Demonstration of Sensor Data Integration Across Naval Aviation Maintenance

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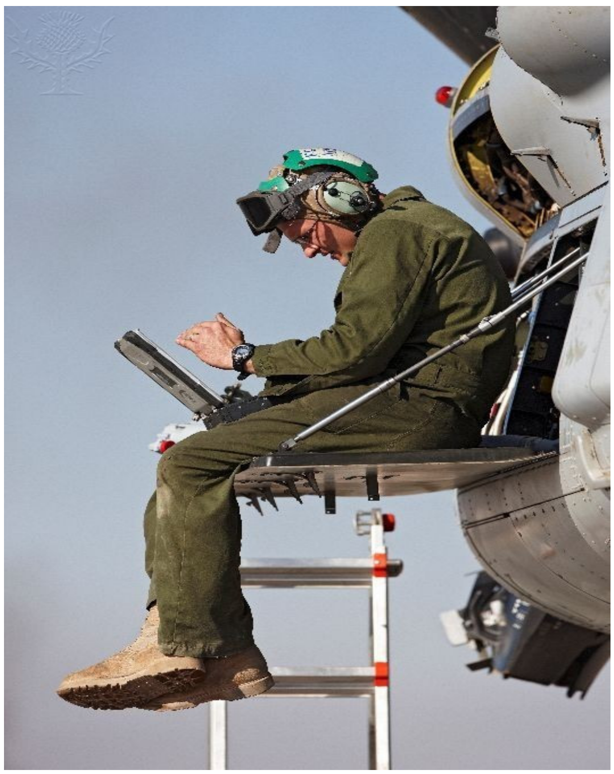

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Abstract

A key goal of the Navy's Digital Warfare Office (DWO) is to use the emerging field of big data analytics to tackle numerous challenges facing the Navy. DWO asked CNA to examine the issue of Super Hornet (F/A-18E/F strike fighter) readiness and recommend data-driven solutions that leverage underutilized sensor data. CNA proposed a pilot program that integrated sensor data across maintenance levels to expedite repairs of aviation parts. The five-month pilot program began on July 10, 2017, at the Fleet Readiness Center at Oceana in Virginia Beach, Virginia, and was implemented on APG-65 and APG-73 radars. We assessed the pilot program through several metrics and found that, during the program, repair time was significantly decreased and repair efficiency increased. Our findings suggest that sensor data integration across maintenance levels may considerably improve F/A-18 readiness.

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Executive Summary

F/A-18 readiness

The Digital Warfare Office (DWO) was established in 2016 under the Chief of Naval Operations to lead the U.S. Navy in transforming from the industrial to the digital age. The goal of the DWO is to enable better decision-making across all of the Navy's mission and functional areas by using the multitude of data that the Navy collects more effectively. The first DWO focus area is F/A-18 readiness. Currently, more than 60 percent of the Navy and U.S. Marine Corps strike fighters are unavailable for missions—but there could be solutions through better use of data. The naval aviation community collects an abundance of aircraft sensor data that have the potential to expedite repairs and hence increase readiness. However, this trove of data has not yet been made accessible to all of the maintenance staff whose work could be improved through its use. CNA proposed a pilot program—focused on the Super Hornet variant of the F/A-18 strike fighter jet—to test a possible solution to the readiness problem.

Pilot Program

CNA conducted a two-month pilot program that integrated aircraft sensor data, known as Built-in-Test (BIT) data, into the maintenance repair process. BIT data are recorded automatically on Super Hornets during flight when a fault occurs in the aircraft. Squadron maintenance crews (organizational-level (O-level) maintainers) rely heavily on BIT data to troubleshoot repairs during unscheduled maintenance on the flight line. By providing intermediate-level (I-level) maintainers access to the BIT data (which they did not previously have), the root cause of failure could potentially be more quickly identified. Faster repairs could then lead to an increase in the number of mission-capable aircraft. Having more airplanes "up" (i.e., mission capable) and ready to complete mission sets translates to better readiness levels.

The pilot program began on July 10, 2017, at the Fleet Readiness Center (FRC) at Oceana in Virginia Beach, Virginia, and was implemented on APG-65 and APG-73 radars. Before the pilot program, parts were inducted into the I-level maintenance without accompanying sensor data, which contain information on the part's failure.

The pilot program implemented a process improvement by requiring that BIT data be sent to I-level maintenance, along with the part in need of repair, to assist maintainers in troubleshooting the problem and establishing a maintenance plan of action.

CNA Assessment

To assess the pilot program, CNA constructed and tracked several metrics pertaining to repair time and effectiveness. The two metrics of primary interest were: (1) time to reliably replenish (TRR) and (2) number of parts ordered per repair. TRR is the time required to troubleshoot and repair failed equipment and return it to normal operating conditions. Our analysis found that when I-level maintainers had access to and used BIT data, the average TRR for radar repairs was reduced by 45 percent compared with the average TRR of non-pilot program 2017 data. We used a Monte Carlo approach to assess the significance of these results to determine whether the pilot program's mean TRR occurred by chance alone. Our confidence in the improvement shown in TRR during the pilot program is 96 percent. The pilot program also showed that the average number of parts ordered per repair was reduced by 40 percent when BIT data were available and used.

These results suggest that the integration of BIT data throughout the maintenance process could assist maintainers in more quickly and effectively detecting the root causes of failures. With expedited fault detection, fewer unnecessary parts would need to be ordered, saving time and money.

Recommendations

Based on our findings, we recommend that the Naval Aviation Enterprise (NAE) leverage sensor data integration at another FRC (e.g., Lemoore), specifically for repairs of a system that has a large impact on the readiness of the Super Hornet fleet (e.g., generator control units). This new effort should include training for both O- and I-level maintainers on how to efficiently and effectively provide and use BIT codes for repairs. Ideally, the effort would last at least six months, so that the impact of sensor data integration on readiness could be captured for analysis and evaluation.

During the course of the pilot program, we discovered a few issues with infrastructure, data transfer, data interpretation, and data rights that will need to be resolved before the full benefits of BIT data can be realized. If BIT data were to be integrated across the entire fleet, the NAE would need to consider the following:

1. How to incorporate a cyber-secure electronic transfer of sensor data from the O-level to the I-level
2. How to develop robust sensor diagnostic reasoners that could be updated and matured based on real operational maintenance practices and findings
3. How to contract for the rights to sensor data in future platforms and systems
4. What storage and computing infrastructure would be necessary to house, query, and analyze such massive datasets

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Glossary

BIT	Built-In-Test
CASS	Consolidated Automated Support System
CDF	cumulative distribution function
CNO	Chief of Naval Operations
DWO	Digital Warfare Office
EMT	Elapsed Maintenance Time
FAME	F/A-18 Automated Maintenance Environment
FRC	Fleet Readiness Center
I-Level	Intermediate Level
MAF	Maintenance Action Form
MMH	Maintenance Man Hours
MU	Memory Unit
NAE	Naval Aviation Enterprise
NALCOMIS	Naval Aviation Logistics Command Management Information System
NAVAIR	Naval Air Systems Command
O-Level	Organizational Level
RBA	Ready Basic Aircraft
SRA	Shop Replaceable Assembly
THD	tactical hard deck
TRR	Time to Reliably Replenish
WO	work order
WRA	work replacement assembly

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Introduction

The Chief of Naval Operations (CNO) established the Digital Warfare Office (DWO) in 2016 to develop a framework that prioritizes data-driven decision-making in an increasingly informationalized environment. A key mission of the DWO is to use the emerging field of big data analytics to tackle the numerous challenges that the Navy faces. The Navy already collects a multitude of data, but this data is often underutilized and not shared across organizations. DWO is leading initiatives to leverage data science and digital technologies to produce indicators of positive outcomes that, once matured, could have transformative impacts on the Navy's competitiveness.

The first challenge the DWO approached is Super Hornet (F/A-18 E/F strike fighter) readiness. Military readiness is quantitatively defined as the number of resources available in individual units (e.g., strike fighter squadron) versus the stated requirements of that unit [1]. Readiness is the ability of military units to carry out their assigned missions and tasks; it can be affected by equipment, training, and availability of spare parts, among other factors [2].

F/A-18 readiness involves a large number of systems, organizations, and processes with linkages and complex interdependencies, as well as a myriad of data and metrics. VADM Paul Grosklags, Commander, Naval Air Systems Command (NAVAIR), wrote of the aviation readiness shortfall that "squadron commanding officers are having to make tradeoffs, whether it is a training mission or operational requirement, on a daily basis because they do not have the required number of Ready Basic Aircraft (RBA)[1]" [4]. In fact, in 2016, one in five pilots in a strike fighter squadron did not fly enough hours to meet the tactical hard deck[2] (THD), the minimum number of hours a pilot must fly per month for safety of flight [5]. Only 40

[1] Ready Basic Aircraft is defined as "the minimum configuration required to conduct day or night [Instrument Meteorological Conditions] flight operations with necessary communications, [Identification Friend or Foe], navigations, flight and safety systems required by applicable [Naval Air Training and Operating Procedures Standardization] and [Federal Aviation Administration] regulations. This aircraft does not require a Functional Check Flight and does not require shipboard operations equipment (no outstanding L or Z [Equipment Operational Capability] discrepancies)" [3]. An aircraft that is RBA may not necessarily be mission capable.

[2] The THD is 11 flight hours per month.

percent of Super Hornets in the Navy's fleet today are up and capable of carrying out their mission sets. Although that number may not be a direct measure of readiness, because it does not address how many jets the Navy is required to have up to meet its operational needs, it does reflect the challenges naval aviation is facing in managing its strike fighter inventory. The CNO turned to DWO to develop potential digital solutions to this problem.

DWO asked CNA to examine the F/A-18 readiness issue and provide data-driven solutions that tap into the abundance of underutilized data resources. This paper presents the results of CNA's pilot program, which implemented a process improvement in aircraft maintenance to expedite repairs.

Opportunities for Improvement

We believe that readiness could be improved from a maintenance perspective by leveraging a dataset in naval aviation that originates from sensors in the aircraft: Built-in-Test (BIT) data. With minimal additional effort, maintainers could take advantage of this type of diagnostic information to quickly and efficiently identify the root cause of failure and thus expedite repairs and improve readiness.

What are BIT data?

BIT data originate from sensors installed on Super Hornet aircraft to detect and isolate faults down to the subcomponent level [6]. Military avionics systems rely heavily on BIT data, which are used by the organizational level (O-level), or squadron level, to troubleshoot repairs during unscheduled maintenance on the flight line. The data are recorded on the aircraft's maintenance card, known as the memory unit (MU), and are also displayed in real-time to the pilot. When a BIT code appears on the pilot's display panel during flight, s/he can use a lookup table to determine which aircraft system may have failed or is degraded. BIT codes also identify failures in critical flight subsystems that are essential to the aircraft's integrity and airworthiness.

Where can the Naval Aviation Enterprise (NAE) leverage BIT data?

When the strike fighter pilot returns from a flight with a failed component, s/he uploads the MU into Boeing-developed software known as the F/A-18 Automated Maintenance Environment (FAME). FAME ingests the BIT binary data recorded in the MU during pre-, mid-, and post-flight and translates the data to human-readable text. The software will also aggregate frequent BIT codes and information on affected components to identify important trends. After uploading the MU into FAME, the pilot creates a Maintenance Action Form (MAF) with his/her notes from the flight. O-level maintainers at the flight line use the information from the MAF, with the aid of the BIT data from FAME, to troubleshoot problems. The BIT data help maintainers fix problems quickly so that the downed jet can return to its mission set.

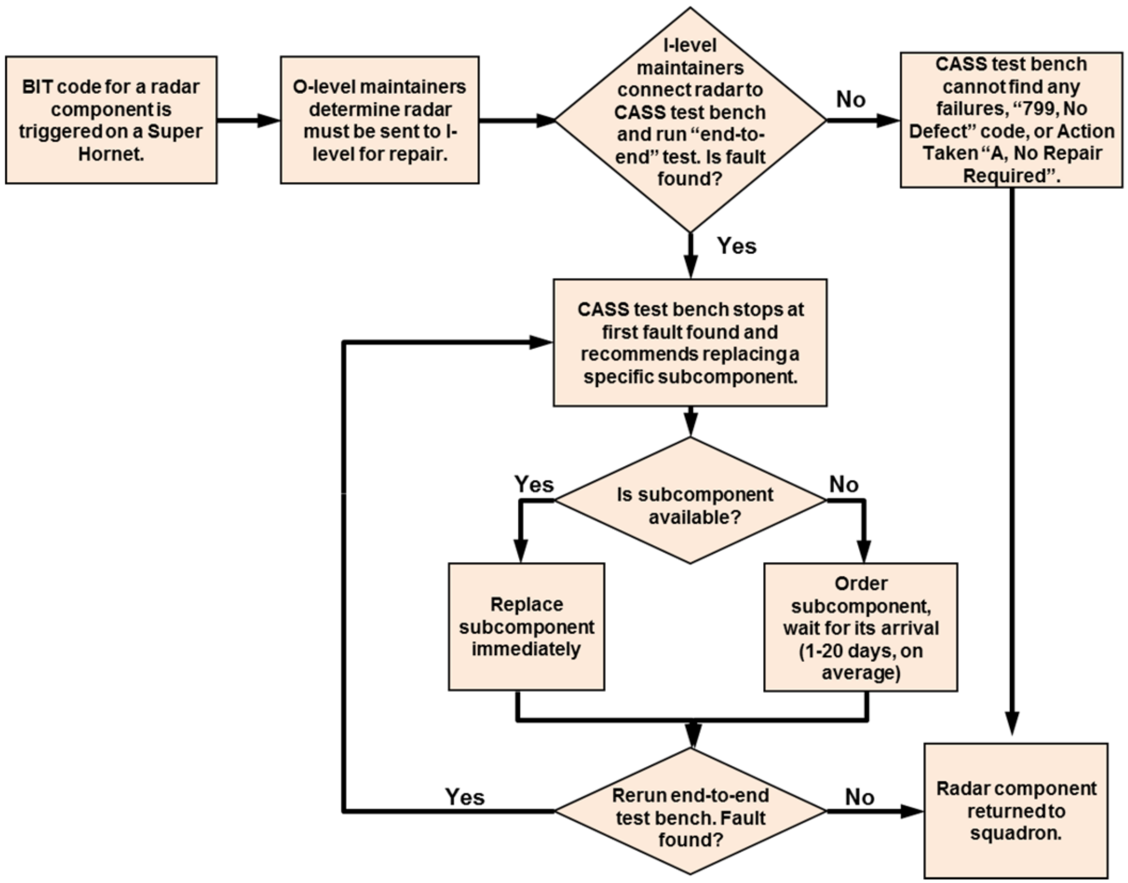
When the failure is too complex and requires a deeper level of repair, the O-level maintainers enter additional information onto the MAF and send the affected part to intermediate level (I-level) maintenance. *I-level maintainers have access to the updated MAF but are never provided with BIT diagnostic information.* An example of the repair flow from O- to I-level for a radar transmitter is illustrated in Figure 1.

At the I-level, as shown in Figure 1, maintainers attempt to identify failures by connecting the component to a Consolidated Automated Support System (CASS) test bench and conducting an end-to-end test.[3] The CASS test bench is not foolproof; our analysis revealed that more than 10 percent of the time the CASS test bench will not be able to detect any issues with the part. In these cases, the maintainer will record in the MAF that the gripe could not be duplicated, and the part will be returned to the squadron with no repairs executed. Alternatively, the CASS bench might identify the first detectable subcomponent error in a prescribed sequence of tests and will not continue to further fault test until that error is mended. The error might not actually be the root cause of failure, only a symptom of the problem. Consequently, once the subcomponent is replaced or fixed, the entire part will be connected to the test bench only for it to detect additional failures. This leads to multiple iterations of parts orders and wasted maintenance man hours before the underlying issue is identified.

We hypothesize that if the BIT data were shared at the I-level, the root cause of failure could be detected faster. Quicker repairs ultimately lead to an increase in the number of mission-capable aircraft. More airplanes up and ready to complete mission sets means better readiness levels.

[3] An end-to-end test on the CASS bench consists of a sequence of coded routines that test all subcomponents (known as shop replaceable assembly, or SRA) in the broken component (known as work replaceable assembly, or WRA).

Figure 1. Traditional repair flow from O- to I-level



Source: Adapted from [7].

Pilot Program: Use of BIT Data

CNA focused on improving readiness through better use of data in the maintenance process. One way to improve readiness through maintenance is to decrease the time it takes to repair a gripe. Reducing time to repair is related to how quickly a maintainer can correctly diagnose the problem and fix it, without ordering unnecessary parts. For example, Navy analysis of maintenance data showed that technicians had trouble diagnosing faults and ended up ordering many parts in multiple maintenance iterations. As a result, the first pass yield—the fraction of time that problems are resolved in the first maintenance pass—is less than 50 percent [8]. The number of maintenance passes directly affects the time it takes to repair a component. Previous CNA analysis showed that the average number of days it takes to close out any F/A-18E/F component repair in the first maintenance pass is 20 [7]. By the third maintenance pass, the number of days increases by 100.

Pilot program set-up

The pilot program began on July 10, 2017, at the Fleet Readiness Center (FRC) at Oceana in Virginia Beach, Virginia. Data were collected for five squadrons (VFA-32, 34, 83, 105, and 106) over a two-month period, with the last collection taking place on September 14, 2017. Analysis was performed only on APG-65 and APG-73 radars. The following radar components were repaired:

- Antennas
- Receivers
- Data processors
- Transmitters
- Power supplies

Pilot program modifications to the traditional process

The pilot program required two major modifications, one each at the O-level and the I-level, so that the BIT data could be transferred and interpreted correctly. The two major changes, outlined below, altered the procedure in Figure 1 to what is seen in Figure 2 (shown by the rectangles with the red font):

1. O-level maintainers were required to send a printout of the BIT data from FAME[4] (for example, "B codes = 125, 432, 067, O codes = 042, A codes = 125[5]") to the I-level maintainers, along with the broken part and the MAF (also known as a work order, or WO). Parts sent without the BIT data were not designated as pilot program repairs by the I-level and were not utilized in the analysis.

2. If a radar component was sent to I-level maintenance with the FAME printout, maintainers were required to enter the BIT codes into a diagnostic reasoner developed by PMA-265.[6] The reasoner provided information on the most probable subcomponent(s) that needed to be repaired. Maintainers would then utilize the translated BIT data, along with the CASS bench test results, to determine the best course of action (i.e., what subcomponent to test and repair).

    a. When I-level maintainers updated the MAF, they were asked to mark pilot program repairs with either *SM65* for APG-65 repairs or *SM73*[7] for APG-73 repairs in the "system reasoner" field of the Naval Aviation Logistics Command Management Information System (NALCOMIS).

This effort did not dictate an exact repair process to the I-level maintainers. Instead, the pilot program required maintainers only to consider both the BIT data and CASS test bench recommendations. This way, I-level maintainers at Oceana, with the help of the maintenance master chief petty officer, could construct a repair plan that was easiest for them to implement. After speaking with the maintainers and looking at the repair comments in the data, we determined that there were three main courses of action taken with the BIT data, as shown in Figure 2 by the diamonds with the blue font:

1. Trust the BIT data: Some of the BIT codes are well understood by maintainers. They trust these codes implicitly and use them to diagnose and fix parts. For

[4] Ideally, O-level maintainers would extract the BIT data from FAME and share it with the I-level maintainers electronically via cloud computing or some sort of SharePoint site. This was not done for the pilot program due to time and resource restrictions.

[5] B = Operator or Initiated BIT, O = Start-up/Power-on BIT, A = Accumulated/Periodic BIT

[6] The reasoner is in the form of an Excel macro that has the ability to translate the list of BIT codes entered by the maintainer into insightful output. The output is continuously updated based on real-world maintenance data.

[7] *SM65* and *SM73* were chosen by the master chief and maintainers at Oceana.

example, BIT 104 for the APG-73 radar is always known to indicate a fault in the radar transmitter, specifically in the low voltage circuits.

2. Trust the BIT data after verification: Some of the BIT codes are not well understood, so a flight line check[8] would be performed to verify that the BIT code was indicating the correct failure. The BIT code was accepted only after it passed the flight line test. If a flight line check failed, the gripe was addressed with the CASS bench recommendations.

3. Do not trust the BIT data: In these cases, the BIT code was not well understood, and the maintainer, for reasons unknown to the CNA analysts, did not trust or use the BIT data in the repair plan. In these cases, the repair was conducted without the aid of BIT data.

Data collection

All of the data used in our analysis were derived from NALCOMIS. An aviation technician first class at Oceana extracted the necessary fields for the analysts and compiled them in a Microsoft Access database. The database held information on all radar repairs from January 1, 2017, to November 14, 2017, including those from the pilot program (marked by *SM65* or *SM73*). We received data updates every two to three weeks for the duration of the pilot program.

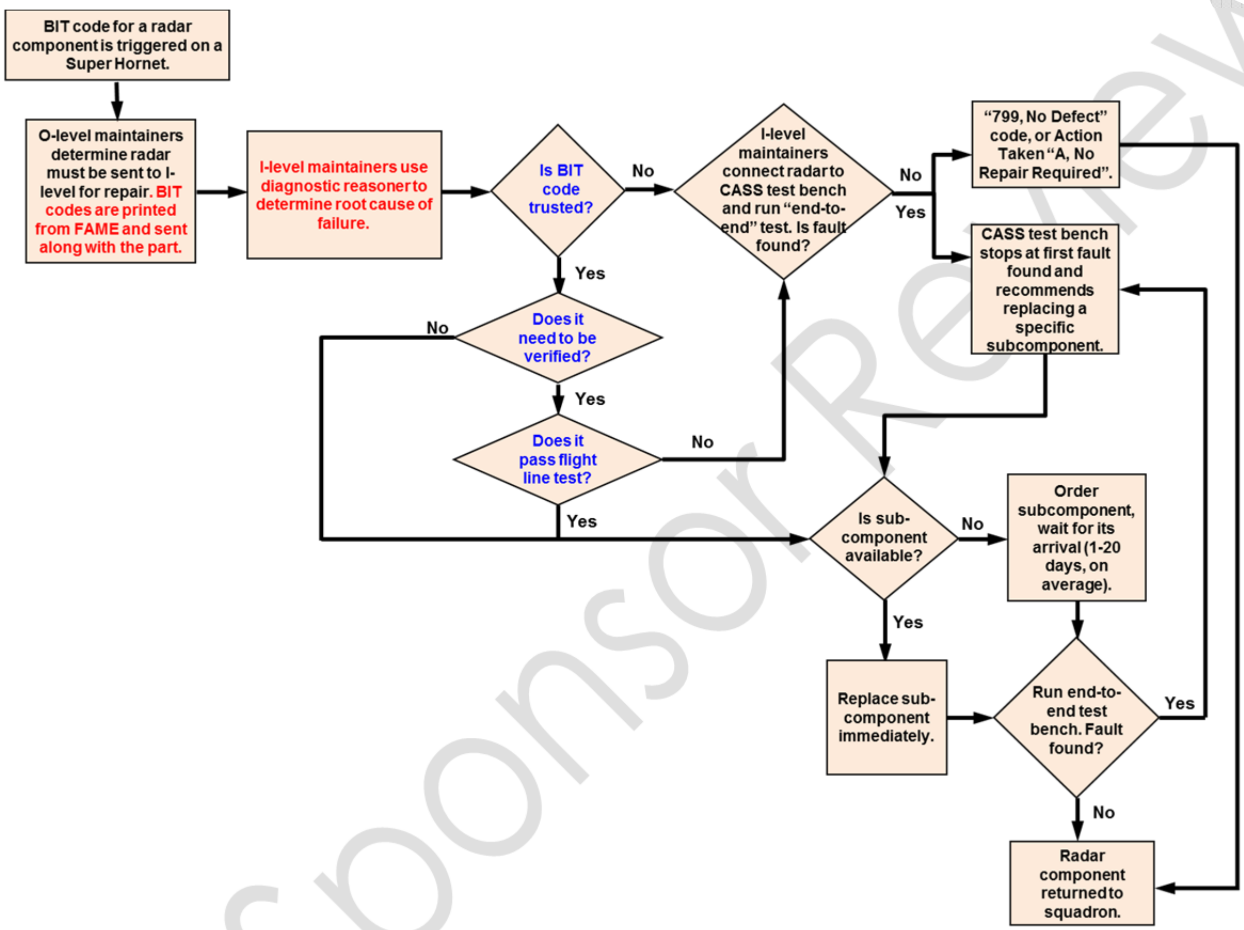
Data collection caveat

During the pilot program, three out of five high-powered CASS test benches were out of service. This situation delayed repair times for radar transmitters and power supplies, which demand high voltages and can be tested only with a high-powered CASS bench. As a result, we omitted these two components from the data collected for both the pilot program and baseline[9] all together. Out of 112 pilot program data points collected, 42 (37.5 percent) were removed, leaving us with 70 repairs to use in our analysis. Out of 350 baseline data points, 137 (39 percent) were removed, leaving us with 213 repairs in this dataset.

[8] The part would be sent to the O-level, placed back on the aircraft, and tested at the flight line to determine if the gripe was corrected with the aid of the BIT data.

[9] The baseline dataset is what the pilot program is compared to (non-pilot program data) and is described later in the Data Selection section.

Figure 2. Pilot program repair flow from O- to I-level



Source: Adapted from [7].

Pilot program metrics

Maintenance repair time

We measured maintenance repair time with the following three metrics:

1. Time to Reliably Replenish (TRR): The time required to troubleshoot and repair failed equipment and return it to normal operating conditions. It is measured as the delta between the time a part is received at the FRC (i.e., the induction date) and when it leaves the FRC with a "complete" tag. It includes the time the part is on the shelf at the FRC waiting for inspection, subcomponents, and/or repair, but does not include any supply lead time.[10][11]

2. Elapsed Maintenance Time (EMT): "Time, in hours and tenths, that maintenance was being performed on a job" [9].

3. Maintenance Man Hours (MMH)[12]: "The total number of accumulated direct labor hours (in hours and tenths) expended in performing a maintenance action" [9].

We used TRR as the primary repair time metric because it provides the best insight into how quickly the root cause of failure was diagnosed. EMT and MMH might not have as much of a direct impact in reducing pilot program repairs because all repairs are still required to be verified on the CASS test bench [10]. Nevertheless, we measured these secondary metrics to ensure consistency of increase/decrease in overall repair time.

Efficiency

TRR is affected by the efficiency of repairs, which is determined in part by how successful a maintainer is at diagnosing and fixing the cause of a failure without

[10] Supply lead times can be long if a part is shipped from a deployed squadron to FRC Oceana for repair.

[11] TRR includes all repairs, even if a gripe could not be duplicated (malfunction code 799). Including 799 repairs (~2.5% of the data) did not change the results.

[12] EMT and MMH are related but not equivalent. From [9]: "if five men complete a job in 2.0 hours of continuous work, the EMT=2.0 hours and the man hours=10.0."

having to order parts in multiple iterations. The following two metrics were chosen as a proxy to quantify efficiency:

1. Order iterations: The number of maintenance passes for a repair in which one or more orders were made

2. Number of parts ordered: The total number of parts ordered in a repair

Details of these metrics are described in Appendix A: Metrics.

Data Selection

The results of this study are based on two datasets: the baseline dataset and the pilot program dataset. The baseline dataset includes information on all the APG-65/73 repairs inducted at Oceana from January 1, 2017, through July 10, 2017. There are 213 repairs in the baseline dataset, none of which were part of the pilot program. The pilot program dataset includes information on APG-65/73 repairs inducted at Oceana from July 10, 2017, through November 20, 2017, that were marked as part of the pilot program and where BIT data were called out as being available to the I-level maintainer in the MAF. There are 39 repairs documented in the pilot program dataset. We describe the selection of data in more detail below.

There are 70 repairs tagged with a "*SM65*" or "*SM73*" in NALCOMIS, indicating that these 70 repairs were supposed to be part of the pilot program. However, not every repair tagged as part of the pilot program actually included I-level access to BIT data during the repair process. This could occur if a part were inducted to the I-level as part of the pilot program (resulting in a *SM* being placed in the MAF), but when the I-level maintainer conducts the repair, which can happen several days after induction, s/he realizes that the BIT data that was sent from O-level are incorrect.

To determine whether repairs were inappropriately tagged as part of the pilot, we examined the notes provided for each repair by the I-level maintainer. These notes were included in every MAF in the "corrective action" block and were unformatted free-text. Out of the 70 repairs, only 39 explicitly indicated that BIT data were available for the repair. Below are examples of corrective actions listed for those 39 repairs:

1. "REMOVED AND REPLACED 4A1IDENTIFIED VIA BOA[13] CODE 311 ON MAF AND IN CASS TEST NUMBER 3106 IN PROGRAM 3525041…"
2. "RESEATED MULTIPLE SRA'S IDENTIFIED VIA BOA CODE 161..."
3. "BOA DATA RECEIVED INDICATED A PROBLEM WITH 2A12..."

[13] BOA is another term for BIT data.

4. "RDP RECEIVED WITH BOA CODES: O: RDP 054,435. A: 054/01 WITH SMART CALLOUTS BEING 4A2, 4A6, AND 4A15…"

In cases such as the above examples, it was clear the appropriate data were provided to the I-level maintainer. However, many corrective actions indicated that the BIT codes provided by the O-level pointed to the incorrect component. Examples of such corrective actions included:

1. "BIT DATA POINTED TO A PROBLEM WITH THE TRANSMITTER NOT THE RADAR RECEIVER..."
2. "BOA DATA POINTED TO A PROBLEM WITH THE XMTR NOT THE RR…"

In both of the above examples, radar receivers were under repair, but the BIT data provided were for radar transmitters. The FAME software, from which the BIT data were extracted by O-level maintenance, contains many different BIT datasets for different components and aircrafts. What likely happened in such cases is that the O-level simply provided the BIT data for a different component[14] than what was actually sent to I-level for repair. For the scope of this pilot demonstration, only minimal training was provided to the O-level on how to extract BIT data, which is the likely cause for such errors. More comprehensive training could help maintainers fully leverage these datasets.

For other repairs tagged as part of the pilot, comments expressly noted that BIT data were not considered during the repair (for reasons unknown to CNA). An example:

3. "BORESIGHTED, REALIGNED AND REMOVED AND REPLACED THE LISTED PARTS IN ACCORDANCE WITH AW-640LO-740-030… PILOT PROGRAM NOT USED."

Many repairs contained corrective actions that made no mention of the pilot program or any receipt or use of BIT data. When there was no indication of BIT data utilization in a repair, it was removed from the pilot program dataset.

Our final pilot program sample contains information on 39 repairs where there was explicit indication that BIT data were available for the I-level maintainer to leverage. Even in these cases, the BIT data were not always deemed useful. In the following section we show the results of our analysis on this dataset. Analysis on the full 70 data points is provided in Appendix B: Unfiltered Data.

[14] BIT codes are provided in FAME for every component that failed a routine diagnostic test during a Super Hornet's flight. Some BIT codes, and their time sequences, indicate failure, while others are cautions or warnings of degrades.

Pilot Program Results

In this section, we present the results of the pilot program. Table 1 summarizes the comparison of pilot program results with the baseline data.

Table 1. Comparison of pilot program results with baseline data

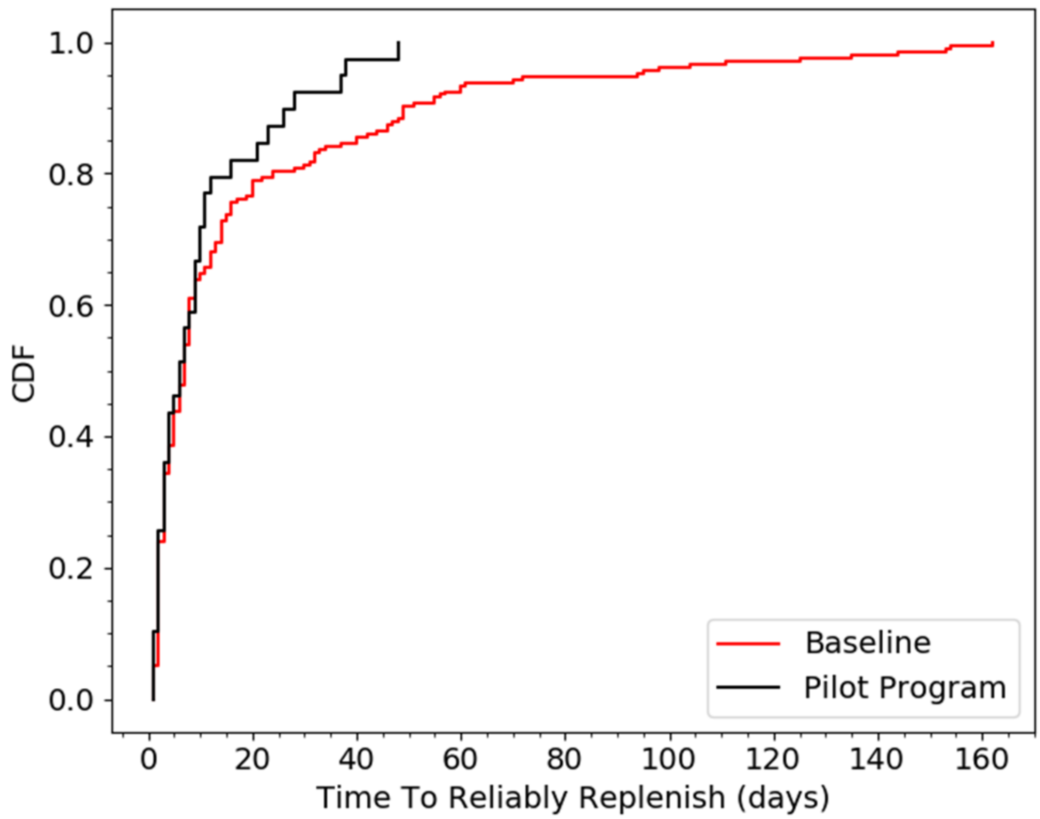
Maintenance Repair Time			
Metric	Pilot Program	Baseline	Percent Difference
Mean TRR (Days)	10.17	18.38	44.6%
Mean EMT (Hours)	17.76	21.88	18.8%
Mean MMH (Hours)	43.47	53.73	19.1%
Efficiency			
Metric	Pilot Program	Baseline	Percent Difference
Mean # of Order Iterations	1.15	1.73	33.6%
Mean # of Parts Ordered	3.05	5.39	43.4%

Our analysis found that the primary repair time metric, mean TRR, was significantly reduced when maintainers at the I-level had access to BIT data. In the pilot program dataset, the average TRR was reduced by 45 percent, down to 10.17 days, compared with the baseline of 18.38 days per repair. The improvement in the mean TRR stemmed from the pilot program's reduction of very long repair times. This is shown in Figure 3, where the cumulative distribution function (CDFs)[15] of the pilot program

[15] A CDF is the probability that a metric is less than/equal to a particular value. In Figure 3, the CDF is the probability that the TRR is less than/equal to the number of days indicated on the x-axis.

is compared with the baseline. For the pilot dataset, all repairs took less than 50 days to complete, whereas in the baseline dataset the TRR for many repairs extended beyond 90 days. Incorporating BIT data into I-level repairs eliminated a great fraction of instances of long repair times. The pilot program also shows a decrease in the hands-on repair times, EMT and MMH, from the baseline by approximately 20 percent.

Figure 3. CDF comparison of TRR between the pilot program dataset and baseline dataset



The reduction in TRR for the pilot program was partially driven by a reduction in the number of parts being ordered per repair, as well as a reduction in the number of order iterations per repair. In the 2017 baseline data, the average number of parts ordered per radar repair was 5.4, while during the pilot, the average number of parts ordered was reduced to 3.0 (a more than 40 percent reduction in average number of parts ordered per repair). These results suggest that the integration of BIT data throughout the maintenance process could assist maintainers in more quickly and effectively detecting the root causes of failures. Expediting the identification of root cause of failures translates to fewer unnecessary parts ordered, a reduction in the money spent on unnecessary parts, and a reduction of unnecessary logistic delays.

Validity of Results

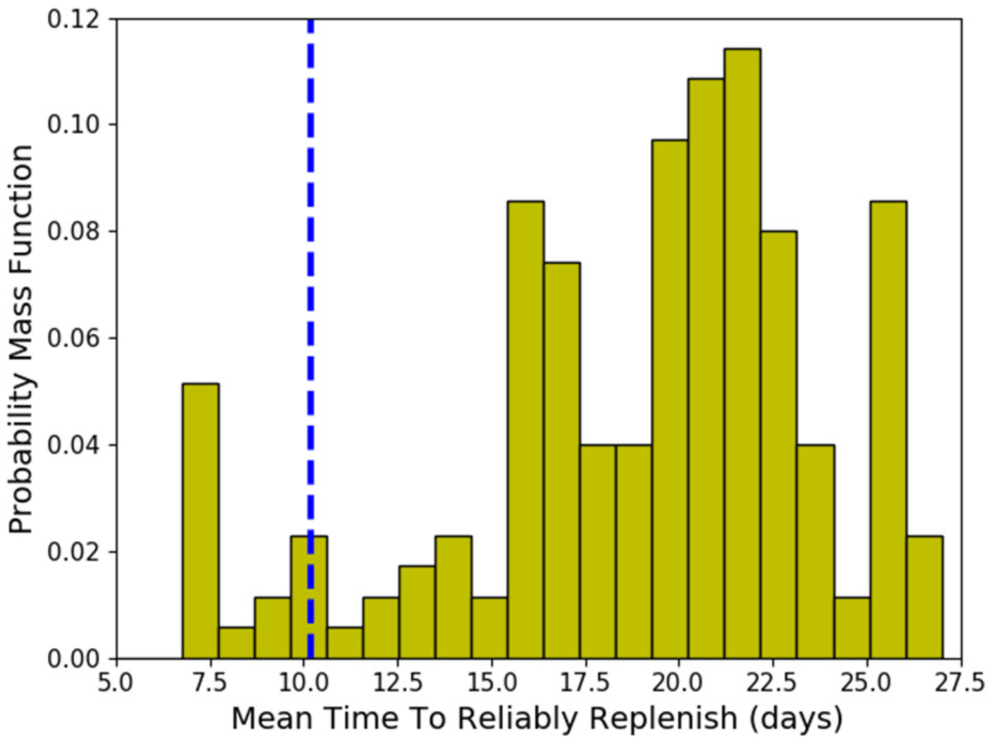
When validating our results, we focused on the primary metric of interest, mean TRR, and used a Monte Carlo approach to assess the significance of the results of the pilot program. With this approach, we were able to determine that the probability of obtaining a mean TRR that is less than or equal to the pilot program mean TRR of 10.17 days from a randomly drawn sample is four percent.

The Monte Carlo approach we used draws a random sample of 39 consecutive[16] repairs from the baseline dataset. After the sample is chosen, the primary metric (mean TRR) is calculated for the sample. The process is repeated a million times to create a distribution of the mean TRR, which is then compared with the same metric from the pilot program data.[17] Figure 4 shows the distribution of mean TRRs for the collection of the million draws of 39-point sample, with the mean TRR for the pilot program (10.17 days) indicated by the blue dotted line. The probability of obtaining a mean TRR that is less than or equal to the pilot program mean TRR of 10.17 days from a randomly drawn sample is four percent. In other words, the baseline data has only a four percent chance of reproducing the pilot's TRR results by chance.

[16] Historical maintenance data show variability among repair times for different quarters of the year. For consistency with the pilot program, we drew samples of consecutive repairs instead of randomly chosen repairs.

[17] A diagram of this process can be found in Appendix C: Flow Diagram of Monte Carlo Approach

Figure 4. Monte Carlo comparison of baseline program versus pilot program data mean TRR[a]

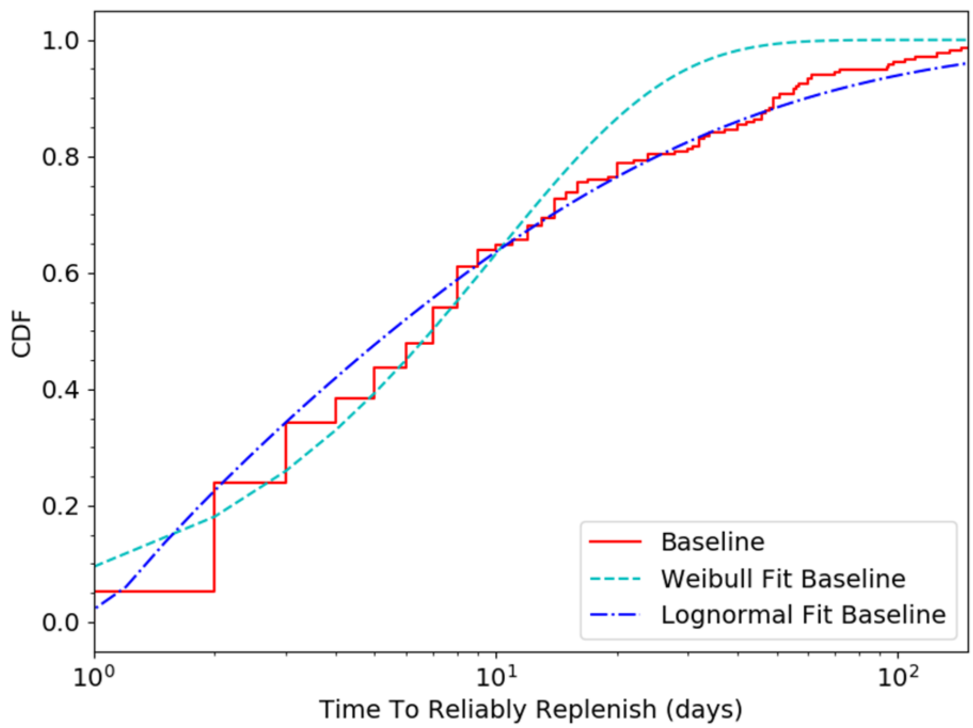


[a] The pilot program mean TRR shown in blue dotted line.

Why Monte Carlo?

Statistical tests come in two broad classes: parametric and nonparametric analyses. Nonparametric tests are useful when the data do not follow a specific distribution. The TRR distributions in Figure 5 show that the baseline distribution cannot be entirely represented by a standard distribution such as Weibull or Lognormal. Although not shown, the same is true for the distribution of TRR in the pilot program. This means that nonparametric methods likely provide more accurate statistics when comparing the pilot program and baseline distributions. The problem with using standard nonparametric tests for statistical significance, such as Kolmogorov-Smirnov or Anderson Darling, is the variability found across tests. For example, the Anderson Darling test is more accurate when the distributions in question have longer tails, while the Kolmogorov-Smirnov test is more sensitive to deviations near the center of the distribution than at the tails. For these reasons, this analysis used a Monte Carlo approach to determine how likely or unlikely the pilot program results came from the baseline data distribution.

Figure 5. Illustration of Weibull and lognormal CDF fit to the baseline distribution



Conclusions and Recommendations

The pilot program was able to successfully improve the time and efficiency of repairs by integrating BIT data throughout the maintenance process. Sensor data may therefore considerably improve readiness for Super Hornets by expediting repairs of parts that may be keeping jets in a non-mission capable status.

Because of the limited sample size, short duration of this pilot program, and system used (i.e., APG-65 and 73), we recommend that NAE expand the effort to integrate sensor data at another FRC (e.g., Lemoore) on a system that has a large impact on the readiness of the Super Hornet fleet. A candidate system is the generator control units, which have been a top degrader for Super Hornets for some time [11]. This new effort should include training for both O- and I-level maintainers on efficiently and effectively providing and using BIT codes for repairs. This effort would ensure that the right data are accessible and useful to I-level maintainers to maximize the outcome. Ideally, this effort would last at least six months to allow the impact of sensor data integration on readiness to be captured for analysis and evaluation.

The pilot program revealed a few outstanding issues that need to be addressed to maximize the benefits of BIT data. They included infrastructure, data transfer, data interpretation, and data rights. If the Navy decides to integrate BIT data not just for one system in one location but rather across the fleet, the NAE must consider: 1.) how to incorporate a cyber-secure electronic transfer of sensor data from O- to I-levels, 2.) how to develop more robust sensor diagnostic reasoners that can be updated and matured based on real operational maintenance practices and findings, 3.) how to contract for the rights to sensor data in the future, and 4.) what storage and computing infrastructure is necessary to house, query, and analyze such massive datasets.

Appendix A: Metrics

We describe how each metric is calculated.

Table 2. Description of metric calculations

Metric	Calculation
TRR	Completed Date – Induction Date
MH	Directly reported in NALCOMIS
EMT	Directly reported in NALCOMIS
Order Iterations	The number of orders per repair is stated in NALCOMIS. An order iteration accounts for all orders made on the same day. If the order was made the following day, that is an additional order iteration.
Parts	Reported in NALCOMIS and added for all subcomponents ordered during a repair (job control number)

Appendix B: Unfiltered Data

As noted in the Data Selection section, 70 repairs were tagged with a "*SM*", indicating the I-level maintainer should have had access to and used BIT data in the repair process. Only in 39 of the 70 repairs was it clear BIT data were actually used, and the results for those 39 repairs are presented in the body of this work. In this appendix, we present the analysis on all 70 data points for completeness. Table 3 summarizes the metrics for the unfiltered 70 data points, along with the same metrics for the baseline data and the pilot program data described in the Pilot Program Results section.

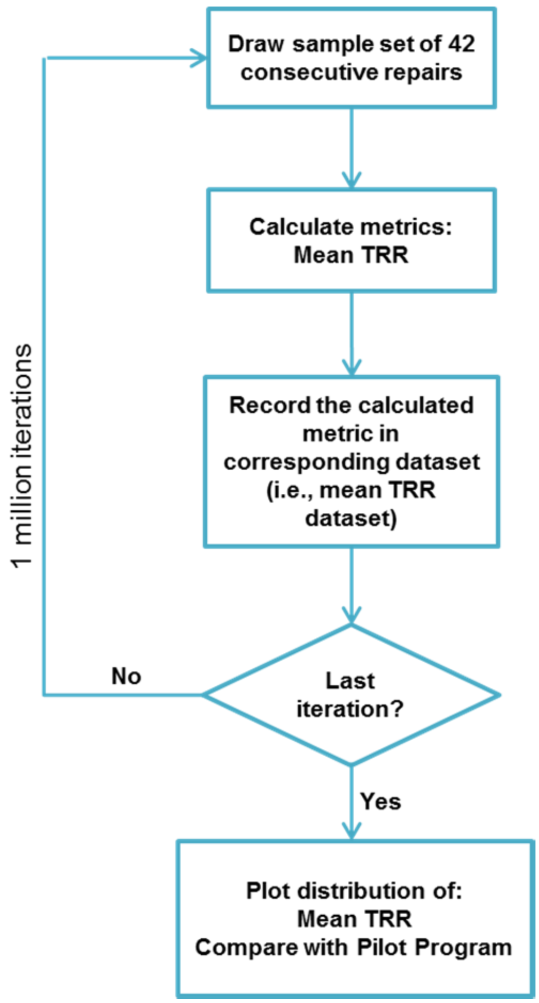
Table 3. Comparison of metrics for the filtered pilot program data with baseline data

Metric	Baseline	Unfiltered Pilot Program	Percent Difference	Pilot Program: BIT used	Percent Difference
Mean TRR (Days)	18.38	12.5	32.0%	10.17	44.6%
Mean # of Order Iterations	1.73	1.51	12.8%	1.15	33.6%
Mean # of Parts Ordered	5.39	4.29	20.6%	3.05	43.4%
Metric	Baseline	Unfiltered Pilot Program	Percent Difference	Pilot Program: BIT used	Percent Difference
Mean EMT (Hours)	21.88	23.93	-9.4%	17.76	18.8%
Mean MMH (Hours)	53.73	64.03	-19.2%	43.47	19.1%

In the unfiltered pilot program dataset, the average TRR was reduced by 32 percent, down to 12.5 days from the baseline of 18.38 days per repair. When we isolated and analyzed only the repairs that we are confident had access to BIT data—the BIT used dataset in Table 3—the reduction in average TRR was nearly 45 percent, down to 10.2 days from the baseline of 18.38 days. Though both the unfiltered pilot program and pilot filtered (i.e., pilot BIT used) datasets demonstrated the ability to lower the number of part orders and reduce TRR, our analysis of the EMT and MMH metrics is more difficult to interpret. The full pilot dataset revealed longer hours spent turning wrenches through the EMT and MMH metric than the baseline EMH and MMH. However, of the 70 repairs in the full pilot dataset, those that had the longest EMTs and MMHs did not indicate the use of BIT data to detect the root cause of failure, while the pilot BIT incorporated data showed a 20 percent reduction in both metrics. It is not clear why the maintainers might have needed more hands-on time to fix parts in the unfiltered pilot program dataset.

Appendix C: Flow Diagram of Monte Carlo Approach

Figure 6. Monte Carlo approach diagram



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