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Advanced Technologies to Enable Optimized Maintenance Processes in Extreme Conditions: Machine Learning, Additive Manufacturing, and Cloud Technology

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Abstract

The way routine maintenance is conducted is not an optimal way to handle maintenance in extreme battlefield conditions. This is a common maintenance problem across various domains, such as repairing battle damage to aircraft or ships without access to a port or depot. The extreme conditions context can also include repairing the Alaska pipeline in the extreme cold, or handling repairs during COVID-19. The researcher examined how modern technology can optimize productivity and reduce the cycle time of the extreme maintenance process. The results of this research found that three emerging technologies: additive manufacturing, cloud in a box, and machine learning (ML), could improve process value, save labor costs, and reduce cycle time. ML had the most significant impact on improving productivity and cycle time. When all technologies were utilized together, productivity and cycle time improvement were more significant and consistent. The research accounted for the riskiness of these technologies, which is necessary to accurately forecast the value added for this extreme maintenance process context. This research is vital because getting correct valued repairs done quickly for the Department of Defense can make the difference between winning and losing a conflict.

Introduction

Parts of this introduction were previously published by Springer Nature in *HCI for Cybersecurity, Privacy, and Trust* (Miller & Mun, 2023). Extreme maintenance conditions, such as during combat operations or personnel shortages as during the COVID pandemic, create many unique repair and maintenance challenges. These challenges include the battle front line availability of technical data or specifications to make the repairs, the lack of parts, and decision support aids to assist with transforming repair data into information and knowledge that lead to making timely decisions. The lack of timely maintenance information leads to uninformed and suboptimal maintenance decisions, especially when edge networks are data-limited, that increases the risk to a given complex repair and the employees making the repairs. For example, the naval enterprise system architecture (ground and aviation) has limited technical data in these edge networks. The communication limitations of the edge networks have led to interaction-based failures, resulting in inefficient information exchanges among maintenance-related systems and repair personnel.

Innovative maintenance approaches with modern IT, can potentially overcome these extreme maintenance case problems. Information systems are needed to provide mechanisms that will enable leadership to make data-driven resource decisions at all levels of the maintenance process by using locally available data derived by leveraging this new IT. With access to the required technical information, and without having to do all the current manual workarounds to get the data needed to make precise repair decisions, the repair team can actually do the repairs in a timely and efficient manner. The problems arise when the maintenance technicians are forced to do workarounds because they do not have the required technical information available locally.

This extreme maintenance problem requires innovative use of U.S. Naval IT resources to foster the potential of increased process productivity as well as reductions in process cycle times for repair. The three IT artifacts examined in this study (additive manufacturing [AM], machine learning [ML], and cloud in a box [CIB]) should provide the kinds of mechanisms that will enable leadership to make more well-informed IT investment decisions resulting from the innovative leveraging of these new IT technologies.

When deploying new IT solutions in organizations, it is hard for information scientists to gather the required data on IT decisions to determine the impact on employees (Leonard-Barton & Kraus, 2014). If the local maintenance personnel deliver innovative repair ideas, aided by modern IT artifacts that help improve process productivity, these ideas can be embedded in ML, potentially resulting in more optimized processes that add value to their organization. Currently, routine aviation maintenance knowledge (e.g., at the depot level) used to optimize processes is not readily available for potential use in extreme maintenance conditions, and the results of that routine maintenance knowledge are not passed from one generation of maintainers to the next.

Purpose Statement

The purpose of this research is to test the value added of three modern information technology artifacts (i.e., AM, ML, and CIB) to optimize process productivity and cycle time for extreme maintenance conditions. The current research study extends the use of process optimization theory (Castillo, 2011) to include the effect of modern information technology on extreme maintenance process productivity and cycle time. This research is essential because there is a gap in the process optimization literature with regard to optimizing maintenance processes with modern information technology in the context of extreme maintenance. The current research is important because failure to make correct repairs to battle-damaged equipment can make the difference between winning and losing a conflict.

Research Goals

One of the research goals is to make a theoretical contribution to the economics of information technology (EOIT) domain by testing the effects of three new IT artifacts (AM, CIB, and ML) to provide process optimization options that would potentially increase process productivity (i.e., return on investment [ROI]) and reduce process cycle time for extreme maintenance processes. The results of this research should provide greater confidence in decision-makers’ IT investment predictions based on information from process optimization model forecasts. The Department of the Navy (DoN) must improve its extreme maintenance processes to maintain readiness in battle conditions. Business process reengineering (BPR) techniques can be used to model the effects of AM, CIB, and ML on productivity and cycle time (Miller & Mun, 2023).

Thus, I propose an information sciences-based investigation of how using modern information technology in extreme maintenance conditions can extend the existing EOIT optimization-focused theories by testing new IT artifacts (AM, CIB, and ML) in a new but pervasive context. For example, AM can provide maintenance technicians with part-generation options that should accelerate the repair cycle. The CIB can house technical information that would feed ML technology and can work in a network disconnected environment (e.g., extreme maintenance at the battle front). The ML IT option under review in this study involves three dimensions: algorithms, systems, and people (Stoica et al., 2017). In this context, ML focuses on accessing technical data (e.g., using the CIB technology), and the ML algorithm learns based on performance feedback from the maintenance personnel.

The types of ML algorithms proposed in the current research are commonly utilized in bioinformatics (Frazier, 2022). These kinds of ML algorithms are used to improve the predictions of the effects of various variables that "repair" biological systems. The results from this domain of research on the use of ML will form the basis for the parameter expectations of the performance of ML to aid repair and maintenance decision-making. This kind of ML should provide extreme maintenance technicians with information to adapt and improve their repair decisions, which include, in particular for the current study, repair evaluation, and parts ordering decisions.

The current research utilizes integrated risk management (IRM) to forecast the effects of using the three IT artifacts to optimize extreme maintenance subprocesses that have been optimized using BPR techniques. By doing so, the current study will expand the scope of EOIT optimization theories through the use of robust forecasting techniques in the context of extreme maintenance decision-making.

Literature Review

This study uses naval aircraft maintenance in particular due to the complexity of the problem. The aircraft battle damage repair (BDR) requires specialized repair and damage analysis, skills, and tools from depot-level maintenance organizations in order to perform complex equipment structure modifications or to perform routine or urgent equipment and system repairs. The baseline model in the current study is derived from the existing depot-level maintenance processes as verified by subject matter experts (SMEs) who perform those depot and extreme maintenance functions during wartime operations. The Forward Deployed Combat Repair (FDCR) teams must be highly mobile and able to operate with very limited communication reach back to the depot resources and repair information. The logistical and maintenance constraints in extreme maintenance conditions (e.g., wartime field theater) will require the U.S. Navy to deploy civilian technicians forward to use new, more timely, and efficient processes by leveraging emerging technologies. This kind of maintenance research has a very high priority, as witnessed by the current efforts that are underway with Navy research teams who are studying the battlefield tactics of the Ukrainian military, including maintaining equipment in extreme battlefield conditions (NPS Information Sciences PhD Seminar Series, Oct 2023).

Baseline process models for extreme maintenance have not been documented previously. BPR optimization techniques require a baseline process model to inform and compare As-Is baseline process performance to To-Be forecasts regarding decisions about how to best utilize IT to optimize core processes (Hammer, 1990; Hammer & Champy, 1993; Housel & Bell 2001). Without such BPR models it is very difficult to justify investment in modern IT options that are designed to optimize processes, especially for extreme maintenance process optimizations that are urgently needed in the U.S. military. For example, if we want to test the potential use of AM, CIB, and ML to optimize the extreme maintenance repair process, we must have an As-Is baseline model to compare to To-Be forecasted improvements. The quantitative methods and models presented in this research will contribute to predicting the impact of modern IT artifacts used as process optimization options in the context of extreme maintenance processes. If the FDCR teams have these three technologies in place, and the IT technologies perform as expected, then the extreme maintenance process cycle time and process productivity performance should show improved optimization.

The current research makes theoretical contributions to information sciences through EOIT by gauging the ability of new IT technology to impact productivity and cycle time in extreme maintenance conditions. The economic theories of EOIT consider the effects of introducing IT on corporate productivity (Goldfarb & Tucker, 2019; Shapiro & Varian, 1999). Further, in EOIT theory, researchers have hypothesized about the effects of these IT inputs at the process level (summarized in chapter three of Housel and Bell [2001]) on a firm's productivity. The theories ultimately rely on organizational accounting data to test their assertions empirically (Brynjolfsson & MacAffe, 2014; Elliot, 1992; Pavlou et al., 2005). Hitt et al. (1994) framed their research using EOIT and concluded that information technology positively affects an organization's productivity.

This research also seeks to extend process optimization theory (Castillo, 2011) to extreme maintenance processes. In process optimization, value added can be calculated at the subprocess level (Housel & Kanevsky, 1995). In extreme maintenance, the overall core repair process can be decomposed into its subprocesses. Although the outputs of the subprocesses are different, they can be compared by converting them to common units using the knowledge value added (KVA) theory.

These new IT aided models can potentially assist decision-makers by speeding up the data-to-decision (D2D) times and reducing risk (e.g., aircraft downtime). The current research results should be useful in extending EOIT theory by demonstrating how these IT artifacts can potentially be used to speed up the D2D times for repair decisions and how it might lead to overall increases in extreme maintenance process productivity. The results of the current study should help address theoretical gaps in the EOIT research on process optimization by the potential application of process modeling techniques that focus on the use of modern IT artifacts in the context of extreme maintenance requirements.

When applied early in the redesign of processes by modeling the impact of modern IT on process productivity and cycle time, the current study methods can lead to increased IT investment portfolio optimization decision-making within the context of real operations. The IT investment portfolio optimization techniques used in the current study provide a way to generate hypotheses similar to those of a study. Albert and Hayes (2002) found that hypothesis generation efforts should be incorporated early in the acquisition process and tested further with field experiments. Extending prior maritime research by Mun and Housel (2010), the current study will use Monte Carlo simulation with real options. This research addresses the gap in assessing the value of these new IT technologies in process optimization for extreme maintenance conditions.

Analysis

The current study explores several extreme maintenance use cases via modeling and simulation techniques (i.e., the current As-Is approach with the forecasted To-Be approach using new IT). This research is run from the perspective of a Leibnizian (Analytical-Deductive) inquiring system in which the guarantor of the knowledge claims is the self-evidence of the inputs and the deductive soundness of the operations. The validity of this research was established through a clear explanation of the input selection reasoning, a detailed explication of all derived analytical expressions, and a comparison between simulation results and the theoretical predictions of the derived analytical expressions. Complex data analytics packages were used to analyze the data for statistical insight and to process thousands of trial runs on the data and the emerging technologies to provide a complete view of the problem.

A comprehensive view of the problem within extreme maintenance is lacking in that the emerging technology is examined individually and not holistically. There is an absolute necessity to use emerging technology (AM, CIB, and ML) more efficiently within naval aviation maintenance-based decisions. That is why the final model engages all the technologies together (AM + CIB + ML) in the appropriate subprocess. The technical data sets can be challenging to acquire and comprehend. The magnitude of these specialized data sets offers analysis complexities within an extreme maintenance realm that is large, distributed, and varies from mission to mission.

Data Overview

The data analytics were based on current input from SMEs in extreme maintenance conditions. The analysis was conducted using the data from the surveys discussed in the previous chapter. Field experiments informed the surveys and cost data of the labor by the technicians performing the repairs and managers of those technicians. The surveys were completed by individuals familiar with the current As-Is extreme maintenance process on land and in maritime situations. In either case, the extreme maintenance constraints were applied to the current As-Is process, and forecasts were built into the models. Further, the To-Be models for AM, CIB, and ML were informed by experts in those technologies and the extreme maintenance process. The consistency of different sets of observations that measure the same factors was tested using statistical methods during the data exploration. Further, the correlation between variables of a survey with a pairwise comparison between two variables can be linear or nonlinear and either positive or negative. These linear coefficients are often insufficient and require other tests that check the data points across both the columns and rows for data consistency and reliability (e.g., the intraclass correlation coefficient [ICC] test).

The forecasted events for these models are targeted at three years. Using the technology to forecast further is possible, but future events behaving or occurring in the way expected may have greater volatility. The models can be extended past three years of the study but may require updating of the process maps and data parameters to maintain accuracy and precision. The reliability of the models refers to the repeatability of findings. If the study were repeated, would it yield the same results? If the measurement results are consistent and if the experiment is valid, then the data is considered to be reliable. This section explains the data analysis so another researcher can produce the same stable and consistent results as this study. While the validity of the models refers to how well a test measures what it is purported to measure, validity is more related to how strong the hypothesis outcomes are. It answers the question, are we right? Internal and external validity are tested with multivariate models such as regression and econometrics.

One assumption in this study is the limited data over an extended period. The extreme maintenance conditions for aviation in the modern era are quite new, especially when considering modern weapon systems (fifth-generation aircraft and unmanned aircraft). The processes and technologies in this research are mature but under-documented and mainly untested on a large scale. The data gathered was based on a year of field experiments with an organization that often conducts sea and land repairs. This assumption may affect the generalizability, as not all organizations perform extreme maritime maintenance. Also, the data is collected from military and civilian employees; not all organizations have this blend of employees. Additionally, the U.S. Navy is a private, not-for-profit organization that, of course, may differ slightly from a for-profit public company, yet productivity and cycle time are still driving factors in both non-profit and for-profit organizations. Lastly, it should be noted that more data collected over a more significant period would increase the accuracy and precision of the models.

Exploratory Data Analysis

This subsection provides an exploratory data analysis of the data collected to include statistical tests described in the Analysis section. The variables are reviewed, and insights that will later be used in simulations are generated as parameters and settings for those models. The first variable explored is the subprocess complexity. As discussed earlier, KVA is based on complexity theory and information theory, which is essential to understanding which subprocesses engage a more significant part of the workforce's time. Further, the learning time for a subprocess is correlated with the complexity of that subprocess. The longer it takes to learn a subprocess, the more complex that subprocess. Table 1 displays the rank order of complexity for the maintenance subprocesses. It shows that the repair subprocess requires the highest learning time and is the most complex sub-process in extreme maintenance and that for most subprocesses, learning time is not as substantial as it is for the repair process. The second most complex subprocess is the depot repair decision, or whether the repair can be completed on-site or needs to be conducted in a higher echelon of maintenance with more access to tools, labor, and infrastructure. Rank Order is a more accurate measure of complexity with a ratio scale than adjusted Rank Order with an ordinal scale.

Table 1. Extreme Maintenance Subprocess Complexity and Learning Time

Sub-Process #	Sub-Process	Rank Order (in complexity)	Rank Order Adjusted	Learning Time (hours)
1	Maintenance Request	2.91	1	5.74
2	Depot Repair Decision	4.45	6	21.35
3	Maintenance Induction	3.73	4	6.34
4	Part Inventory	3.36	2	5.84
5	Repair	5.55	7	41.10
6	Inspection	4.18	5	13.48
7	End Item Delivery	3.45	3	6.14
			Total LT	99.98
			Correl (RO & LT)	0.95

Learning time is the time someone needs to learn how to perform a particular set of tasks but not the amount of time to actually perform those tasks. The descriptive statistics for the learning time based on the surveys are compiled across the seven subprocesses. The range of learning time is approximately 35 hours, with a mean across the subprocesses of 14 hours. The minimum learning time is around 6 hours, with the maximum learning time being 41 hours. This data review provides parameters for the To-Be models and the four moments. We can also set up a basic statistical test based on the information listed in Table 2 for standard deviation and mean. Data skewness is greater than one, resulting in a positive skew of the distribution. Lastly, the learning time fourth moment or a Kurtosis of 2.9 means that the distribution is more peaked and has fatter tails than normal.

Table 2. **Learning Time Descriptive Statistics**

Learning Time Descriptive Statistics Summary Statistics	
Sub-Processes	7
Arithmetic Mean	14.28429
Geometric Mean	10.63972
Trimmed Mean	14.28429
SE Arithmetic Mean	4.98427
Lower CI Mean	4.31574
Upper CI Mean	24.25283
Median	6.34
Minimum	5.74
Maximum	41.1
Range	35.36
Stdev (Sample)	13.18715
Stdev (Population)	12.20893
Lower CI Stdev	9.10304
Upper CI Stdev	25.25902
Variance (Sample)	173.90093
Variance (Population)	149.05794
Coef of Variability	0.92319
First Quartile (Q1)	5.99
Third Quartile (Q3)	17.415
Inter-Quartile Range	11.425
Skewness	1.7671
Kurtosis	2.90775

The descriptive statistics just described are visualized with the Box and Whisker Plot shown in Figure 1 to give a spatial visual of the descriptive data. The figure further shows the positive skew of the learning time and average time to complete per subprocess. The learning time and average time to complete is skewed based on the repair and repair decision subprocesses. The X-axis in this chart has no meaning.

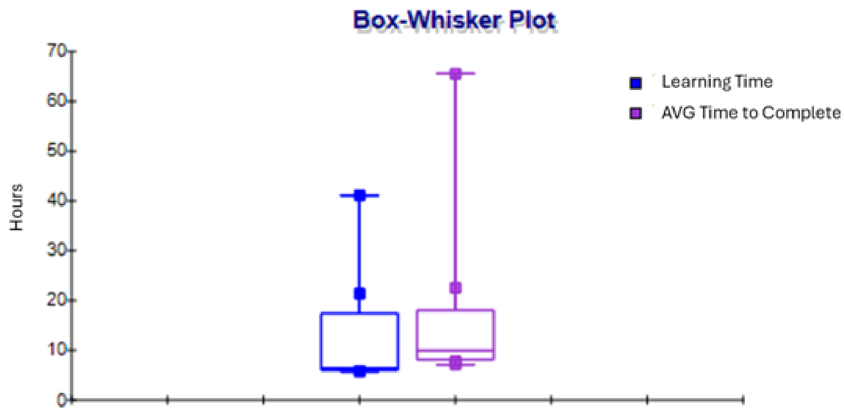

Figure 1. Learning Time and AVG Time to Complete by Sub-Process

The As-Is Expected Project Schedule shown in Figure 2 further shows what subprocesses impact the extreme maintenance most. Furthermore, the Tornado Analysis shows that Repairs, Field Repair Evaluation, and Inspection are the subprocesses that should be targeted for new technologies and process optimization. The repair process and the field evaluation process have the most impact on the overall extreme maintenance process. The delivery of the repaired aircraft and maintenance request subprocesses have the most negligible impact on productivity and cycle time. As with most project management, spending effort on the bottleneck subprocess offers the most room for productivity and cycle time improvement. If time permits, a focus on inspection of the aircraft post repair, maintenance induction, and part inventory subprocesses will be of value because the impact on cycle time and productivity may be minimal in terms of the days it takes to return the item to service.

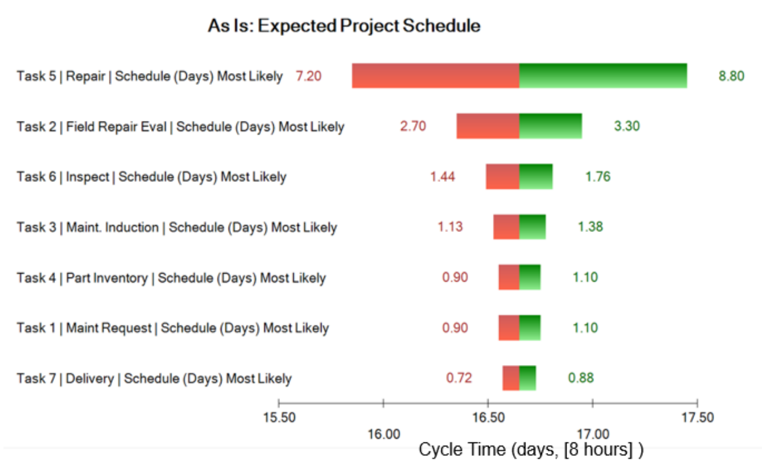

Figure 2. The As Is Project Schedule for Subprocesses

The investment portfolio for the five models (As-Is, AM, CIB, ML, and AM + CIB + ML) is displayed in Figure 3 as a new technology portfolio. This data forecasts the baseline As Is process with the new To-Be processes (i.e., AM, CIB, ML, and AM + CIB + ML). The investment portfolio demonstrates that the new technology reduces cost and schedule, which is vital in project management. The technology that offers the most benefit to the organization is ML. The Y Axis is the number of days expected for the repair, while the X-axis is the cost of the repairs. So, the technology on the lower left corner of the diagram is beneficial to the organization. For example, ML is completed a day and a half faster and about $8,000 cheaper over two weeks. In contrast, CIB, followed by AM, also offers gains over the As-Is extreme maintenance process but not to the degree that ML does.

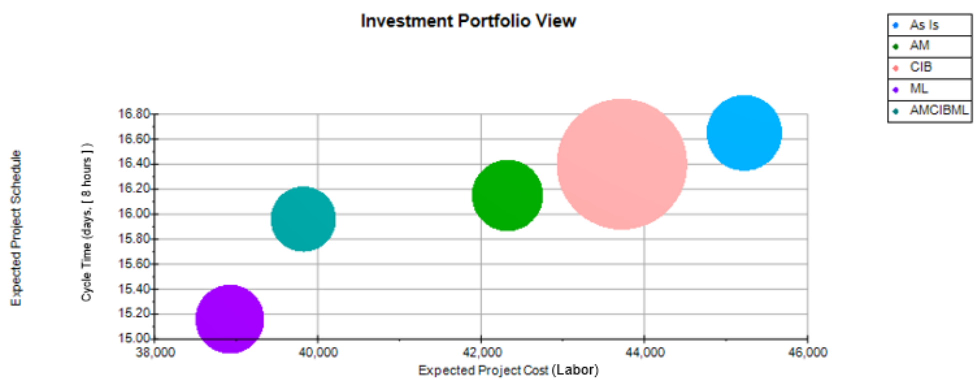

Figure 3. New Technology Investment Portfolio

Based on Monte Carlo simulation, Figure 4 shows the emerging technology's probability density function (PDFs) and the As-Is process with the expected cost. PDFs are a statistical measure used to gauge the likelihood that an investment will have returns that fall within a range of values and indicate the risks involved. The PDFs in Figure 4 are plotted on a graph that resembles a bell curve, with the data lying below the curve. Also, the skewed angle at either end indicates greater/lesser risk or reward. The wider the curve, the greater the range of possible values. The As-Is process and CIB offer the greatest range and higher risk. In contrast, ML and all the technologies combined represent less variance, less risk, and a higher reward.

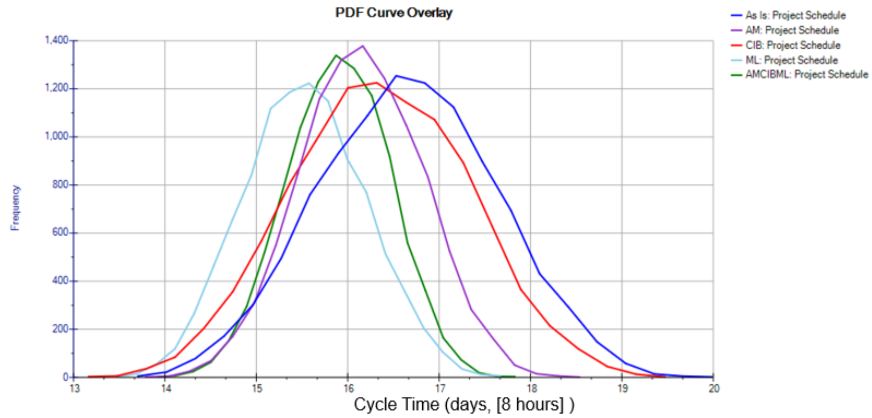

Figure 4. Predicted Schedule Saving of the Emerging Technology

a. HYPOTHESES TESTS

The hypotheses test evaluates the use of new technology against the As-Is case. The eight hypotheses are as follows:

- Hypothesis 1: ML-informed repair decisions will lead to improved extreme maintenance process cycle time compared to current extreme maintenance repair prediction decision methods.
- Hypothesis 2: ML effects the extreme maintenance process productivity to improve.
- Hypothesis 3: Using AM improves extreme maintenance process cycle time compared to traditional supply chain parts acquisition methods.
- Hypothesis 4: AM improves extreme maintenance process productivity compared to traditional supply chain parts acquisition methods.
- Hypothesis 5: CIB technology improves extreme maintenance process cycle time compared to traditional reach-back methods.
- Hypothesis 6: CIB technology improves extreme maintenance process productivity compared to traditional reach-back methods.
- Hypothesis 7: AM + CIB + ML technology improves extreme maintenance process cycle time compared to traditional methods.
- Hypothesis 8: AM + CIB + ML improves extreme maintenance process productivity compared to traditional methods.

The As-Is, AM, CIB, ML, and AM + CIB + ML cases provide three-point estimates for the minimum, the most likely, and maximum estimates for cycle time. As shown in Figure 4, these point estimates follow a triangular distribution. The cycle time in days is the X-axis, while the rate of change is the Y-axis in Figure 5.

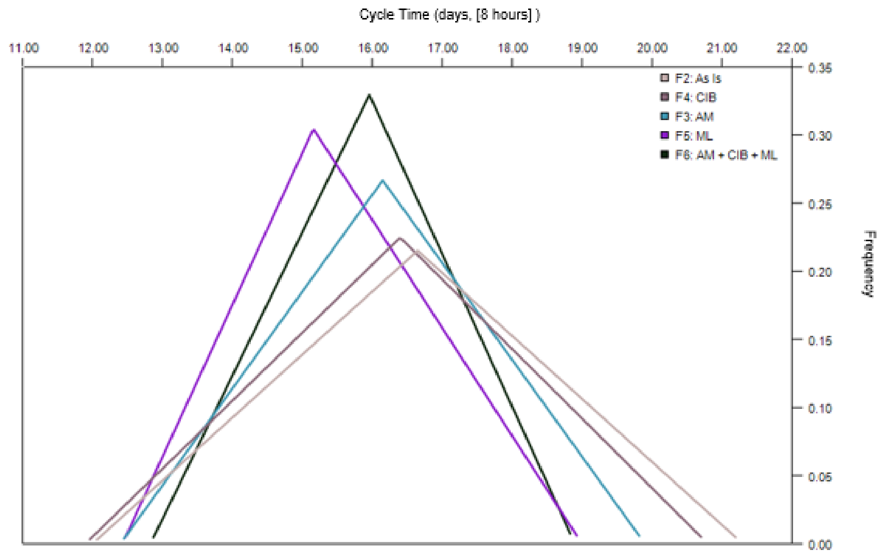

Figure 5. **Cycle Time Triangle Distribution**

The parameters are then inputted into the Risk Simulator software to generate data based on the As-Is and four To-Be process models and are fully simulated. As the analysis section discusses, these parameters reflect current survey data and SME forecasting input. The hypotheses test data are outputs of simulations run with a thousand data points for each of the five models using the risk simulator. The data described are shown for the To-Be AM+CIB+ML model in Figure 6, and the simulation results obtained are utilized in the hypotheses tests.

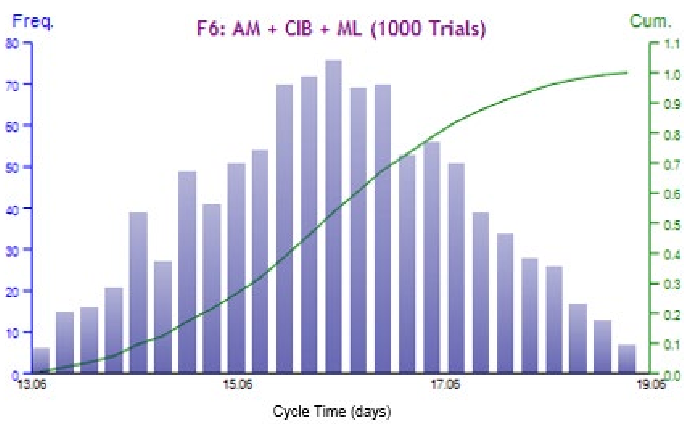

Figure 6. **Hypothesis Distribution Simulation Data**

The hypotheses tests are parametric two-variable t-tests independent with equal variance. They are not dependent; for example, if the technician fixes an aircraft, runs the test, and then fixes the same aircraft again, that does not fit the conduct of this study. In this study, the technician could be fixing different types, models, or series of aircraft. Since the technicians are repairing different aircraft, the overall aircraft repair process has similar situations. So, similar situations have equal variance, which means the class of aircraft is being repaired by similarly trained individuals. Therefore, the hypotheses test utilizes equal variance. Furthermore, this study is not testing between aircraft, surface vessels, votes, and submarines. This is why we use a parametric two-variable t-test independent with equal variance.

The hypotheses for cycle time are directional hypotheses. Hypothesis one states that ML improves cycle time compared to traditional prediction methods; hypothesis three states AM increases cycle time compared to traditional supply chain parts acquisition methods; and hypothesis five states CIB technology improves cycle time compared to traditional reach-back methods; hypothesis seven states AM + CIB + ML technology improves extreme maintenance process cycle time compared to traditional methods. Table 3 shows a directional main effects hypothesis. The CIB, hypothesis five, is that p-values are less definitive but can still reject the null hypotheses. Finally, hypothesis seven is that AM + CIB + ML technology improves cycle time compared to traditional reach-back methods, which is statistically significant.

The hypotheses tests conducted are multiple T-tests with the As-Is model compared to the To-Be Model and ANOVAs. The simulation data is broken up into groups of hundreds of data points for the AM, ML, CIB, and the three technologies combined. The simulation data was generated with a random seed of one and was analyzed with a pairwise T-test. The data generator allows the simulation of all four To-Be processes. Table 3 shows that AM, ML, and AM+ML+CIB all have an effect on cycle time, while CIB effects are enough to reject the null hypotheses 50% of the time based on the significance level of 0.05. Using AM technology, the null hypothesis can be rejected 70% of the time at the significant level of 0.05. Once ML technology is added, it is 100% of the time at the significant level of 0.05 and 0.01.

Table 3. **Cycle Time Hypotheses Tests One Tail**

Hypotheses T-Test (Right Tailed, One-Tail) Results (P-Values)				
Sample	**AM**	**CIB**	**ML**	**AM+CIB+ML**
1–100	0.202949	0.035302	0.000001	0.001389
101–200	0.003927	0.088065	0.000000	0.000096
201–300	0.017506	0.034693	0.000000	0.002298
301–400	0.002766	0.329675	0.000007	0.000085
401–500	0.276834	0.398832	0.000003	0.007049
501–600	0.003153	0.139105	0.000000	0.000107
601–700	0.007370	0.029176	0.000000	0.000009
701–800	0.031494	0.425067	0.000051	0.002155
801–900	0.145179	0.006349	0.000001	0.000153
901–1000	0.004225	0.007521	0.000007	0.000089
Significant (α=.05)	70%	50%	100%	100%
Significant (α=.01)	50%	20%	100%	100%

An ANOVA was conducted to look across all the independent variables at the same time. A single-factor, multiple-treatment ANOVA was chosen because each factor is applied to the same extreme maintenance repair process. Table 4 demonstrates that one or more technologies have a statistically significant effect at Alpha 1% on at least one of the levels.

Table 4. **Cycle Time ANOVA Single Factor Multiple Treatment**

Hypotheses Test with ANOVA Results (P-Values)		
Sample	**As-Is, AM, CIB**	**As-Is, AM, CIB, ML, AM+CIB+ML**
1–100	0.1770	0.0000
101–200	0.0252	0.0000
201–300	0.0752	0.0000
301–400	0.0172	0.0000
401–500	0.8502	0.0000
501–600	0.0221	0.0000
601–700	0.0396	0.0000
701–800	0.1148	0.0000
801–900	0.0271	0.0000
901–1000	0.0116	0.0000
Significant (α=.05)	60%	100%
Significant (α=.01)	0%	100%

The power analysis for these tests is post hoc, with two variables, with 10 samples of 100, for the T-test (Figure 7). The Sigma of group one is 16.5346, and the Sigma of group two is 1.634913 with a hundred sample size with two tails and an alpha of 0.05 with minor effects, so the power is only about 12%. Having 1,000 data points does bring the power up to about 74.94%.

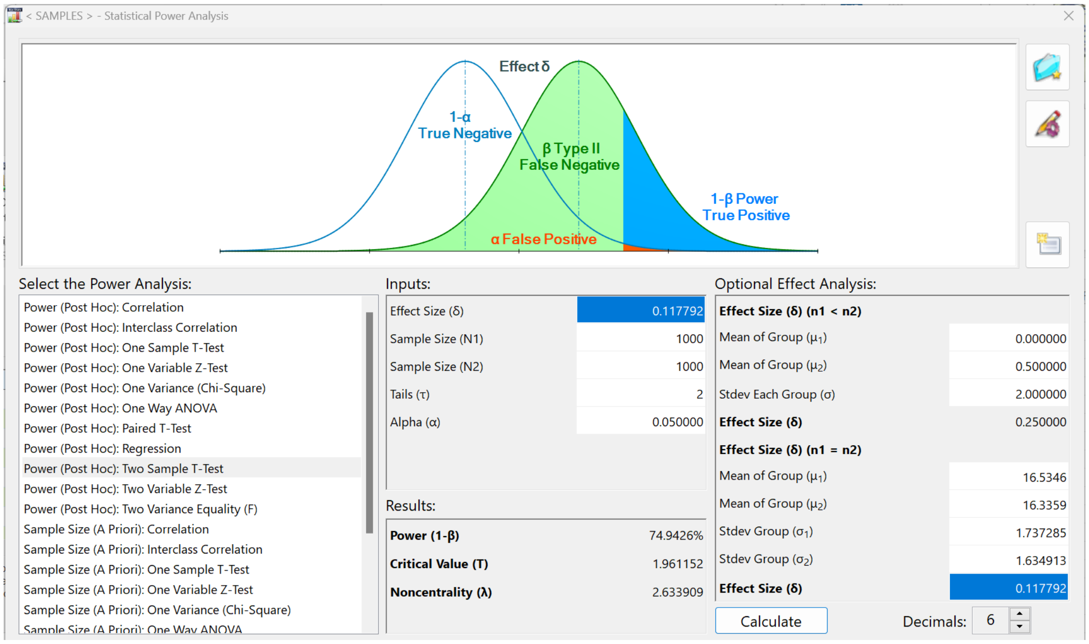

Figure 7. Power Analysis for Hypotheses Tests

At the corporate level, ROI and ROK are productivity ratios in accounting, as seen in Table 5. ROI is based on revenue in the extreme maintenance case for a non-profit organization, like the military, in which there is no revenue. The fact that there is no revenue is not an issue for ROI, as market comparables can substitute for revenue.

Table 5. Productivity As-Is and To-Be ROI

Sub-Process #	Sub-Process	As-Is ROK	As-Is ROI	To-Be ROI AM	To-Be ROI CIB	To-Be ROI ML	To-Be ROI AM, CIB & ML
1	Maintenance Request	77.23%	10.72%	10.72%	10.72%	11.00%	11.00%
2	Depot Repair Decision	95.27%	41.99%	41.99%	41.99%	42.50%	44.00%
3	Maintenance Induction	66.39%	-3.82%	-3.82%	-1.00%	0.00%	1.00%
4	Part Inventory	70.93%	3.75%	5.00%	4.00%	4.00%	4.50%
5	Repair	62.82%	-5.95%	-2.00%	-2.00%	1.50%	3.50%
6	Inspection	100.41%	49.80%	49.80%	50.50%	51.00%	50.50%
7	End Item Delivery	88.57%	29.54%	29.54%	31.00%	30.00%	30.50%
ROI Totals			126.03%	131.23%	135.21%	140.00%	145.00%

Table 6 shows the results of the productivity hypotheses. Hypothesis 2: ML effects process productivity to improve, and hypothesis 4: AM increases productivity compared to traditional supply chain parts acquisition methods. Additionally, hypothesis 6 states that CIB improves productivity compared to traditional reach-back methods. Finally, hypothesis 8 states that AM + CIB + ML improves productivity compared to traditional reach-back methods.

Table 6. **Productivity Hypothesis Testing**

Hypotheses T-Test (Left Tailed, One-Tail) Results (P-Values)				
Sample	**AM**	**CIB**	**ML**	**AM+CIB+ML**
1–100	0.000100	0.197900	0.002107	0.000778
101–200	0.033700	0.014390	0.000686	0.001050
201–300	0.004625	0.145225	0.000147	0.000008
301–400	0.014260	0.004070	0.000010	0.001569
401–500	0.000110	0.009500	0.000564	0.000191
501–600	0.056720	0.032137	0.001158	0.006239
601–700	0.011170	0.235800	0.000693	0.056232
701–800	0.004590	0.002750	0.000337	0.002207
801–900	0.000062	0.472000	0.000653	0.021535
901–1000	0.016810	0.387479	0.000003	0.012274
Significant (α=.05)	90%	50%	100%	90%
Significant (α=.01)	50%	30%	100%	70%

The productivity hypotheses are evaluated using the same methodology as the cycle time hypotheses. The forecasting parameter estimates are derived from the literature review and SME input. The ANOVA results are shown in Table 7.

Table 7. **Productivity ANOVA Results**

Hypotheses Test with ANOVA Results (P-Values)		
Sample	**As-Is, AM, CIB**	**As-Is, AM, CIB, ML, ALL**
1–100	0.0047	0.0069
101–200	0.1032	0.0046
201–300	0.0854	0.0001
301–400	0.0128	0.0003
401–500	0.0035	0.0015
501–600	0.1365	0.0125
601–700	0.1709	0.0204
701–800	0.0071	0.0037
801–900	0.0013	0.0161
901–1000	0.1637	0.0005
Significant (α=.05)	50%	100%
Significant (α=.01)	40%	70%

Conclusion

In various extreme conditions such as aircraft or ship battle damage repair, extreme cold Alaska pipeline repair, and COVID-19 repair processes, the use of modern information technologies such as ML, AM, and CIB are not being leveraged to optimize productivity and reduce cycle time in these critical maintenance processes. The literature on process optimization does not address the use of modern technology for optimization in extreme maintenance conditions. Therefore, the purpose of this research was to estimate the value added by information technology to optimize process productivity and reduce cycle time for extreme maintenance processes. This research aimed to extend process optimization theory to include the effect of modern information technology in extreme maintenance conditions. It is critical in the DoD context because failure to repair battle-damaged equipment remotely (without access to the depot), correctly, efficiently, and quickly can make the difference between winning and losing a conflict.

Furthermore, extreme maintenance reach-back to the depot for resources or data is problematic, using existing repair processes and systems as the technician must assume they must operate independently. The current research demonstrated that the three technologies (AM, CIB, and ML) technologies potentially offer ways to significantly improve the ROI of the extreme maintenance process and reduce the cycle time of the process. AM alone will potentially decrease cycle time and increase productivity compared to traditional supply-chain parts-acquisition methods. CIB technology will potentially improve cycle time and productivity compared to traditional reach-back methods, in spite of its newness and potential performance volatility. The research clearly demonstrated that ML technology can also be used to improve cycle time and productivity compared to traditional extreme maintenance decision-making prediction methods. The extreme maintenance research findings are summarized in Table 8.

Table 8. **Extreme Maintenance Findings Summary**

Extreme Maintenance Finding Summary			
Technologies	**Cycle Time (Schedule/Cost savings [Labor])**	**Productivity (Value)**	**Comments**
AM	**Moderate improvement**	**Significant improvement**	**Technology gains offer an immediate impact with little fielding challenges.**
CIB	**Slight improvement**	**Slight improvement**	**New technology, high volatility, enabler for AM & ML.**
ML	**Significant improvement**	**Significant improvement**	**Highest improvement of all technologies. Implementation might be a challenge due to data availability and extreme maintenance hosting environment.**
AM + CIB + ML	**Significant improvement**	**Significant improvement**	**Recommended option due to improvements in Cycle Time/ Productivity, and complementary technologies that reduce risk to increase upside.**

The results of this research clearly demonstrated that the three IT technologies have the potential to significantly improve the productivity and cycle time of an extreme maintenance process. As such, this research extends the current EOIT and process optimization research areas to include this critical context. Further, this research extension can cover the extreme maintenance domain in for-profit (e.g., North Slope Oil extraction operations) and non-profit organizations (e.g., battlefronts without convenient reach back to a maintenance depot).

Research Limitations

One of the issues is that the potential emerging technologies (AM, CIB, ML) have not been tested in extreme maintenance conditions. This study does not test them, and the potential for these emerging technologies is being modeled economically. The dissertation proposes that investment decisions are based on modeling and simulating their value in extreme maintenance. The ML techniques are often subject to the inability to identify flaws and errors, and there are difficulty in identifying scope and reliability models.

Future Work

The real problem facing the U.S. Naval Mission is automating the fleet to include autonomous vessels. By 2045, the U.S. Navy is estimated to have 500 vessels, with at least 150 being autonomous (Tangredi & Goldorski, 2021). If we extrapolate to the aviation fleet, we can expect at least a third to be unmanned. These unmanned aerial systems (UASs) will need maintenance. This is a paradigm shift for extreme maintenance because repairs will not focus on human safety. Maintenance in the future will have more significant gains with new technological improvements, such as AM, ML, and CIB. New technologies that scale will be critical, that is, the AI/ML architecture explored within future Joint Task Force (JTF) extreme maintenance operations. The commanders can shape the battlespace by maintaining combat power and utilizing these system capabilities.

Additional analysis of the warfighting staff and AM, CIB, and ML can transform process optimization and ultimately enable decision-makers to manage extreme maintenance risk based on the data. Also, future work is needed to explore any weaknesses with CIB and address AM cyber vulnerabilities (i.e., data poisoning) in the extreme maintenance use case.

UAS assets' acceptable repair thresholds can change the level of acceptability for parts and repairs in general. As long as a UAS can accomplish its mission, a triumphant return of the asset to friendly territory might not be necessary. The secondary contribution of this research is the use of the methodologies of evaluating emerging EOIT and contextualizing extreme maintenance processes to refracture the existing RO approach to unmanned systems. Future research will take this research and continue to test and refine the model and conduct field experiments where possible. As discussed earlier—the more accurate the data, the better the forecast for the models.

Author Statement

The views expressed in this article are those of the author and do not reflect the official U.S. Navy policy or position of the Naval Air Systems Command, Department of Defense, or the U.S. Government. This is not a product of NAVAIR.

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