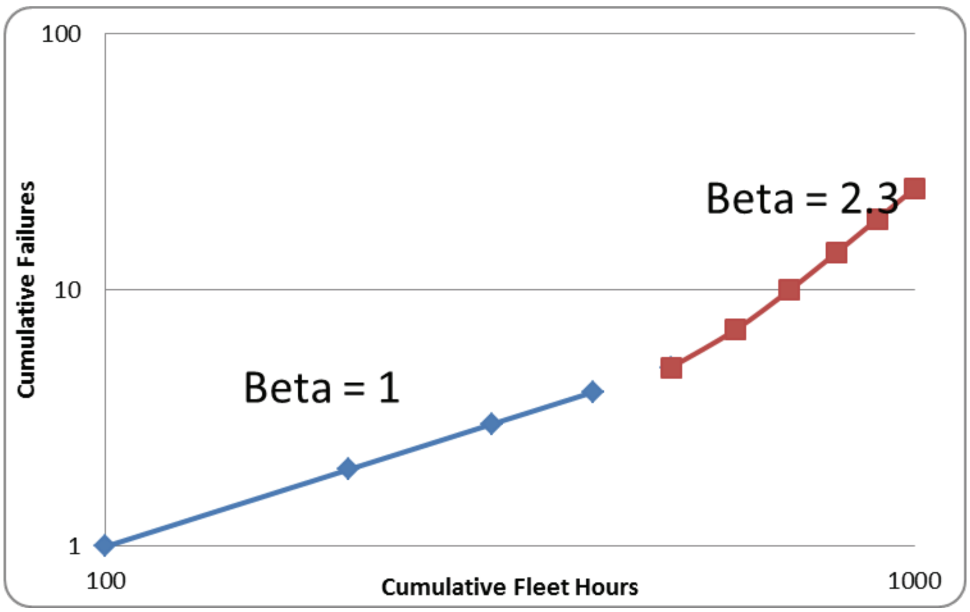
[13] See Appendix A for a description and references for the Crow-AMSAA method.

[14] The log-log relationship between the expected number of failures as a function of time and the parameters λ and β is expressed in by linear equation $\log E[N(t)] = \log \lambda + \beta \log t$. The parameters λ and β can be estimated by using several linear regression techniques including least squares, maximum likelihood estimators (MLE), or generalized linear models (GLM). See Appendix A for details.

A beta value of one indicates that part usage is not changing over time; a beta value of less than one indicates an increase in time between failure[15] (improved reliability); and a beta value greater than one indicates a decrease in time between failure (degrading reliability).

The Crow-AMSAA method requires cumulative fleet time and failure data to make the beta assessment. Figure 4.4 presents a notional example of the Crow-AMSAA method used to identify a Type A or Type B part quality issue for a valve used on Army helicopters.

Figure 4.4. Example of Crow-ASMAA Plot



Every month, each helicopter in the fleet flies 10 hours, giving a total of 100 flight hours per month for the fleet. The x-axis tracks the cumulative fleet flying hours, and the y-axis tracks the cumulative valve failures seen in the fleet. For the first 500 flight hours (the first five months), a valve failure occurs every 100 flight hours. Fitting the Crow-AMSAA model to these points results in a beta value of one, indicating that the mean time between fleet valve failures is time invariant (i.e., one should expect the same number of valve part failures per fleet flight hour month after month[16]).

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[15] Failure in this case does not necessarily mean that the part was defective. There are multiple reasons why a part may be removed from a weapon system, including normal wear, incorrect diagnosis of a problem, or taking advantage of other maintenance to replace a part early.

[16] The part removals count as one failure or one defect. There could be multiple causes for the removal for each part, but these are not counted separately.

The steeper linear region in Figure 4.4 is indicative of an increase in the number of failures per flying hour. In this region, an additional valve failure occurs in the fleet every 100 flight hours. In the first 100 fleet hours there are 2 failures; the next 100 fleet hours there are 3 failures; the next 100 fleet hours there are 4 failures; etc. The beta value for this linear region is 2.3. When the Crow-AMSAA beta is greater than one, it indicates that the average time between part failures in the fleet is decreasing. Something has happened that has caused the helicopter valve to fail more frequently: a design change in the valve; an emergent manufacturing issue; the helicopter is operating under different conditions; or a new mechanic is improperly trained—these are all plausible explanations.

The Crow-AMSAA method contains many characteristics that make it an ideal method to identify Type A and Type B part quality issues. First, it is capable of handling many types of data deficiencies, including missing data, multiple failure modes, batch problems, and few data points. The Crow-AMSAA method is able to identify an emerging quality issue much quicker than other statistical techniques like a moving average (Abernethy, 2004).

For the UH-60M case study, cumulative fleet time is obtained from the Logistics Information Warehouse (LIW) database. This database tracks Army aircraft flight time and landings on a monthly basis. Order data is retrieved from the Corps/Theater Automatic Data Processing Service Center (Army) (CTASC) database. CTASC data represent retail orders that are made up of orders from the units that are operating the aircraft.

We employ two schemes to limit the number of false alarms, i.e., estimating a beta greater than one when the true beta is less than or equal to one: (1) we use a second data source, the Equipment Downtime Analyzer (EDA), which captures the parts ordered in response to a failure that caused the aircraft to be down overnight, and (2) we estimate a 95 percent confidence interval[17] around our estimate of beta and use the lower bound as the indicator value.

A Type A or Type B quality issue is identified when the 95 percent lower confidence bound on the estimate of the beta value is greater than one for both EDA and CTASC data. Figure 4.5 illustrates a part with a potential Type A or Type B quality issue.

[17] A confidence interval around a parameter estimate establishes the range of values that could be observed with repeated sampling and estimation of the parameter. For example, a 95 percent confidence bound of 1.74 and 1.82 indicates that if 100 independent samples from a population were drawn and beta values estimated for each, 95 out of 100 of those estimates should fall between 1.74 and 1.82. By taking the lower bound of the confidence interval as our indicator value, we increase our confidence that the true value of beta is greater than or equal to the lower bound.

Figure 4.5. Crow-ASMAA Plot for Component Found on UH-60M Helicopter

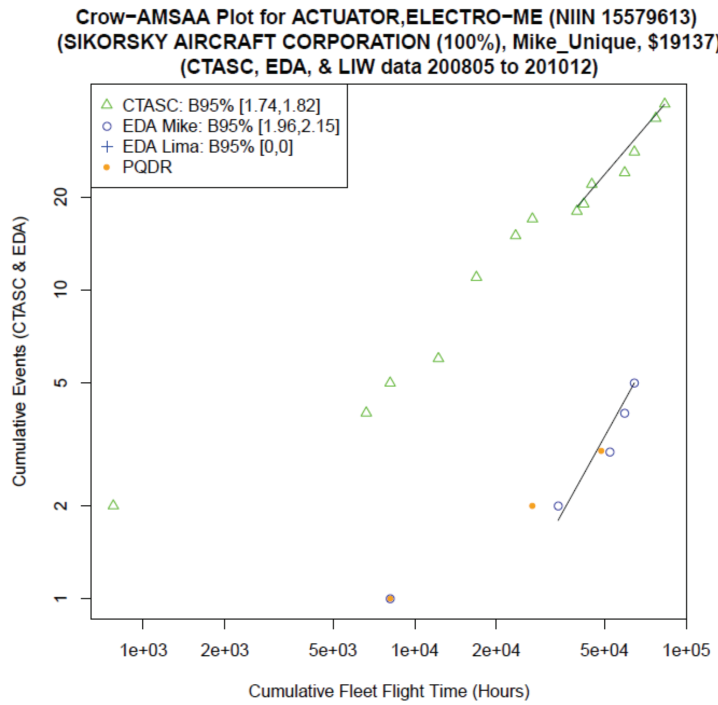


Figure 4.5 is a log-log plot of the cumulative flight hours (x-axis) and the cumulative number of demands (y-axis). The triangles represent the plot of cumulative flight and demand data using the CTASC data, while the hollow circles do the same using the EDA data. As mentioned earlier and detailed in Appendix A, the beta values are fit using the most recent linear region. We developed an algorithm that automatically works back from the most recent observation, adding previous observations until a break is detected in the linear region. In this example, the algorithm has captured the last seven CTASC data points and last four EDA data points for the beta calculation, the lines in this figure represent regression lines, and the slope of the regression line has a lower 95 percent confidence limit of 1.74 for the CTASC data and 1.962 for the EDA data. In addition to the EDA and CTASC data, the PQDR data are plotted. The box in the upper left shows that the 95 percent confidence interval on the Crow-AMSAA betas for both the CTASC and EDA data are above one, flagging this part as a potential problem. The solid circles plot the cumulative PQDRs; this data when it exists provides additional information to support our findings.[18]

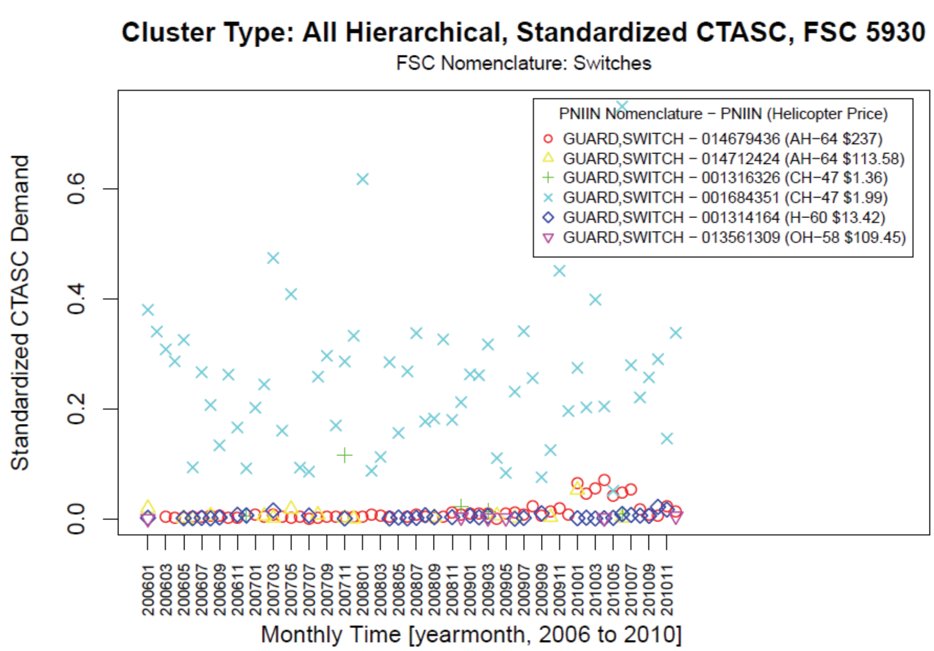
[18] As noted in Chapter 2, PQDRs are not filed for every quality issue. Therefore, we cannot use PQDR data to validate our methods, but it does serve as supporting information.

Type C Part Quality Identification

Type C part quality issues are concerned with parts that exhibit a higher usage rate than similar parts. We follow a two-step approach to identify these parts. First, we cluster like parts together. We use a hierarchical clustering method to group similar parts within a Federal Stock Class (FSC) based on part features including part nomenclature (general description of the part) and price, weight, and dimensions (height, width, and length).[19] Second, we compare the usage, normalized by flight hours, of each part in the cluster and identify if any outliers exist. We calculate the part usage in this second step as the number of orders per month seen in the CTASC data divided by the cumulative flight hours logged on that part.

In Figure 4.6 we show an example of a part that has a much higher usage than similar parts that were grouped within the same cluster. The figure shows one a switch guard that has a much higher usage rate compared to other switch guards with similar price, weight, and dimensions. In the second step of our clustering method we use a statistical test to identify outliers, allowing for full automation of this method. See Appendix B for further details.

Figure 4.6. Example of Clustering Method Results



[19] See Appendix B for more details on the clustering methodology.

Estimating the Cost of Poor Part Quality

As described in Chapter 3, we will focus our efforts on estimating how increased part use due to potential quality problems will increase the costs of maintenance and inventory needed to meet readiness goals. We start with the list of parts identified as potential Type A, B, or C quality issues and estimate the increased costs if current failure rates are not reduced.

Cost of Increased Maintenance

Our calculation of maintenance costs is limited to the maintenance activity at the organizational level. In most cases, parts are not repaired at the organizational level. Rather, parts are replaced and sent to the authorized maintenance activity for repair.

When a part is removed from an end item at the organizational level, the replacement part is purchased from the Army Working Capital Fund, typically from an OMA account. For reparable parts, the exchange price reflects the effective cost of the item (direct and indirect labor to repair the part and any surcharge). For consumable parts, the price is provided by the latest unit price in the Fed Log,[20] which includes an administrative surcharge. We did not include labor charges at the organizational level because actual repair hours are not recorded, and we assume the cost of direct labor is a sunk cost at this level. However, the model could easily be expanded to include an estimate of this cost using standard hours and the frequency of exchange,[21] which would allow us to capture the total or true cost associated with the failure of parts on an end item.

To estimate incremental cost due to poor quality, we need a baseline of the number of replacements (Q_0) that would take place at the organizational level if the part was performing within acceptable quality standards (beta = 1), and an estimate of the replacements (Q_1) if the part was not performing to standard (beta > 1). For a Type A and B quality issue, Q_0 is the expected number of failures if the emerging quality issue never occurred (the beta value never increased above one). Q_1 is the number of failures we expect to see under the current quality issue (the forecast of failures using the estimated beta value that is greater than one). For the Type C quality issue, Q_0 is the expected failures of the similar parts that fell within the cluster, whereas Q_1 is the expected failures of the part under investigation. We develop a forecast of Q_0 and Q_1 over the next six months to generate a six-month forecast of costs. Thus, equation (1) is the cost due to increased maintenance:

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[20] Federal Logistics Information Service (Defense Logistics Agency, 2011).

[21] Many end item repairs may involve several parts, so the standard labor hours would have to be allocated across the parts.

Cost due to increased maintenance is:

$$(Q_1 - Q_0) * \text{price} \tag{1}$$

Cost of Increased Inventory

We assume the Army will adjust inventory levels to maintain required readiness and estimate inventory levels under the two scenarios described above. We use the Customer Service Level (CSL) formula (Vollmann, 2005) to solve for the reorder point (ROP), assuming an 85 percent fill rate[22] target, and using demands from all SSAs off the shelf to the organizational-level customer. We compute a ROP_0 for the baseline quality scenario and a ROP_1 under the deteriorated quality scenario.

$$CSL_i = 100 - \left(100/EOQ_i\right)\sum_{d=1}^{n} P\left(d_i\right)\left(d_i - rop_i\right), \tag{2}$$

where

d_0 = the forecast of demand over the next six months if the quality problem is fixed
d_1 = the forecast of demand over the next six months if the quality problem persists
$P(d_1)$ = probability of demand if reduced quality
$P(d_0)$ = probability of baseline, or problem is fixed
rop_1 = reorder point if problem persists
rop_0 = baseline or reorder point if problem is fixed
EOQ_1 = economic order quantity if problem persists
EOQ_0 = baseline or economic order quantity problem fixed

Incremental inventory costs due to poor quality are:

(Average IP problem persists - Average IP problem fixed) * Price ,

where

IP = Inventory position = *rop* + ½ *EOQ*.

[22] The fill rate parameter can be varied as desired, and an 85 percent fill rate target is consistent with the Army's retail inventory performance goals.

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5. UH-60M Case Study Results

The UH-60M is the newest variant of the Black Hawk utility helicopter family, with inductions of new UH-60M models beginning in 2007. This model has many upgraded components and unique systems that are not found on the older UH-60L and UH-60A models. In particular, the UH-60M model has an "all glass" cockpit that contains all digital electronics and displays that are unlike the analog instruments found on the UH-60A and UH-60L. As such, the operational reliability performance of these new components is not well known. Since this model is still in manufacturing, issues discovered in the field can be corrected during production, which is generally less costly than correcting problems in the field. In addition, the UH-60M model has been heavily utilized in current combat zones. For these reasons, the Black Hawk Program Office has been closely tracking the reliability performance of the UH-60M model (RAND, 2011).

The Black Hawk Program Office Reliability and Maintainability (RAM) group is primarily responsible for tracking the reliability of the UH-60M model. This office works in conjunction with engineers from the Aviation and Missile Research Development and Engineering Center (AMRDEC), who manually "score" logbook[23] data to identify systems that are causing abnormal aircraft downtime. The Black Hawk RAM office also incorporates information from the field using PQDRs to identify parts that need immediate attention or that should be considered for future redesign. It is important to note that the primary focus of this office is on the manufacturing and design reliability of the UH-60 and its component systems. Reviews of the AMRDEC data and other systems intelligence are used biannually to identify and execute fixes for systems that need corrective action in the Black Hawk UH-60M fleet. This attention to the UH-60M model has been instrumental in providing information to gauge the application and validity of our methodologies.

Type A or B Poor Quality Parts on the UH-60M

For this part of the case study, we analyze a total of 5,910 parts that are found on the UH-60M. Though this helicopter has many more parts, we limit our analysis to parts that caused the UH-60M to be out of service overnight as recorded in the EDA data. We examined CTASC and EDA data for the April 2008 and December 2010 timeframe. Using the Crow-AMSAA method, a total of 34 parts were identified as having a Type A

[23] Each aircraft has an electronic logbook that records the flying and maintenance events on the aircraft. The data format is not conducive to automated analysis, but requires manual interpretation from subject manner experts.

or Type B[24] quality issue. We prioritized these 34 parts using our cost calculation (repair plus inventory costs) and present the top 10 in Table 5.1.

The parts are prioritized by quality costs in the column labeled “Total CoQ,” and the actual part price is identified in the third column. The noteworthy observation from the comparison of the total CoQ and the price of the part is that a high-priced part does not necessarily correspond with a high cost due to poor quality (e.g., the control generator with unit price ~$5,000 has higher cost implications than the rotary blade with unit price ~$200,000). There are two reasons for this: (1) the CTASC beta[25] is ~1.6 for the control generator, much greater than the beta of ~1.08 for the rotary blade; and (2) the volume of orders in calendar year 2010[26] is much greater for the generator. In fact, the rotary blade is driven onto the list by its price. The beta value is only slightly higher than one, which is not a significant indicator of a quality issue. However, due to the price of this item, further investigation is warranted. Even a small decrease in beta through a change in design or maintenance could produce worthwhile cost savings.

The last column of Table 5.1, 2010_EDA_N, indicates how many recorded downtime events were associated with the particular part in the EDA data. This column is used to gauge the readiness impact caused by the part quality issue. For example, the rotary blade was associated with 12 overnight downtime events, whereas the electro-mechanical actuator unique to the UH-60M model had nearly double (23) such events in a year’s time.

The “PQDR” column of Table 5.1 is binary and identifies whether the part has had at least one PQDR submitted in the time period examined (April 2008 to December 2010). For most high-priced items, at least one PQDR was submitted. However, this is not always the case for lower-priced items (under $100). As discussed in Chapter 2, there are multiple reasons why a part failure might not generate a PQDR. For example, NIIN 015118345,sensor unit laser, priced at $36,000, has a beta value of ~1.3 and has experienced nine EDA deadlining events in 2010 (2010_EDA_N) in calendar year 2010, yet no PQDRs were filed.

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24 The only difference between a Type A and Type B error is the behavior after the uptick in poor part quality behavior. Only time will reveal if these part quality issues will remain (Type B) or self-correct themselves by returning to the same usage level (Type A).

25 Refer to the “CTASC Beta” column in Table 5.1.

26 Refer to the “CTASC_2010_Q” column in Table 5.1.

Table 5.1. UH-60M Parts with Type A and B Indicators as of December 2010

NIIN	Nomen	Price	PQDR	AC	CTASC Beta	Percent Ordered from Vendor	Repair Cost	Inventory Cost	Total CoQ	2010_CTASC_Q	2010_EDA_N
015046723	CONTROL,GENERATOR	$4,852.00	yes	Mult_AC	1.625	93%	$2,209,120.25	$526,442.00	$3,126,321.14	390	24
015461148	BLADE,ROTARY WING	$199,336.00	yes	Mike_Unique	1.081	80%	$853,106.87	$398,672.00	$1,254,699.93	12	4
015004770	RECEIVER-TRANSMITTE	$46,217.00	yes	Mult_AC	1.330	84%	$562,335.67	$600,821.00	$1,206,803.08	77	24
011625035	SERVOVALVE,HYDRAULI	$10,090.00	yes	Mult_AC	1.294	33%	$746,781.53	$292,610.00	$1,039,391.53	282	16
012988467	ACCUMULATOR,PNEUMAT	$9,629.00	yes	Mult_AC	1.408	NA	$615,275.35	$365,902.00	$981,177.35	279	7
015579613	ACTUATOR,ELECTRO-ME	$19,137.00	yes	Mike_Unique	1.777	100%	$381,653.48	$172,233.00	$577,397.13	23	3
010892850	BRAKE,MULTIPLE DISK	$1,878.41	yes	Mult_AC	1.138	97%	$393,413.25	$82,650.04	$476,063.29	907	70
015118345	SENSOR UNIT,LASER D	$36,875.00	no	Mike_Unique	1.319	69%	$42,750.60	$221,250.00	$284,212.68	41	9
015588744	COMPUTER,FLIGHT CON	$70,160.00	yes	Mike_Unique	1.171	NA	$48,056.75	$210,480.00	$269,724.52	25	4
013917116	PANEL,FAULT-FUNCTIO	$4,293.66	yes	Mult_AC	1.365	NA	$172,341.64	$49,377.09	$257,602.67	67	13
015541623	SKIN,AIRCRAFT	$343.00	yes	Mike_Unique	1.569	100%	$50,095.40	$12,176.50	$171,080.31	138	5
012612044	ACCTUATOR,ELECTRO-ME	$7,804.00	yes	Mult_AC	1.013	12%	$120,006.43	$31,216.00	$151,222.43	942	53
014965565	STRAP,WEBBING	$1.50	no	Mult_AC	1.049	100%	$329.17	$66.00	$135,271.19	2881	11
013363497	CABLE ASSEMBLY,SPEC	$616.54	yes	Mult_AC	1.092	100%	$110,115.66	$22,503.71	$132,619.37	1140	37
011396338	SWITCH,PRESSURE	$318.75	yes	Mult_AC	1.575	100%	$99,201.41	$23,906.25	$123,107.66	267	16
011373398	TIRE,PNEUMATIC,AIRC	$607.95	yes	Mult_AC	1.023	100%	$4,172.19	$7,903.35	$49,075.54	1796	53
010986005	PACKING WITH RETAIN	$4.19	yes	Mult_AC	1.404	100%	$39,382.44	$8,136.98	$47,519.42	13223	108
011269456	INNER TUBE,PNEUMATI	$53.75	no	Mult_AC	1.244	100%	$22,931.23	$4,676.25	$27,607.48	996	9
008892495	RIVETXSOLID	$15.35	no	Mult_AC	3.745	100%	$16,605.58	$5,587.40	$22,192.98	70	38
008033044	WIRE,NONELECTRICAL	$76.22	no	Mult_AC	1.219	100%	$14,754.09	$3,201.24	$17,955.33	804	943
014982223	BATTERY,STORAGE	$1,889.56	yes	Mult_AC	1.045	100%	$10,760.53	$1,889.56	$17,377.52	85	13
011056582	LIGHT,LANDING,AIRCR	$3,717.00	yes	Mult_AC	1.014	15%	$9,644.71	$3,717.00	$13,361.71	233	21

NIIN	Nomen	Price	PQDR	AC	CTASC Beta	Percent Ordered from Vendor	Repair Cost	Inventory Cost	Total CoQ	2010_CTASC_Q	2010_EDA_N
005589763	NUTXCASTELLATEDXHEX	$9.58	no	Mult_AC	1.281	100%	$9,433.56	$1,963.00	$11,397.46	2224	27
011080476	LEAD,ELECTRICAL	$23.81	yes	Mult_AC	1.116	100%	$7,451.35	$1,500.03	$8,951.38	1617	20
010144596	O-RING	$4.98	yes	Mult_AC	1.134	100%	$4,441.23	$901.38	$5,342.61	5103	61
011053633	HANDLE,DOOR	$14.55	no	Mult_AC	1.117	100%	$2,884.13	$625.65	$3,509.78	1319	10
01651958	O-RING	$0.91	no	Mult_AC	1.358	100%	$1,091.82	$247.07	$1,338.89	2188	70
011539682	WEAR STRIP,CARGO DO	$4.69	no	Mult_AC	1.018	100%	$875.08	$171.19	$1,046.27	5911	60
011247622	SEALING COMPOUND	$11.90	no	Mike_Unique	1.213	NA	$686.99	$160.65	$847.64	121	13
001451161	LAMP,INCANDESENT	$26.74	no	Mult_AC	1.035	100%	$551.82	$120.33	$672.15	486	24
001557784	LAMP,INCANDESENT	$0.19	no	Mult_AC	1.510	NA	$463.50	$117.42	$580.92	3198	80
011234601	SCREW,MACHINE	$0.16	no	Mult_AC	1.068	100%	$161.81	$36.24	$198.05	9631	75
000103090	CLIP,RETAINING,AVIA	$0.14	no	Mult_AC	1.028	100%	$102.92	$21.35	$124.27	18324	44
001611017	O-RING	$0.13	no	Mult_AC	1.007	100%	$2.66	$0.91	$3.57	2113	14

An important aspect of this methodology is to identify both parts with poor quality as well as the associated suppliers. In Table 5.1, the "% Order from Vendor" column identifies the portion of parts ordered from that supplier in the last year. For example, 12 percent of the electro-mechanical actuators (NIIN 012612044)[27] were ordered from an external supplier, while the other 88 percent were received as a reworked part from the Army's maintenance depot. This identified part quality problem may not be an issue with the vendor, but with how the depot is reworking the part. Further investigation would be required to answer this question.

UH-60M Parts with Type C Poor Part Quality Behavior

In this section of the case study, we analyze a total of 3,363 parts that are used on the UH-60M. This analysis is somewhat more limited, since we examine only a portion of the FSCs associated with the 5,910 parts that we examined for the Type A or B component of this case study. Out of the 3,363 parts examined, 83 were identified with a Type C part quality issue.[28] Table 5.2 lists the top ten Type C part quality issues by their cost.

Many of the columns in Table 5.2 are similar to those in Table 5.1 (price, PQDR, % from Vendor, and total cost). The additional columns are Mean Time Between Replacement[29] (MTBR) for the cluster, the MTBR for the NIIN, and the difference between the two (MTBR Delta). For example, the cluster containing the flight control computer (NIIN 015588744) has an overall MTBR of 3,644 hours. This means that on average there is an expected part replacement every 3,644 flight hours for parts contained in this cluster. The MTBR of the flight control computer, listed first in Table 5.2, is 684 hours. Having to replace a flight control computer every 684 hours is a significantly higher rate compared to like parts that have an MTBR of 3,644 hours, if the increased failure rate persists, the projected cost to the Army is $3.4 million in additional inventory and maintenance costs over the next six months. If it was determined that the difference in MTBR was due to a design flaw, then a redesign of this part could be warranted if it could increase the MTBR from 684.

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27 NIIN or National Item Identification Number, is a 9-digit numeric code which uniquely identifies an item of supply.

28 We continue to refine the clustering algorithm to improve the initial clusters and reduce false positive identifications.

29 MTBR is similar to MTBF (mean time between failure). The difference is that here we are using order data instead of failure data.

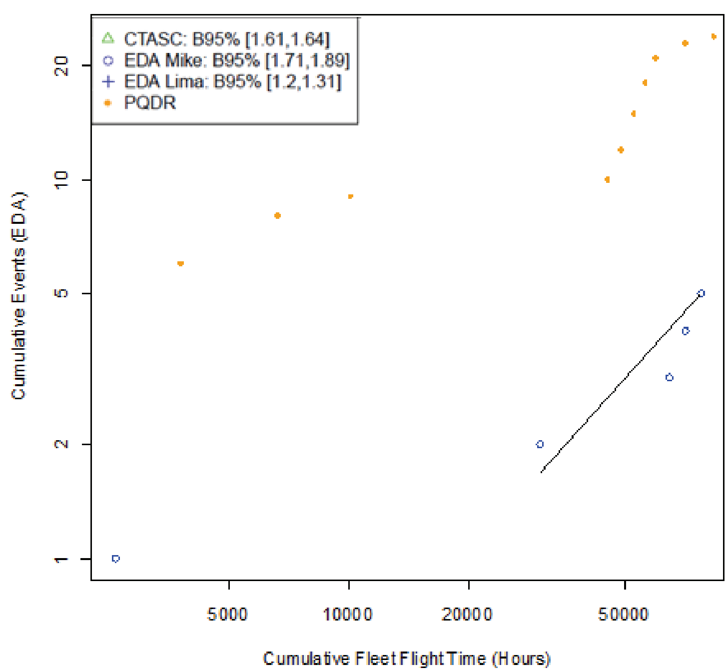
Table 5.2. UH-60M Parts with Type C Use Patterns

NIIN	Nomen	Price	PQDR	Percent from Vendor	Top Identified Vendor	Percent ARCENT Increase	2010_CTASC_Q	2010_CTASC_N	2010_EDA_Q	2010_EDA_N	NIIN MTBR	Cluster MTBR	MTBR Delta	Six-Month Forecast Repair Cost	Six-Month Forecast Inventory Cost	Six-Month Forecast Total
15588744	COMPUTER,FLIGHT CON	$70,160	yes	NA	Supplier unknown	48%	25	9	4	4	684	3644	2960	$2,668,857	$771,760	$3,440,617
15589547	COMPUTER,FLIGHT CON	$92,960	yes	100%	Vendor 1	-30%	3	3	9	8	802	3479	2676	$819,619	$836,640	$1,656,259
15579608	DATA ACQUISITION UN	$23,030	yes	100%	Vendor 1	38%	69	60	9	9	656	1973	1317	$679,488	$230,300	$909,788
15428455	STABILATOR	$33,632	yes	100%	Vendor 1	-2%	18	12	1	1	913	6114	5201	$521,070	$336,320	$857,390
15427904	STABILATOR	$33,632	yes	99%	Vendor 1	20%	23	17	0	0	962	6238	5276	$4,902,336	$302,688	$792,924
15588746	COMPUTER,FLIGHT CON	$77,786	yes	100%	Vendor 2	-11%	18	16	18	12	833	3650	2816	–	$700,074	$700,074
15579613	ACTUATOR,ELECTRO-ME	$19,137	yes	100%	Vendor 1	18%	23	13	3	3	980	2455	1475	$340,047	$114,822	$454,869
15448954	PANEL,CONTROL, ELECT	$31,824	yes	100%	Vendor 1	16%	22	17	0	0	1016	5802	4786	–	$286,416	$286,416
15525400	PANEL,CONTROL, ELECT	$5,905	no	100%	Vendor 1	0%	13	8	0	0	1018	5724	4705	$182,264	$53,145	$235,409
15448566	PANEL,CONTROL, ELECT	$23,625	yes	100%	Vendor 1	-12%	33	23	2	2	1122	5823	4700	–	$189,000	$189,000

Discussion of Select Parts Identified with a Type A, B, or C Part Quality Issue

In Table 5.1, we identify the control generator as a top quality driver with a Type A or B quality issue.[30] This part has an acquisition price of just under $5,000, yet it is identified to have a greater cost impact than the main rotor blades, which cost nearly $200,000. The control generator usage, along with its higher CTASC beta value, is causing this part to have a greater cost impact than the rotary blade. The total retail orders recorded in CTASC for the generator were 390 versus 12 for the blade (see 2010_CTASC_Q column in Table 5.1). In addition, the PQDR column in Table 5.1 indicates that at least one PQDR has been submitted for this part. In the Figure 5.1 below, the cumulative PQDR submissions are compared to the cumulative EDA events.

Figure 5.1. PQDR Submissions and EDA Events on Crow-AMSAA Plot for Control Generator

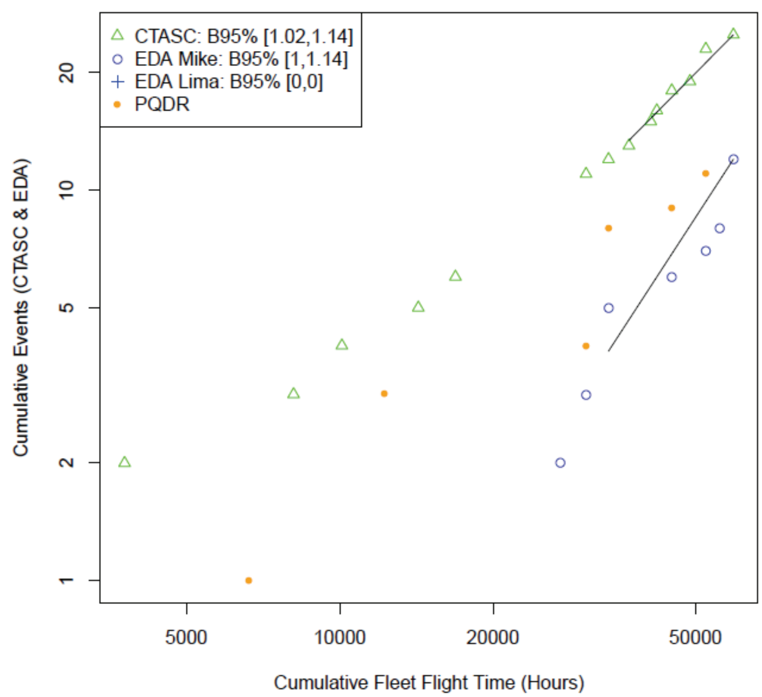


[30] The Crow-AMSAA method identifies an emerging part quality issue at its onset. To distinguish between a type A or B issue requires observing the beta value over the next several months.

For this particular part, the frequency of PQDR submissions and EDA events simultaneously increased. The same observation holds when the CTASC data is compared to the PQDR submissions. This data was presented to the Blackhawk RAM office who's data[31] from AMRDEC (based mostly on reports from operations in Afghanistan) had not indicated a problem with the control generator. Examining the narratives in the PQDR reports submitted for this generator did not provide additional information except that there may be a problem with generators shorting. However, further investigation revealed that control generators short-out due to a high power wash the helicopter receives when it is brought back from theater. This insight was provided by a former crew chief who was responsible for maintenance of fielded Army helicopters.

The second top type A or type B quality issue is the UH-60M main rotary blade. Figure 5.2 shows the Crow-AMSAA plot for this NIIN.

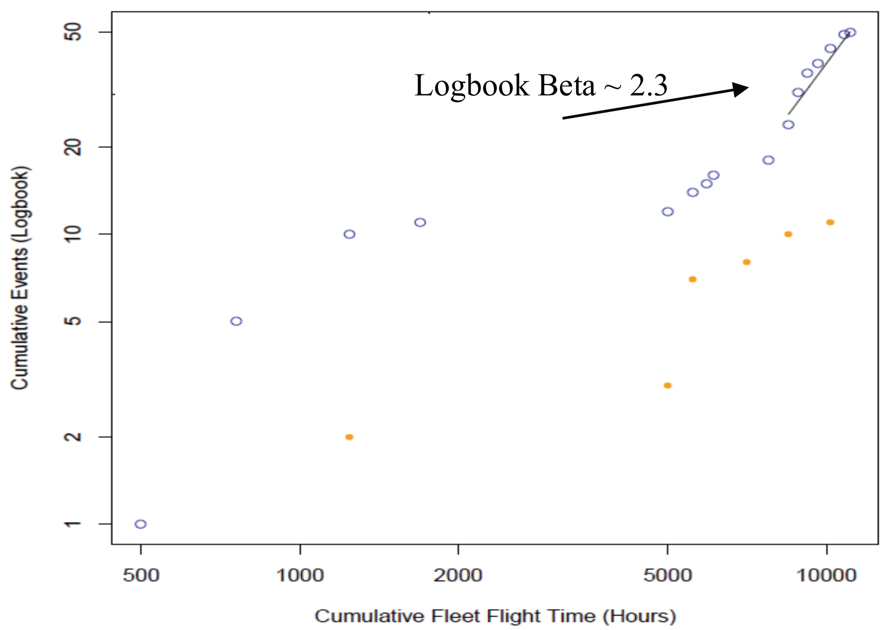
Figure 5.2. UH-60 Main Rotary Blade Crow-AMSAA Plot



[31] The purpose of the Blackhawk RAM office and its collaboration with AMRDEC is to eliminate reliability issues affecting safety and readiness. Because of the heavy use of the UH-60M in Afghanistan, the RAM office has focused on reports from the theater. Our approach is examining the cost implications of poor part quality across the entire fleet regardless of where the helicopters are operating.

The Crow-ASMAA plot for the UH-60M rotary blade indicates a slight increase in order and repair frequency with the beta 95 percent confidence intervals barely exceeding one. This slight increase is just enough to make this part second in the Type A or B part quality issue list in Table 5.1. To validate this finding, we obtained a copy of the logbook[32] data that is scored by AMRDEC and analyzed it using the Crow-AMSAA method. While the data plotted in Figure 5.2 includes all aircraft, the analysis using the logbook data seems to indicate that rotor blade removals are a much larger issue for UH-60M helicopters in Afghanistan, with a beta value of ~2.3 (Figure 5.3).

Figure 5.3. Crow-AMSAA Analysis of Logbook Data on the UH-60M Main Rotor Blade



The logbook data[33] plotted in Figure 5.3 captures scheduled and unscheduled rotor blade repair and replacement. There is a distinctive bend in the plot, at around 5,000 flight hours,[34] that indicates an increasing frequency in maintenance events for the rotary

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[32] The logbook data requires manual scoring to make it suitable for analysis. Due to the vast volume of data and time required, only 10 percent of aircraft logbook data is scored, most of it for aircraft located in Afghanistan.

[33] Each Army helicopter maintains an electronic logbook. Maintainers will enter maintenance dialog that captures repairs done on the helicopter. These logs are in free-flow narrative text fields.

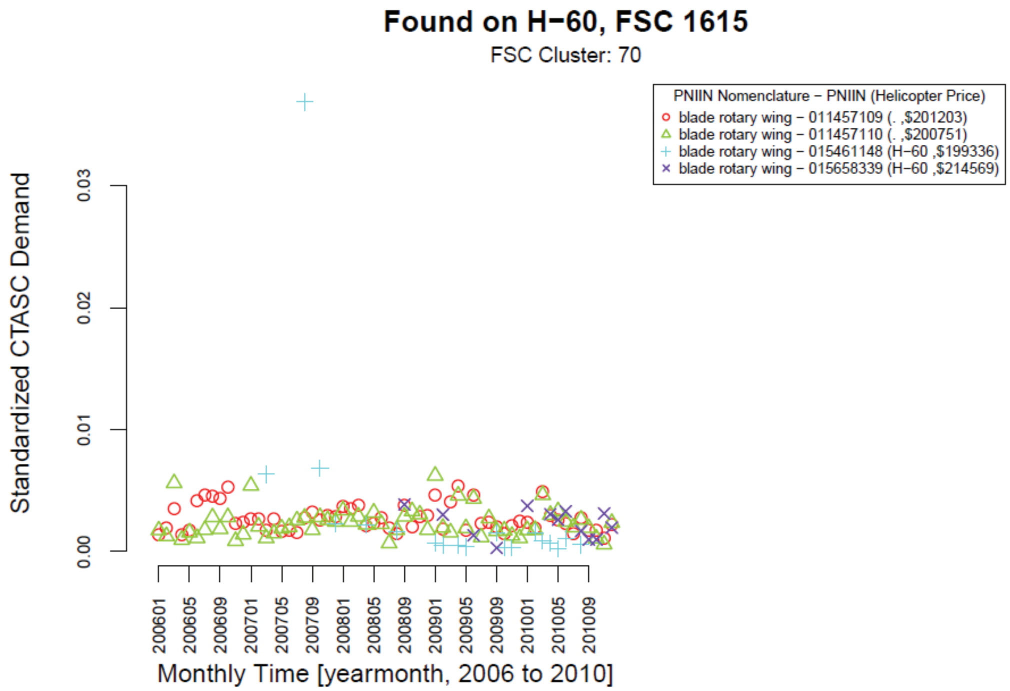
[34] The total number of fleet hours in this plot using the logbook data is much less than the other plots using the CTASC and EDA data, since only 10 percent of the logbook data is scored, i.e., cleansed enough for analysis. Further, the logbook data was predominantly from aircraft deployed in Afghanistan, where the environmental conditions resulted in the coating of the blades.

blade. By examining the narratives in the logbook, it appears there are two potential issues. First, approximately 61 percent of the unscheduled events require repair or reapplication of a coating that protects the blade from desert sand and grit. This type of repair does not require a replacement of the blades, and would not be captured by the EDA or CTASC data. This explains why the Crow-AMSAA plots using CTASC and EDA do not indicate a significant issue (see Figure 5.2). However, the number of repairs of the coating are not increasing or decreasing through the time period examined, indicating that this is not the issue causing the bend in the curve.

The second issue revealed by the logbook narratives deals with rotary blade replacement: there are no blade replacements in the first 5,000 flight hours; there are six blade replacements between 5,000 and 10,000 flight hours, and half of those are due to an inability to balance the blades. This significant increase in blade replacements most likely caused the bend in the Crow-AMSAA plot in Figure 5.3. From the data we could not determine the reason for problems balancing the blades; this would require further investigation. One hypothesis is that repeated coatings of the blades along with the harsh environmental conditions in Afghanistan could be contributing to balancing problems. Since these are replacement repairs, this issue most likely caused the slight increase in the beta of the fleet demand data for the blades—see Figure 5.2—although this is less pronounced than the logbook because it is based on demands for all helicopters, not just those with coated blades in Afghanistan.

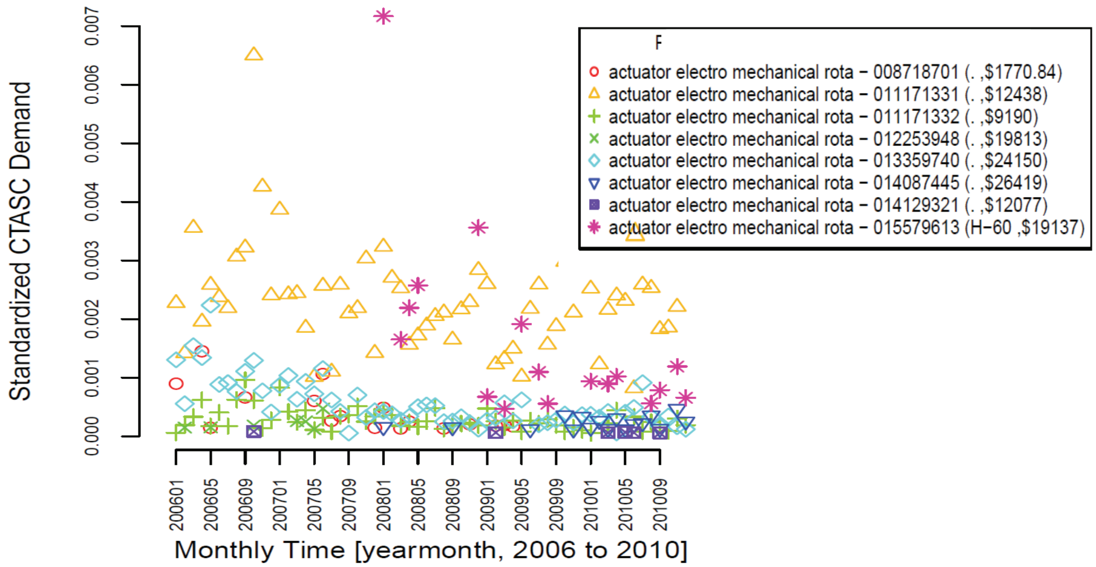
Figure 5.4 compares the performance (standardized by flight hours) of four rotary-wing blades used on the UH-60 A–M models. The NSNs labeled UH-60 (symbols +, ×) are unique to the UH-60M model. A close examination of the points in Figure 5.4 indicates that the performance of the coated rotary blade (NIIN 015461148) appears slightly better than that of the noncoated blades. However, this performance may not hold out in the future, as the Crow-AMSAA analysis identified that the frequency of blade replacements is slowly increasing. The conclusion, in this case, is that this part should continue to be monitored closely.

Figure 5.4. Cluster Analysis Comparing UH-60M Main Rotary Blade with Similar Rotary-Wing Blades



Another part identified as a Type C quality issue was an electro-mechanical actuator found only on the UH-60M model (NIIN 015579613). The cluster containing this part is shown in Figure 5.5.

Figure 5.5. Cluster Comparison of Electro-Mechanical Actuator



Of the eight actuators in this cluster, two have much higher usage compared to the others. The UH-60M unique actuator has a MTBR of 980 hours, whereas the average MTBR of the cluster is 2,488 hours. When this data was presented to the Black Hawk RAM office and AMRDEC, they were unaware of any potential issues with this part, but we were informed that the UH-60M model, along with the Lima and Alpha models, have a similar actuator[35] that has been approved to go through a reliability improvement program. We then talked to the item manager for this actuator, who was not aware of any specific issues but indicated that the demands for the part have been increasing.

This case study identifies over 100 parts that exhibit emerging or existing reliability issues. After we provided these 100 parts to the Army—prioritized by their potential incremental cost due to poor quality—problems with many of the parts were verified by SMEs. In one instance where SMEs were unable to provide confirmatory evidence, further investigation revealed that the SMEs had limited visibility of potential problems, or the part quality problem was narrowly defined to manufacturing defects, thus eliminating potential process problems (e.g., the power wash that was increasing control generator failures).

[35] Differing nomenclature is the reason these actuators were not clustered with the UH-60M's. When the nomenclature was adjusted, all these actuators clustered. We are currently examining ways to adjust for different nomenclatures.

6. Observations and Recommendations

This research explored the feasibility of using readily available demand and end item maintenance history to identify potential issues with part quality and to estimate their associated cost impacts. The value in the approach we have presented comes from its power to analyze the performance of thousands of parts, and by assigning a cost, to prioritize a list of parts with the highest potential return on investment.

The methods presented can be used to identify possible part or process quality issues by weapon system or across weapon systems. These can then be reported and corrective actions tracked by different levels of AMC management.

The initial case study presented in this report, continuing analysis, and conversations with subject matter experts all indicate that the methods developed during this phase of our research demonstrate potential for identifying problem parts and processes. The proposed approach can be viewed as the first step of a multi-step quality management process, i.e., it identifies and prioritizes potential problems; however, it does not reveal the root causes of problems. The information provided should be incorporated with other existing part quality management data, such as the PQDRs and logbook reports, to select quality improvement projects with the highest potential rate of return.

Various Organizations Are Concerned with Part and Process Quality

In Chapter 2 we described how the Army currently reports part quality problems using PQDRs and subject matter experts. In addition, there are various organizations responsible in one way or another for assuring quality. These include:

- the program offices;
- RDECOM organizations such as Aviation and Missile Research Development and Engineering Center (AMRDEC), which provide engineering support to program offices and conduct supplier audits;
- AMC/G-4 Continuous Process Improvement (CPI), a recently established group responsible for setting policy on quality for AMC;
- the Defense Contract Management Agency (DCMA), responsible for overseeing contract requirements and assuring that items conform to specifications; and
- the Life Cycle Management Centers (LCMCs), responsible for managing maintenance activities including logistics, materiel and supply chain management, and strategic sourcing.

For instance, under the Aviation and Missile LCMC (AMCOM), the Integrated Materiel Management Center's (IMMC) Aviation Logistics Command has offices for Aviation Fleet Management Quality Assurance and a Quality Assurance Surveillance

Program. While many organizations have responsibility for varying aspects of quality, we saw no evidence that information regarding quality problems is communicated in a coordinated fashion to AMC leadership.

The tools these organizations use to track part quality are heavily reliant on PQDRs. Using PQDR data limits quality assessment to manufacturing issues, while others like maintenance practices, part design flaws, training gaps, etc. are not captured by PQDRs. For these reasons, the Army manually examines logbook narratives to identify parts that are being affected by these other types of quality issues. This manual process requires significant SME resources that would be better utilized in determining the source of an identified part issue instead of compiling the data manually in order to identify it.

The Army Needs an Enterprise-Level View of Cost of Quality

Currently, AMC leadership has limited visibility of emerging or existing part or process quality problems that could lead to diminished readiness and increased costs. Often, problems are brought to the attention of leadership only after they have reached a critical juncture. A case in point is a recent concern that a bolt that is used on a critical component would require replacement because of manufacturing defects. While it turned out that this issue did not require the immediate replacement of all bolts of this type in the fleet, it was a reminder of how the poor quality of even inexpensive parts can have severe impact on costs and readiness. AMC leadership was aware of this problem because of its potential far-reaching effect on the fleet. However, there are other instances of part or process quality issues that may be not be brought to the attention of leadership because their cost or readiness implications are unknown and it is not possible to judge the severity of the problem.

Significant Cost Avoidance Is Attainable

Poor-quality parts and processes lead to unfavorable consequences on safety, readiness, or costs. AMC management and personnel focus diligently on assuring readiness and safety. During the last decade of conflict in Iraq and Afghanistan, there were strong pressures to increase production throughput at the depots and the availability of parts across the services to meet the surge in demands from the field. In this environment, the cost of poor quality may have taken a back seat to more pressing demands. A briefing by the DCMA (Swenson, 2009) states that because of schedule and mission requirements, there is pressure on DCMA inspectors to accept nonconforming material. As a consequence, more parts enter the supply chain with reduced performance and reliability, contributing to equipment downtime and increased repair and inventory costs. A study on the effect of nonconforming material on manufacturing lead times and delivery schedule performance (Nandakumar, 1993) concludes that the true cost of poor quality may be underestimated if only direct costs such as scrap, labor, and rework are considered. The aforementioned imply that significant cost reduction is attainable through a systematic attempt to improve the quality of process and parts.

As the United States emerges from these conflicts, budgetary pressures will require the DoD to decrease their cost while maintaining readiness and assuring safety. Measuring and managing the cost of poor quality is an essential part of accomplishing this objective.

A Pilot Study Creating a Reporting Mechanism

We recommend that AMC establish a pilot to test and validate the tools presented in this report and to establish a systematic reporting of the cost of poor quality across the enterprise.

Developing a prioritized list of potential part quality problems provides a tool but not a process for its use. This pilot will identify what is required to integrate the tools and methods for identifying poor-quality parts and estimating their cost implications. As mentioned previously, many organizations are involved in assuring different aspects of quality. AMC should define metrics that will allow each organization to report progress toward cost and quality goals and systematically report this information to AMC leadership in venues such as the weekly production update (WPU). This will allow AMC leadership to monitor trends in cost of poor quality over time and help focus attention on top cost drivers.

The cost of implementing will depend on the cost of collecting the data, managing the data, and performing the analysis. We believe any incremental cost would be outweighed by the potential benefits. The cost for data collection should be nominal, since all the necessary data is already available. Additional costs for extracting the required data and maintaining the required database would depend on whether this tool can be incorporated into an already existing data analysis framework or if a new one needs to be created. Because most of the analysis is automated, the burden on the analysts is reduced; the root cause analysis that is already performed would be redirected using a prioritized list of parts created by the method.

A potential weakness of this method and one that would undermine its usefulness is an overabundance of false indications of part quality problems. We have sought to mitigate this risk by imposing multiple conservative criteria that must be met before we identify a part as a potential problem. However, even so there is a chance that the root cause of a problem may be difficult to ascertain, thus leading to a frustration on the part of the analysts and reduced confidence in the tool. The pilot test should closely monitor this risk and attempt to calibrate the results of the analysis to minimize it.

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Appendix A. Crow-AMSAA Method

Depending upon the reliability of changes in the fleet that would cause the reliability to change (e.g., new maintenance procedures, part improvement, training, etc.), the MTBF of parts in the Army fleet will improve or worsen at different rates.

The Crow-AMSAA method is based on a discovery made in the 1960s concerning the relationship between cumulative fleet time and cumulative fleet failures, which is known as the Duane postulate. This postulate states that the relationship between cumulative fleet time and cumulative fleet failures is often linear on a log-log scale (Crow, 2010). The Crow-ASMAA method builds upon the Duane postulate by calculating the expected number of failures:

$$E\left[N(t)\right] = \lambda t^{\beta}, \tag{A.1}$$

where *N(t)* is the expected number of failures up to a fleet time *t*, λ is the scale parameter, and β is the slope on the log-log plot.

$$\log E\left[N(t)\right] = \log \lambda + \beta \log t \tag{A.2}$$

The parameters λ[36] and β can be estimated by using several linear regression techniques including least squares, maximum likelihood estimators (MLE), or generalized linear models (GLM).

In this analysis, we use the MLE to calculate beta and lambda; see equations (A.3) and (A.4) respectively.

$$\textstyle\sum_i^K N_i \left[\frac{t_i^{\hat{\beta}} \ln t_i - t_{i-1}^{\hat{\beta}} \ln t_{i-1}}{t_i^{\hat{\beta}} - t_{i-1}^{\hat{\beta}}} - \ln t_k \right] = 0 \tag{A.3}$$

$$\hat{\lambda} = \frac{\sum_{i=1}^{k} N_i}{t_k^{\hat{\beta}}} \tag{A.4}$$

The β in the Crow-ASMAA method has a similar interpretation as the Weibull β. When β is less than one, the failure inter-arrival time is increasing—fleet failures are happening less frequently as fleet time increases, which means the MTBF is improving with time.

[36] When β =1, λt represents the number of failures at time *t* for a system with a stable failure rate over time.

When β is equal to one, the failure inter-arrival time is neither increasing nor decreasing with time—the MTBF remains constant. When β is greater than one, the failure inter-arrival time is decreasing—the MTBF is worsening across time.

Significant changes in the fleet will cause the β and λ values to change in (A.1) and introduce new linear regions on the cumulative failures versus cumulative flight hours log-log plot.

For example, Sun et al. (2005) used the Crow-AMSAA method to monitor the reliability of the condensate air removal system pumps in a nuclear power plant. The plotted data on the log-log plot had two distinct linear regions. The first region had a β value less than one—MTBF was improving—and the most recent linear region had a β greater than one—MTBF was worsening. This change in the β value alerted system engineering[37] that there was an issue and during the subsequent investigation, it was discovered that moisture entering one of the bearing assemblies was the cause. Abernethy (2009) used the Crow-AMSAA approach to assess how an in-service maintenance change affected the number of failures seen in a system. The second linear region in this log-log plot had a β value less than one, indicating that this maintenance change was improving the system reliability.

These examples illustrate that significant changes that affect part reliability performance can be identified by examining failure data on a log-log plot where the x-axis is the cumulative operating time and the y-axis is the cumulative failures. Also, fitting (A.1) to these linear regions will estimate the β value, which is used to quantify the effect of the change.

The Crow-AMSAA method relies on a few assumptions and is considered best practice among other similar reliability techniques. To properly use the Crow-AMSAA method, the failure data must be linear on a log-log plot and there must be at least five failure points (Abernethy, 2009). Also, if the Crow-ASMAA method is used to distinguish between different linear regions due to a reliability improvement in the fuel pump, aircraft fuel pump failures should be random. Many facets of the Crow-AMSAA method have been analyzed. Overall, this method is considered best practice in its realm of application (Abernethy, 2009): an Air Force study by McGlone (1984) found that the Crow-AMSAA method has the most accurate forecasts; the U.S. defense standard MIL-HDBK-189 states that the Crow-ASMAA method is the best for reliability growth management; and Wang and Coit (2005) concluded that the Crow-AMSAA method is best for identifying changes in reliability trends.

[37] It took system engineering nine months to realize that there was a problem with this pump from using the Crow-AMSAA method. One reason for this delay is that it takes at least five failures to fit a new linear region with this technique (Abernethy, 2009).

Appendix B. Clustering Like Parts

Cluster analysis aims to both combine parts with similar features and separate parts with differing features, thus producing rather homogenous groupings of parts known as clusters. Clustering is an unsupervised method that relies upon a feature set to construct a similarity measure that is then used to identify structure within the data. Clustering is used across many fields such as information technology, biology, artificial intelligence, and marketing (Gan, Ma, and Wu, 2007). To appropriately allocate this method for part reliability, we apply a hard clustering algorithm known as hierarchical clustering or connectivity-based clustering, which groups similar U.S. Army parts. These groupings allow us to make comparisons of the demand streams of all parts within a cluster.

The U.S. Army classifies all manufactured parts under a Federal Supply Class (FSC). Each FSC category broadly identifies a set or type of parts. All parts within an FSC comprise a dataset, X, that is M by M, where M is the number of parts contained in the particular FSC. The clustering goal is to assign a group index, p, to each part, x_i, where each part, $x_i \in X$, belongs to one cluster, C_p. Within an FSC the parts can be thought of as hierarchy, that is, all nested under one FSC. This data structure lends itself nicely to the hierarchical clustering methods. The end result of the clustering within an FSC is a hierarchical representation where at the leaves (bottom) there is one part (a single observation) and the top (the entire cluster) contains all the data for the FSC.

We use hierarchical clustering to divide parts within each FSC into a sequence of nested partitions. This is an agglomerative (bottom-up) clustering algorithm that starts with every part in its own cluster. Next the pairwise-cluster similarities are computed, and then the most similar clusters are repetitively merged based upon a geometric similarity criterion, generally known as a distance. Clusters are repetitively merged until the preferred number of clusters is achieved (this is discussed later). The decision to use the agglomerative hierarchical method, was based on a comparison of internal measures (i.e., compactness, connectedness, and separation) in the clusters for many types of clustering algorithms, such as k-means, divisive hierarchical, partitioning around medoids, and fuzzy clustering. We characterize the similarity and perform the partitioning of the data through the application of a minimum variance method known as Ward's method (Ward, 1963, and Ward and Hook, 1963), where the objective is to minimize the loss of information at each stage of partitioning. Ward's method characterizes the dissimilarity, D_{ij}, between two clusters, C_i and C_j, by the following equation:

$$D_{ij} = \frac{\left\| \bar{C}_i - \bar{C}_j \right\|^2}{\frac{1}{N_i} + \frac{1}{N_j}}, \tag{B.1}$$

where C_i and C_j are the mean vectors for cluster i and j respectively, and N_i and N_j are the the number of observations in each cluster. Ward's method tends to produce clusters of approximately equal size and is also sensitive to outliers (Milligan and Sokol, 1980). While there are many different types of metrics we could have used (e.g., single-link, complete-link, or group average are all graph methods), we chose a geometric method because this metric subjectively appeared to produce clusters that were most sensible to the Army. This geometric method means that parts within a cluster can be represented by a center point (Gan, Ma, and Wu, 2007).

To construct the dissimilarity matrix, from which the pairwise similarities are computed, we use a feature set consisting of a maximum of six distinguishing part features: nomenclature, price, weight, and part dimensions (height, width, and cube size). Each feature is standardized on a zero to one scale. A dissimilarity matrix is then generated using the Gower general coefficient (Gower, 1971).[38] Weights are assigned to each variable where the weights sum to unity—price is weighted at 0.5, nomenclature at 0.25, and weight and part dimension at 0.0625 each. Under this weighting scheme, price is the primary driver of similarity among the part clusters, followed by nomenclature. If weight or part dimensions do not explain significant variation in the data, they are dropped from the feature set and their variable weight is reallocated to price and nomenclature. Significant variation is determined from a principal components analysis by examining the variable loadings from components that account for 80 percent of the data's variation.

Following the construction of the dissimilarity matrix, the appropriate number of clusters within each FSC is determined and is used as the stopping criterion for the hierarchical clustering algorithm. While numerous statistics have been proposed to decide upon the optimal cluster size (Gentle, 2002), we maximize the within-cluster variance by using the Calinski-Harabasz (CH) Index (Calinski and Harabasz, 1974):

$$\mathrm{CH}(k) = \frac{b/(k-1)}{w/(n-k)}, \tag{B.2}$$

[38] Future research will use additional variables that may by ordinal, categorical, or binary. The Gower metric includes various distance measures for different types of variables. For numeric, continuous variables in Gower, the Manhattan distance is used (Romesburg, 1984).

where k is the number of clusters, n is the maximum number of clusters allowed, which we set to $(M - 1)/4$, b is the between-cluster sum of squares, and w is the within-cluster sum of squares. The value of k that maximizes CH is the number of clusters we use. Milligan and Cooper (1985) performed a Monte Carlo study comparing 30 different cluster validation measures and determined that the CH Index was the superior performer. With the number of clusters known, we restrict the hierarchical cluster algorithm to this number, then apply the algorithm to the dissimilarity matrix and obtain the groupings within each FSC.

The next step involves comparing the CTASC demands of each part within a cluster. For each part we create a time-series by standardizing monthly CTASC demands by the monthly aircraft hours flown. The standardized CTASC time-series for all parts within a cluster are then plotted. Since the features of the parts within a cluster are similar, we hypothesize that the parts are also similar and as such, the standardized demands should also be similar. If a part exhibits unusually high demand relative to the rest of the parts within the cluster, this part would warrant further investigation. We use the nonparametric Wilcoxon-Mann-Whitney hypothesis test to compare one series to the median of all other series. This is a widely used statistical technique to determine whether one of two samples is statistically larger than another. By using a nonparametric test we are able to overcome the distributional assumptions inherent in parametric hypothesis tests. Additionally, with this particular test the samples can have unequal observations. This test does assume that the observations are independent and that they are numeric. Since the data is time-series in nature, it is not truly independent, though we did not find strong serial correlation in many of the standardized demand streams we inspected.

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