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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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ADVANCED TECHNOLOGIES TO ENABLE OPTIMIZED MAINTENANCE PROCESSES IN EXTREME CONDITIONS: MACHINE LEARNING, ADDITIVE MANUFACTURING, AND CLOUD TECHNOLOGY

by

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March 2024

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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.

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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.

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LIST OF ACRONYMS AND ABBREVIATIONS

ABDR	Aircraft Battle Damage Repair
AI	Artificial Intelligence
AM	Additive Manufacturing
ANOVA	Analysis of Variance
AOG	Aircraft on Ground
ASN	Assistant Secretary of the Navy
AvPLM	Aviation Product Life cycle Management
BOM	Bill of Material
BDR	Battle Damage Repair
BLOS	Beyond Line of Sight
BPR	Business Process Reengineering
C2	Command and Control
CIB	Cloud in a Box
CL	Central Line
D2D	Data to Decision
DDIL	Denied, Degraded, Intermittent and Limited (bandwidth)
DM	Data Management
DOD	Department of Defense
DON	Department of the Navy
DV	Dependent Variable
EABO	Expeditionary Advanced Base Operations
EOIT	Economics of Information Technology
FDCR	Forward Deployed Combat Repair
FKSS	Future Knowledge System of Systems
GMS	General Micro Systems
HPE	Hewlett Packard Enterprise
ICC	Inter Class Correlation

IM	Information Management
IOT	Internet of Things
IRM	Integrated Risk Management
ISR	Intelligence, Surveillance and Repair
IT	Information Technology
IV	Independent Variable
JTF	Joint Task Force
KM	Knowledge Management
KVA	Knowledge Value Added
LCL	Lower Control Limit
LOS	Line of Sight
MEF	Marine Expeditionary Force
MI	Migration Integration
ML	Machine Learning
NAVAIR	Naval Air Systems Command
NCSS	Net-Centric Data and Service Strategy
NISE	Naval Innovation Science & Engineering
N-MRO	Naval Maintenance Repair Overhaul
NN	Neutral Networks
N-PLM	Naval Product Life cycle Management System
N-SCM	Naval Supply Chain Management
OODA	Observe, Orient, Decide and Act
PI	Primary Investigator
PUK	Pack up Kit
RM	Risk Management
RO	Real Options
ROI	Return on Investment
ROK	Return on Knowledge
SME	Subject Matter Expert

SOS	System of Systems
UAS	Unmanned Aerial System
UCL	Upper Control Limit
USAF	United States Air Force
USMC	United States Marine Corps
USN	United States Navy
XML	Extensible Markup Language (XML)

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EXECUTIVE SUMMARY

Parts of this executive summary were previously published by Springer Nature in *HCI for Cybersecurity, Privacy, and Trust* (Miller & Mun, 2023). Routine maintenance processes (e.g., peacetime conditions) are not optimized for extreme maintenance conditions. This is a general problem across many extreme maintenance contexts (e.g., aircraft or ship battle damage repair, extreme cold Alaska pipeline repair, and COVID-19 depot repair processes). In extreme contexts, modern information technologies (IT) (e.g., machine learning [ML], additive manufacturing [AM], and cloud in a box [CIB]) have typically not been leveraged to optimize productivity (productivity equals output divided by input or value divided by cost to generate value) and cycle time in these critical maintenance processes. The purpose of this research is to estimate the value added of three modern information technologies (AM and ML for resource requirement prediction, and CIB technology) to optimize process productivity and to reduce cycle time for extreme maintenance processes. This research will extend the use of process optimization theory (Castillo, 2011) to include the effect of modern information technologies in the extreme maintenance context. This research is important because there is a gap in the process optimization literature regarding extreme maintenance conditions and the use of modern technologies for optimization. It is particularly important in the Department of Defense context because failure to make correct repairs to battle damage equipment can make the difference between winning and losing a conflict.

Typically, theories in the Economics of Information Technology (EOIT) are business theories that consider the effects of introducing modern IT to optimize processes and improve competitiveness in for-profit organizations (Shapiro & Varian, 1999; Goldfarb & Tucker, 2019). Based on the general tenants of EOIT theory, researchers hypothesize about the effects of these technology resources on a firm's revenue streams at the whole organizational level. The researchers test these technologies' effects empirically by analyzing organizational accounting data (Hitt et al., 1994; Brynjolfsson et al., 2021). The general results have led them to conclude that using IT has a positive effect on the productivity of a firm. The current research seeks to extend process optimization research to extreme maintenance conditions in a not-for-profit military organizational context.

In process optimization, value added can be calculated at the component subprocess level (Pavlou et al., 2005; Housel & Kanevsky, 1995; Housel & Bell, 2001). The current research will test the effects of three IT artifacts (AM, CIB, and ML) on optimizing maintenance processes that integrate the three technologies to help increase productivity and decrease cycle time. Prior research in bioinformatics by Adams (2022) shows that modern information technologies can positively affect IT investment decisions. These new ways of incorporating modern IT in core processes have the potential to assist decision-makers by speeding up the data-to-decision (D2D) times regarding aircraft maintenance downtime and thereby reducing cycle time operational risk. This research contributes to extending EOIT by testing the effects of these IT artifacts that promise to speed up the D2D cycle time and thereby addresses a theoretical gap in normal maintenance processes by testing the effects of these IT artifacts on productivity in the context of extreme maintenance conditions processes.

This quantitative study was conducted in two phases: first by using knowledge value added (KVA) As-Is baseline productivity analysis and then by using simulation via the integrated risk management (IRM) approach, to forecast the effects of the three IT artifacts on the core extreme maintenance process and its subprocesses. The As-Is KVA process analysis established the baseline performance of the current extreme maintenance process that does not use the three IT artifacts. The simulation forecasted the effects of including the three IT artifacts in the extreme maintenance process's value, cost, and cycle time parameters. The As-Is maintenance process model was based on process subject matter experts' (SMEs) estimates for the model parameters of learning time, cost, and cycle time.

The As-Is use case was a forward-deployed combat aviation repair process. Advanced analytical techniques were utilized and simulated in regard to the To-Be modeling forecasts: real options and integrated risk management. The four To-Be models consist of the effect of ML alone, the effect of CIB alone, the effect of AM alone, and the effect of ML + CIB + AM combined. The ML To-Be process models employed were derived from the use of ML in bioinformatics research that addressed repairs as a treatment of the system much as organic systems are repaired.

This research will make contributions to EOIT and information sciences theory in the context of process optimization using modern IT artifacts by gauging the contributions of the IT artifacts to process productivity and to decreasing process cycle time (Mun & Housel, 2010). Further, the research explored the potential improvements in returns on investment via hypotheses' use cases with simulations that included using real options and IRM modeling in the context of the potential effects of IT artifacts in the unique context of extreme maintenance processes.

This research explored and utilized the IRM framework, which includes real options theory, to forecast the effects of the three IT artifacts by including real options methodology, utilizing strategy decision trees to model real options, and estimating the potential risks of using each technology option. Risk real options can be characterized as defer/execute, expansion, barrier acceptance, and migration options, using the wait and defer/execute option. The real options analysis allows the researcher to test and forecast process models as proofs of concept to more precisely estimate the cost, profitability, and schedule risks of the technology options (Mun, 2015), in the extreme maintenance process context. With the most promising options identified, it is possible to put a contract in place that includes the possibility to wait and see as more valuable information about the performance of the technology options becomes available after implementation, before deciding to execute the new technology (AM, CIB, and ML).

This research revealed both cost savings on labor and improved cycle time for the extreme maintenance repair teams by introducing the emerging technologies of AM, CIB, and ML. Of these emerging technologies, ML had the most radical improvement, followed by all the technologies together, and then AM and CIB. When all technologies are utilized together, the improvement in productivity and cycle time are significant and the most consistent. Lastly, the research explored risk management options and changes to existing processes that would be required to fully realize the improvements resulting from utilizing the technologies.

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I. 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.

Access to the primary repair facility, which is the depot, is not guaranteed in extreme maintenance conditions. Therefore, the repair teams onsite have to be self-sufficient and must assume there is no network and that reach-back (i.e., connectivity to stateside networks is not likely) to get the necessary maintenance information to conduct repairs, is not possible. The extreme maintenance repair teams need to develop a purely local yet robust approach. For example, the repair teams may be on an island, oil rig, or an isolated maritime environment. Any mobile communication could be jammed, intermittent, or broken, so they can't rely on it. Worse yet, in a military conflict environment, where there is heavy reliance on mobile communication, electronic communication could be intercepted, giving the enemy a general status of capability of current military assets.

Innovation is required to deal with these potentially electronic communications-denied environments. W. Brian Arthur's (2009) argument that new IT equated to his concept of "innovation" can be combined in new and valuable ways to overcome these network isolation problems and allow access to the information needed to make repairs in an isolated environment.

In the current study, the presumption is that repair teams currently do not have access to repair information in an isolated environment, leading them to often make many incorrect maintenance decisions and to take excessive time to conduct repairs. The repair teams have historically called back to depot-level professionals to receive needed technical, or equipment part information over satellite phones. However, calling back to the repair facility does not give the level of fidelity needed to make efficient, correct, and timely repairs. For example, repairing something as complex as a jet engine requires precise technical data, that might be contained in a cloud-based 3D model. An extreme maintenance process diagram is provided in the design of the experiment section.

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 a lot of workarounds because they do not have the required technical information available locally.

Machine learning (ML) may be one of the innovative technologies that could be used to reduce the number of people that remote repair teams need because it can be used to automate many of the existing labor-intensive processes. Using ML would potentially lead to the repeatability of common repairs, and also might provide predictions about such issues as mean-time-to-repair scheduling. It also could possibly predict where to get or whether to build (e.g., using additive manufacturing [AM]) required parts before they are needed based on predictions of mean time to failure data. In this potential scenario, using ML and AM would lead maintenance technicians to pre-build parts and replace aging parts based on when they were predicted to fail, before they actually fail. Such predictions would lead to a more "ready" military capability to fight battles, leading to more favorable military outcomes.

For work that would go beyond the normal routine equipment maintenance servicing requirements, technicians should be able to make repair decisions based on what is happening on the ground in remote field situations. In this extreme maintenance context, existing data, contained in a traditional cloud server, for the routine maintenance tasks that are required in any normal operational environment cannot be relied on. Machine learning might be used to consider such unique contexts and make inferences about what should be done to make timely and efficient repairs. ML can be trained with routine maintenance and non-routine maintenance repair data to enable it to forecast, for example, whether to replace the blades in the jet engine or the compressor sooner than the repair technician might believe, albeit incorrectly, would be required.

The potential information on existing maintenance processes (e.g., mean time between failures and technical data), usually available under normal circumstances, does not usually exist in an edge combat repair context. In these remote emerging combat contexts, such as when drones and other forms of attack armament are in need of repair, maintenance problems that do not occur in normal maintenance contexts can arise. In these extreme maintenance contexts, repair teams would likely benefit from the use of ML artifacts, which have been trained in these contexts, to make more precise maintenance predictions and to repair equipment accordingly. These predictions would include what to replace sooner rather than later and, as a result, provide insight into what extreme maintenance subprocesses to adjust to improve productivity and cycle time.

To support access to needed repair information, cloud in a box (CIB) can provide the repair teams with cloud storage and access capabilities even with limited or no connectivity. The CIB IT option can potentially enable AM in extreme maintenance conditions because it can contain the 3D technical data for parts that can possibly be made via the AM IT artifact. The remote conditions add to the constant network connectivity problems and may even lead to network-based adversarial interference or deception, leading to incorrect repairs. Most of our enemies are quite adept at the use of cyber deception, further necessitating having all the relevant maintenance information available in a usable way and quickly accessible remotely at the field repair site. Thus, the a need to test the value added of the CIB option because it has less power requirements, is more secure, and is easier to set up than trying all options to remotely connect to the depot-level cloud information and technical support (i.e., every aircraft stores its own required technical data in the CIB). These CIB devices are usually mobile with a small footprint, easily replaceable, and plug-and-play with a rapid setup.

By adding AM technology in the extreme maintenance case, maintenance personnel do not have to wait for a part from the manufacturer (i.e., a F/A-18 aircraft Boeing part). That delay could take months, but the maintenance technician can create parts on-site using AM. Other potential benefits of AM technology include reduced inventory and less need for manufacturing support equipment, such as a lathe or a Computerized Numerical Control (CNC) machine. It follows that even if a small percentage of the repairs, supported by part production with AM, can be done on-site, this technology would add value by eliminating the delays caused by waiting for parts from the supply chain. It is also likely that the cost of including AM for use in the repair process would most likely be lower than procuring the necessary parts from the original equipment manufacturer using the traditional supply chain. Having the AM manufacturing capability locally also reduces the risks of disruptions in the supply chain, not to mention the longer cycle time to receive the parts.

The repair team might also utilize Pack-up Kits (PUKs) that would include AM capabilities. Having AM included in the PUKs could reduce the wait on the supply system since there would be less need for a vast inventory. Also, potentially using ML would begin to inform what should be in the PUKs based on historical data. However, local ML would benefit from CIB, and when these artifacts are combined with AM, the likely value added of these artifacts would become more compelling for investors (e.g., generals, admirals, or senior executive service leaders).

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 (AM, ML, and 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.

A. PROBLEM STATEMENT

The problem is standard maintenance processes, e.g., in peacetime conditions, are not optimized for extreme maintenance conditions, which can lead to serious disruptions in operations. This is a general problem across many extreme maintenance contexts (e.g., aircraft or ship battle damage repair, extreme cold Alaska pipeline repair, and COVID-19 repair processes). This is a problem because, in extreme maintenance contexts, processes have not been optimized, leading to potentially serious disruptions to operations. However, modern information technology (e.g., ML, AM, and CIB) can be leveraged to optimize productivity and reduce cycle time in these extreme maintenance processes.

B. 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.

C. 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.

D. STATUS OF NAVAL AIRCRAFT MAINTENANCE IN EXTREME MAINTENANCE CONDITIONS: INFORMING THE BASELINE PROCESS MODEL

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 Ph.D. 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 (Housel & Bell 2001; Hammer, 1990, Hammer and Champy, 1993). 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.

E. RESEARCH HYPOTHESES

Research opportunities to study naval extreme maintenance processes, to help inform maintenance process decision-makers, maintenance personnel, and information scientists will lead to new insights about how to fuse new IT to enable more informed process optimization decisions. The following hypotheses were tested using IRM-based statistical methods discussed later in the methods section:

- 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.

F. CONTRIBUTION TO KNOWLEDGE

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 (Shapiro and Varian, 1999; Goldfarb & Tucker, 2019). 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. (Elliot, 1992; Brynjolfsson & McAffee, 2014; Pavlou et al., 2005). Hitt et al. (1994) framed their research using EOIT and concluded that information technology has positive effects on 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.

The current research forecasts the effects of three new IT artifacts(AM, CIB, and ML technology) on optimizing maintenance processes in terms of how the artifacts would affect the productivity and cycle time of extreme maintenance processes. The potential impact of these new IT artifacts on extreme maintenance processes was modeled by leveraging bioinformatics research results that examined comparable processes (Adams, 2022).

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. The results of the current study will explore 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).

When applied early in the redesign of processes by modelling 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 a similar study's hypotheses. Albert and Hayes (2002) found these hypotheses generation efforts should be incorporated early in the acquisition process and tested further with field experiments. Extending prior maritime research by Housel and Mun (2010), the current research will use Monte Carlo simulation with real options. The gap this research addresses is to assess the value of these new IT technologies in process optimization for extreme maintenance conditions.

The report layout is structured as follows: Chapter II is the literature review with further discussion of EOIT, the extreme construct, aviation use case, new technologies (i.e., AM, CIB, ML), relevant theory, and definitions. Chapter III is the research methodology, which covers design, operational variables, assumptions, data collection, the KVA survey, quantitative methods, simulation, and risk management with real options. Chapter IV is the analysis section with a data overview, exploratory data analysis, and statistical inferences. Chapter V consists of hypotheses testing and the IRM section. Finally, Chapter VI is the conclusion with recommendations, research limitations, and future work.

The dissertation includes a detailed table of contents that outlines the various sections of the research. It starts with an introduction that includes a problem statement, a purpose statement, research goals, and the status of naval aircraft maintenance in extreme maintenance conditions: informing the baseline process model. It also covers research hypotheses and the contribution to knowledge. The literature review section covers the EOIT, BPR, and process optimization theories, why the extreme construct matters, aviation use cases for extreme maintenance, decision-making with machine learning, additive manufacturing, cloud in a box, and a review of relevant theory, definitions, and deficiencies.

The research methodology section covers the design of the experiment, operationalization of the variables, assumptions, data collection, KVA survey for extreme maintenance, quantitative methods and simulation, and risk management and real options. The analysis section covers data overview, exploratory data analysis, and statistical inferences using various process models such as the As-Is base model, To-Be AM process model, To-Be CIB process model, To-Be ML process model, and To-Be AM + CIB + ML process model.

The testing and risk management section covers hypotheses tests and integrated risk management, which includes risk identification, prediction, modeling, analysis, mitigation, hedging, and diversification. Finally, the conclusion section includes the conclusion and recommendations, research limitations, future work, and the author's statement. The report includes appendices for Grubbs test subprocess complexity, ANOVA results, and ROI and ROK sub-process analysis. A list of references and an initial distribution list are also included.

II. LITERATURE REVIEW

This literature review explored theories of EOIT, including BPR and process optimization. The current study analyzed theories in investment decision-making with an emphasis on emerging information technologies that can assist in extreme maintenance process optimization. These theories of EOIT and decision-making are well grounded in the field of information sciences. For example, the work of Herb Simon in decision-making has been applied to the problem of evaluating IT investments in numerous studies. Other studies have more narrowly focused on the work of Andrey Kolmogorov's complexity theory, which relied on Shannon Information Theory.

Kolmogorov's complexity theory posits a common unit of change, that is, a common unit of complexity, that can be most precisely defined as a Shannon Information Theory bit (see Cover & Thomas, 2005 for an explanation). The knowledge value added theory uses the construct of unit of change, complexity to describe all outputs of all processes (Housel & Kanevsky, 1995). The basic assumption is that all processes take inputs (that which can be described in terms of cost, or the denominator of the productivity equation) and change them into outputs (the "thing of value" that can be described with high fidelity in terms of the number of common units of change/complexity, required to produce the outputs, or the numerator of the productivity equation). The advantage of this formulation for describing the outputs in terms of common units of change is that all process outputs can be described in common units using a ratio scale. It follows that the productivity of all processes can be compared. When all outputs of all processes are comparable, it follows that the ROIs of every process can be compared and folded into IT investment portfolios (Mun & Housel, 2010; Housel & Mun, 2015) just as all equities, or stocks can be folded into investment portfolios with no loss of performance information. In the current study, the KVA theory was used to make the As-Is, baseline and the To-Be forecast process productivity (in terms of ROI), cycle time measurements (i.e., dependent variables).

While the three modern IT technologies discussed are also used in other contexts (e.g., in bioinformatics), in the current study within the domains of information science EOIT theories, they provide significant process optimization possibilities. For example, ML has been used in the medical field to review massive amounts of data and predict optimal medical treatments (i.e., bioinformatics). In EOIT research (Mun & Housel, 2010; Housel, Ford. Mun. & Hom 2015; Mun, 2015, 2019 Miller & Mun, 2023; Housel & Mun 2015; Komorowski, Housel, Hom, & Mun, 2006), the process optimization effects of AM have been forecasted to reduce inventory (Housel et al., 2015) by producing parts on-site as needed to reduce process cycle time and to reduce the requirement for inventory in the supply chain. Additionally, CIB technology has been used to provide necessary local maintenance information in network denied contexts, resulting in the capacity to use high-speed computing at the edge where it is needed to make a data-driven decision.

Figure 1, a following high-level literature map, shows the most critical research articles that were used to create the current research justification and research design.

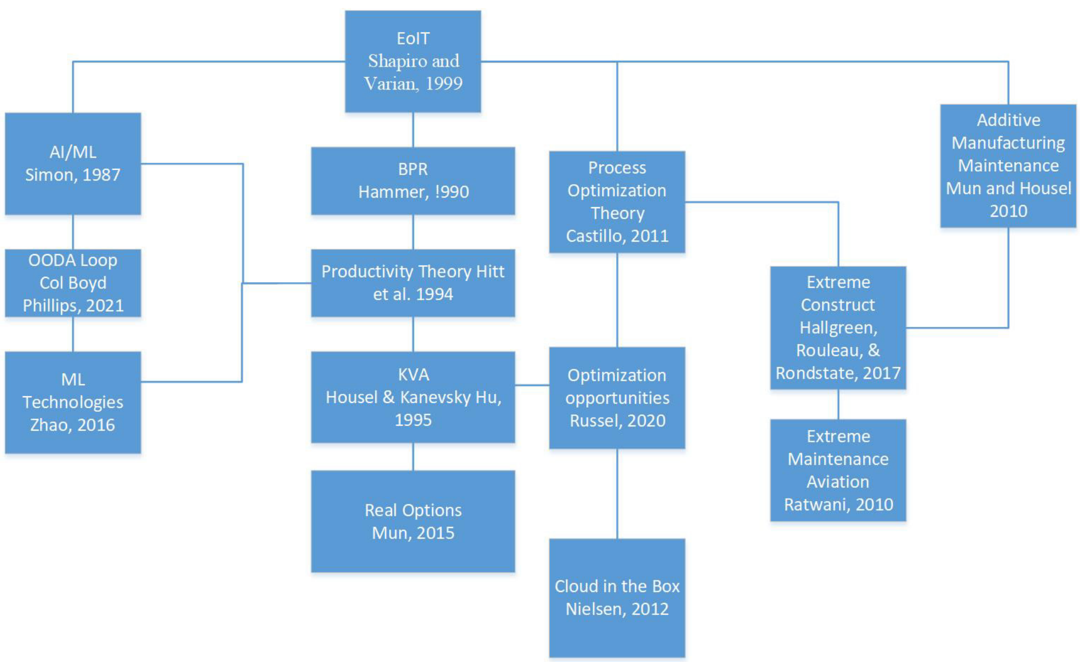

Figure 1. Literature Review Map

A. THE EOIT, BPR, AND PROCESS OPTIMIZATION THEORIES

According to Mirowski (1989), economics laws have been used to formulate value theory in economics. This econo-physics transformation of value theory provided a historical review of how the value concept in economics was formulated based on Newtonian and Einsteinian deterministic energy concepts. Beinhocker (2006) used Mirowski's review to argue for using complexity theory to formulate value theory. The current study's use of the KVA approach is based on formulating the deterministic value metric. These three theoretical approaches have in common the need to formulate a value metric that is defensible on fundamental theoretical grounds, and KVA fulfills this requirement by formulating deterministically derived common value units to describe all process outputs in common units of value.

Further, the EOIT theoretical framework has spawned a wide variety of theories that are, for example, often used to evaluate the functioning of an organization after the introduction of IT (Shapiro & Varian, 1999). In part, EOIT is based on accounting principles accepted for over 500 years as the economic and international standard source for raw As-Is and baseline economic data. These accounting principles are based on historical assessments of the current state of an organization and, therefore, follow a deterministic logic. Alternatively, when forecasting future firm performance based on this historical As-Is, baseline accounting data, forecasting models are necessarily probabilistic in spite of the fact that they use historical, over time accounting data to populate "model parameters."

The primary EOIT theories and approaches explored in the current research are productivity theory, BPR, and process optimization theory. Hitt et al. (1994) introduced a version of productivity theory by utilizing the productivity construct to measure whether the emerging information technology firms use provides competitive advantages. In accounting and most of the EOIT theories and approaches, historical productivity is calculated in terms of a firm's output (the "thing" of value, by definition) divided by its inputs (the investment, cost to produce the thing of value) only at the whole corporate level. The corporation uses the whole organizational output that generates sales revenue as the item of focus that is being produced (widget, repaired aircraft), and the input construct consists of the cost, or investment, to use the required resources (labor and materials) to produce the output. Another essential construct for the current study is estimating the value added by IT at the sub-organizational level. The value added by IT at the core process level has not been resolved by a widely accepted solution (Housel & Bell, 2001; Mirowski, 2009; Beinhocker, 2006) even though one candidate solution (i.e., KVA) has been in use for over 30 years.

The KVA methodology has been used to measure the value added by IT. The KVA process analysis method describes all process outputs in common units that can be measured across all processes and their subprocesses. This KVA approach allows all process and subprocess outputs, and the costs to produce the outputs to be comparable so that the productivity of all processes is made comparable. Consequently, investors, executives, and managers compare the productivity of all processes even though they have non-comparable aggregate outputs (e.g., a maintenance request or a repaired aircraft engine). This comparability allows decision-makers to evaluate the impacts of IT on these disparate processes. Such performance comparable information can be used to support their process optimization investment decisions based on the forecasted effect of the IT on the performance of the overall process and its subprocesses (Housel & Kanevsky, 1995; Housel & Bell, 2001). An organization converts inputs into outputs in modeling the effects of modern IT artifacts on To-Be forecasted process models that can be compared to As-Is, baseline process model performance. This modeling can provide the potential optimization based on the To-Be models according to a production function that can attribute each input's new IT contribution to the output measured by gross marginal benefit. The basic assumption used for modeling the As-Is model was that the As-Is model was the average process based on process SMEs' averaged estimates of the subprocess model parameters (i.e., productivity expressed as ROI using market comparables and subprocess cycle times). The As-Is baseline process was estimated based on an equilibrium state, with expected normal incoming demand based on SMEs' experience with the process. The To-Be models, which forecasted the relative productivity and cycle time effects of the three IT artifacts in various combinations and alone, were based on SMEs' assumptions and prior research (e.g., the effects of ML in biometric research) to estimate the potential changes in the relative productivity and cycle times of the subprocesses.

Parts of this paragraph were previously published by *Springer Nature in HCI for Cybersecurity, Privacy, and Trust* (Miller & Mun, 2023). Organizational optimization theory is focused on productivity improvement (e.g., based on use of information technology to optimize process flow). Even though this line of research is focused on the whole organizational level, it also provides a conceptual framework for sub-organizational process optimization using IT artifacts as well as the key optimization parameters for the productivity ratio (i.e., output/input). This line of research (e.g., Brynjolfsson et al., 2021; Hitt et al., 1994) typically uses modeling and simulation to estimate productivity improvements using various optimization options (especially when using information technology). Process optimization theory typically focuses on incremental improvements in organization productivity based on the presumed effects of IT artifacts.

The BPR, a version of the group of organizational optimization theories, is used to radically (i.e., an order of magnitude improvement in optimization) cost optimizes core processes, primarily through the use of modern technology (Hammer, 1990; Hammer & Champy, 1993), most often using new technology such as the IT technologies used to model process optimization in the current study (i.e., AM, ML, and CIB). The problem with the prior research using BPR is that it does not provide a common unit of value at the process level. It presumes that if the denominator is optimized by reducing it, then the numerator (output), will essentially stay the same. Without common units, this prior research provided no way to compare various process optimizations across an enterprise because the outputs were not described in common units (Housel & Bell, 2001).

Organizational optimization theory (Castillo, 2011) could be used to predict productivity improvements with statistical methods to maximize award functions through sub-process refinement. The gap in the current process optimization theory is that it does not provide for the effect of IT artifacts and does not model the extreme maintenance case, nor does the theory account for the potential value added of modern IT at the subprocess level. Conceptually and operationally, process optimization theory defines process optimization in terms of the productivity ratio (output/input). Given comparable productivity metrics among processes, it becomes possible to develop modeling and simulation of process optimization by framing the IT artifacts as real options that can then be combined into multiple portfolio opportunities (Mun, 2015, 2019; Mun & Housel, 2010).

The success of organizations is tied to the efficiency and effectiveness of their core processes (Niedermann & Schwarz, 2011) because this is the fundamental activity where inputs are turned into value outputs. Process optimization that uses BPR to refine the processes with IT artifacts potentially leads to radically improved process productivity. A review of critical EOIT KVA research that guided the development of the process modeling for the current study is included in Table 1. Why Use the KVA Theory to Model the Extreme Maintenance Process. Parts of the analysis column in Table 1 were previously published by Springer Nature in HCI for Cybersecurity, Privacy, and Trust (Miller & Mun, 2023).

Table 1. Why Use KVA Theory to Model the Extreme Maintenance Process

Authors	Date	Title of Work	Key Concepts	Purpose	Problem	Methodology	Analysis
Shapiro & Varian	1999	Information Rules: A Strategic Guide to The Network Economy	Accounting Principles, Intellectual Property, EoIT Decisions	Framework for EoIT decision for investors to make decisions about IT	Info. Tech. changes rapidly while accounting principles are static	Deterministic accounting with historical situational examples	EOIT is based on accounting principles accepted for over 500 years as the economic and international standard. These accounting principles are historical in nature and deterministic. IT changes rapidly and the framework is required to make decisions
Hitt et al.	1994	The Three Faces of IT Value: Theory and Evidence	Economic Principles, IT Value, Productivity	IT Value vs. Business Performance with the introduction of computer systems	Does IT provide value and improve business performance	Hypothesis testing, with Economic Theory	Introduce the productivity theory by utilizing the productivity construct to measure whether the emerging technology is effective. In accounting, productivity is calculated in terms of process output divided by input at the corporate level
Housel & Bell	2001	*Measuring and Managing Knowledge*	Knowledge Managemen t, Knowledge Economics, Knowledge Value Added	"KVA can be used to generate estimates of the value of the knowledge embedded in the core processes of a firm"	"Business environments value process knowledge on the micro-level but often fail to recognize the importance of process knowledge at the macro-level" (p. 84)	Common Units based on information theory and complexity theory to internalize knowledge use as a task that involves much more than technology	The corporation uses output as the item of interest being produced (i.e., widget, repaired aircraft), and the input construct consists of items required to produce the output (i.e., labor and materials); these inputs are factored in as a cost. Another essential construct is value caused by IT is an enduring concern in EOIT, and it is one without a definitive resolution
Mirowski	2009	Why There's (as yet) No Such Thing as an Economics of Knowledge	Political economy, national wealth, Economics of Knowledge	Review Modern Traditions of the Economics of Knowledge	Economists concede that their constructions of the epistemology of the agent were structurally incoherent	Philosophy of Science, Epistemology, Philosophy	Economics at the cutting-edge treating trade as static allocation with a review of existing modern traditions of the Economics of Knowledge
Housel & Kanevsky	1995	Reengineering Business Processes: A complexity theory approach to value added	Accounting Principles, Business process reengineerin g (BPR)	Reengineering effort with objective value allocation among the component processes with a new approach	"There is no objective, countable way to measure value added by component processes"	"Extension of Kolmogorov's Complexity with an approach to calculating ROI at the component process level"	One popular research method to measure the value that this research will leverage is KVA, which reduces the subprocess outputs to standard units that can be measured across subprocesses to evaluate and optimize the performance of the overall process
Brynjolfsson	2016	Valuing Information Technology Related Intangible Assets	Value of IT concerning Cost and ROI of intangible assets	Review of how companies measure IT investments	Does Investment in IT increase productivity	Business Practices and IT capabilities	This approach implies that investment IT (i.e., cost) in correlated to value, and this is not always the case

B. WHY THE EXTREME CONSTRUCT MATTERS

The focus on the extreme construct in this study and in any information systems research is a recurring topic in the management literature, appearing in over 130 articles that used this construct from 1980 to 2015 (Hällgren et al., 2017). The extreme case structuring of problems is used due to time pressures as well as the urgency of the problems confronting an organization. In extreme cases, the stakeholders are less threatened by potential organizational adaptations, such as using modern IT to improve the performance of core processes. Top-level management usually directs the changes to stay competitive with adversaries by championing the need to increase core process productivity and reduce cycle time. In addition, there is more tolerance for reengineering process failure that might lead to loss of revenue or battlefield capability due to potentially negative effects on process cycle time and productivity. It follows, then, that modeling the extreme maintenance case provided more cooperation from process owners and leadership to explore with the researchers the opportunities such as those modeled in the current study to explore the potential positive effects, as well as risks, of using the three IT artifacts on core process productivity and cycle time.

The extreme construct is often applied in information systems literature as a way to limit the complexity, as well as to reveal the underlying causes of a given research problem. Hällgren et al. (2017) state that

> Or perhaps it is a recognition that extreme contexts provide a unique platform for the study of hard-to-get-at organizational phenomena. For example, they [extreme constructs] may well be able to showcase the best and worst of human and organizational behaviors and accelerate processes otherwise impeded by bureaucracy, power-plays, and politicking. They may provide particularly rich insights into organizational processes of adaptation and prioritization, resilience (following an extreme event), and barriers to inertia (where organizations fail to respond). (p. 35)

Table 2 shows why the extreme maintenance construct was useful in developing the experimental design of the current study.

Table 2. Extreme Maintenance with Emerging Technologies

Construct	Technology	Hypotheses	Boundary Conditions
Extreme Maintenance	AM, CIB, and ML	Factorial	The Extreme Maintenance construct used informs this specific problem within the extreme case, the purpose of the optimization study, and the operationalization of independent variables (technologies), and stimulates the hypotheses to include the limitations like maritime or austere environment (Miller & Mun, 2023)
Productivity/Cycle Time (Dependent Variables)	AM	Directional	In Extreme Maintenance, AM uses target cycle time and focuses on part availability where power, space, and portability constraints are present. The AM device must also have access to data and raw materials to make the parts (Schehl, 2023)
Productivity/Cycle Time (Dependent Variables)	CIB	Directional	In Extreme Maintenance, CIB provides data to artisans to perform and track repairs and enables an environment to order parts and use other technologies (AM, ML). CIB moves "cloud computing concepts and technologies closer to the edge, even if disconnected from the enterprise, can provide capabilities to" local repair teams (Lewis et al., 2014)
Productivity/Cycle Time (Dependent Variables)	ML	Directional	In Extreme Maintenance, ML provides predictive decisions on repairs and part ordering. ML eliminates a majority of guesswork and assists the artisans and managers to focus on other tasks (Gonfalonieri, 2019)

Extreme cases often make it easier to structure a complex research problem. The normal As-Is use case for maintenance has a high level of complexity developed over years of operation and incremental improvements. In normal maintenance there are many policies and procedures that incorporate legacy information systems that have been used over time and, as a consequence, accepted and approved by management and executive leadership. The governing approach in normal maintenance is well documented and was used in the current study to develop the extrapolated As-Is model for maintenance in the extreme context. These maintenance processes often have core stakeholders that are not willing to consider changing existing processes without compelling reasons because they are rooted in the status quo and have reasonable process stability concerns. In extreme maintenance cases, there are compelling reasons for radically improving core process productivity and cycle time, making it less problematic for stakeholders to experiment with modern IT AM, CIB, and ML in the current study to optimize the existing process. Further, there is a real potential for applying the same To-Be model to the routine maintenance process, that includes the three IT artifacts.

Most extreme cases used in research focus on time and the urgency of a given problem. In the extreme case, the stakeholders (process owners) have no time to feel threatened by the need to make radical changes in operations (Bounfour et al., 2023) because top-level management is usually directing the change to stay competitive by increasing operational agility that will lead to increased productivity and/or reduced process cycle time. In extreme cases, failure to foster agile responses to crises can result in lost revenue or underutilization of capital (Bounfour et al., 2023). In the context of this study, reduced cycle time and increased productivity can be the difference in winning or losing a conflict.

C. AVIATION USE CASES FOR EXTREME MAINTENANCE

The aviation use case was chosen due to the supply chain, the extreme maintenance complexity, and the availability of research data to include access to SMEs. Extreme maintenance, in the context of aircraft repair, occurs in the civilian sector and the military battlefront context. These repairs are often made using complex processes governed by limited resources and budget. The current peacetime repair practices may not be applicable or relevant for wartime battlefront operations due to extreme time pressures, unavailability of network reach-back and a lack of necessary resources including production equipment and local expertise. In the commercial airline industry, airplanes that are unflyable (referred to by airlines' maintenance technicians and their leadership as "Aircraft on the Ground" [AOG]) result in loss of revenue. The urgency of commercial airline maintenance problems can be likened to battlefield aircraft processes because both situations result in a high-priority classification (all hands on deck) to get stranded aircraft flying again.

The study is informed by these civilian repair teams as our military SMEs have been in close contact with industry repair teams to understand best practices. Commercial airlines have much the same extreme maintenance process requirements as battlefront maintainers to manage and forecast repair events. In the commercial sector, the manufacturers (e.g., Boeing and Airbus) use elite repair teams that travel the world to make complex repairs to stranded aircraft (Dunlop, 2010). United Airlines Technical Operations uses a Global Emergency Maintenance (GEM) team and has a large maintenance facility at San Francisco Airport from which many of their AOG deployable mechanics originate. Delta Airlines has a TechOps team and Material Services for flight products and airframe maintenance, while the Lufthansa Technik team uses a race-against-time approach to extreme maintenance (Lufthansa Technik, n.d.). In addition, third-party providers support airline repairs and resolve AOG situations, such as Global AOG Support Services by STS Aviation Services and Airframe Maintenance with AAR Corporate (Anglin, 2017). Many of the SMEs involved in the current study have visited these civilian repair teams or engaged in detailed correspondence with them to review their processes.

The idea that wartime exigencies necessitate innovation is clear. Warfare centers, for example, the Naval Air Systems Command (NAVAIR), utilize public-private partnerships to equip and train extreme maintenance teams. The military is forced to develop innovation through necessity to stay one step ahead of the competition. Such innovation is illustrated in modern warfare with the development of the atomic bomb and in the evolving tactics of battlefront operations in Ukraine. The United States and England were driven to develop atomic weapons due to concerns of the Nazis or the Japanese developing the weapon first (Rhodes, 2012). To accomplish such a complex and difficult task, the government, academic, and industrial sections merged into a public and private partnership.

In the instance of extreme maintenance, we see the same public and private partnerships created to address that complex problem. Much of the data required to repair naval aircraft comes from Aviation Product Life cycle Management (AvPLM) is the aviation-centric arm of the Naval Product Life cycle Management (N-PLM) solution (Waldolf, 2023). The N-PLM solution is one pillar of the U.S. Naval Logistics IT vision that integrates with Naval Maintenance Repair Overhaul (N-MRO) and Naval Supply Chain Management (N-SCM), supporting the modernization strategy under the leadership of the Assistant Secretary of the Navy (ASN) for Research Development and Acquisition (RD&A), and the Program Executive Office for Manpower, Logistics and Business (PEO-MLB). As a family of systems, AvPLM leverages Siemens Teamcenter and eQ Technologic Migration/Integration (MI) products to provide authoritative Engineering and Logistics data to the enterprise O/I/D maintenance environment (Foster, n.d.).

The lessons from these threats are fully applicable to the current study of ways to increase productivity and reduce cycle time in the context of extreme maintenance. The government can provide the resources and oversight needed, while academic institutions lead the innovation efforts, and the industrial sector provides the equipment, manufacturing, and supply chain required. AvPLM is the single authoritative source for engineering and logistics data required for maintenance systems with workflows to maintain that data (Foster, n.d.). The goal of AvPLM is to provide a means of preserving platform data organized and associated with other relevant data, enabling synthesis into actionable information. The managed weapon system technical data, comprised of the various original equipment manufacturer (OEM) contract deliverables, aircraft, parts bill of materials (BOM), 2D and 3D models, allowable product configurations, readiness models, maintenance procedures, and configuration changes, are collated to produce an integrated authoritative engineering and logistics data environment. AvPLM is intended to enable program leadership and contract partners to work in concert to support the warfighter throughout the platform’s service life and provide a full spectrum of technical data. AvPLM has not been fully leveraged in the extreme maintenance context. The new technologies (AM, CIB, ML) in this study provide a means to extend AvPLM to forward deployed combat repair teams.

The Aircraft Battle Damage Repair (ABDR) team in the military focuses on maintaining airpower anytime, anywhere. The wartime mission is ABDR, while the peacetime mission is the depots (Mather, 2023). According to Greenwell (2010), the need for ABDR teams is unavoidable and has been seen in fixed-wing and helicopter repair in multiple large-scale and lower-scale conflicts, such as WWII, Vietnam, the Israeli Yom Kippur War, Britain in the Falkland Island War, and the U.S. Air Force (USAF) in the two Gulf Wars. The ABDR teams must be available at the beginning of a conflict with rapid and thorough battle damage assessment by highly experienced personnel that have military equipment structural knowledge (Greenwell, 2010). These teams require creative skills and experience with complex repairs, the use of spares, technical drawings, models, and manuals. In modern times, repair can involve unmanned aviation assets (Intelligence, Surveillance and Reconnaissance [ISR]) platforms). Given the limited number of these teams that can be made available on the front line during a conflict, it is necessary to try to replicate some of their capabilities using, for example, the three IT artifacts explored in the current study. One of the goals of this research is to determine how these IT artifacts can support and replicate the capabilities of these ABDR teams in extreme maintenance conditions.

ABDR capabilities can be key in the outcome of a conflict (Ratwani, 2010). ABDR team capabilities allow for maintaining a high sortie rate with a highly productive rate of repair that is defined as 50% of damaged aircraft being returned to combat within 24 hours and 80% being returned to combat within 48 hours (Ratwani, 2010). The ABDR team's capability to provide for these productive, fast cycle time equipment repairs might not be attainable in modern conflict within the current context. But, if an optimized ABDR capability can be sustained at the battlefront, then the number of available aircraft could be quadrupled over ten days of combat compared to the current state of remote aircraft repair.

The repair procedures assess damage by structure within a given set of damage categories. The damage categories that are suitable for ABDR capabilities are categorized as: degraded, repairable, and acceptable damage. Some repairs are not required immediately (nonessential structure) and can wait as the repair does not affect airworthiness or mission capability (Ratwani, 2010). Clearly, then, if an ML artifact can quickly categorize the damage level, the remote repair team can optimize its repair cycle times.

These ABDR teams enhance DOD aircraft sustainment processes at different USAF bases. The Air Force brings ABDR engineering teams to its bases to accomplish its combat mission quickly and productively. There are about 150 airmen trained in ABDR in the USAF that could make a difference in combat success. These airmen represent the top of their trade and are capable of performing multiple tasks and types of repairs (Rosa, 2023). In the U.S. Army, the Aircraft Combat Maintenance & Battle Damage Repair (ACM/BDR) program fulfills a similar function. The Navy also relies on fleet units forward deployed and their systems command at NAVAIR to provide these necessary capabilities.

Finally, because an ABDR event can be compared to medical triage and care in which waiting time and prioritization play a large part, some useful perspectives on ML can be gleaned from the literature (Aflilal et al., 2016; Petsis et al., 2022).

D. DECISION-MAKING WITH MACHINE LEARNING

Parts of this section were previously published by Springer Nature in *HCI for Cybersecurity, Privacy, and Trust* (Miller & Mun, 2023). In edge decision support systems, decision-making, and problem-solving can be partnered with intelligent machines to achieve optimal productivity and suitable courses of action (Simon et al., 1987). John Boyd's Observe Orient, Decide, and Act (OODA) Loop describes the decision-making cycle and can be applied to assessing the effects of transformative modern IT artifacts with regard to the speed of the decision-making cycle (Phillips, 2021). ML partners with human agents in a highly proficient and complex way and provides productivity optimization opportunities (Glikson & Woolley, 2020). ML-assisted decision–making can help manage complex logistics and manufacturing problems where the decisions can reduce the need for inventory. Complex decision-making in an extreme maintenance context can predict courses of action when aided by ML technologies (Zhao et al., 2016). Therefore, it is logical to combine the benefits of ML with AM and CIB, allowing multiple systems and their data sources to optimize maintenance process productivity and cycle time (Russell, 2020).

Decision-making research is connected with utilizing ML in bioinformatics, that is applicable to the current study. According to Adams (2022), bioinformatics is a scientific discipline using certain ML technology to collect, store, analyze, and disseminate biological data and provide information for medical-based decisions such as cancer predictions and treatment decisions. These predictions can be mortality rates and when future treatment is required. These predictions and treatments can be very similar to repairs on human-made systems (e.g., aircraft). It is reasonable, then, to extrapolate the bioinformatics ML decision-making research results to provide some preliminary parameter expectations to assess in making estimates of risk as well as timing for repairs and predicting requirements for maintenance type forecasting decisions.

The stakeholders in this research are a subset of top-level military decision-makers, maintenance professionals, and information scientists. In the context of the current study, a decision maker is someone in authority that the organization empowers to make choices regarding the maintenance resources and provide approvals for the maintenance professionals. Maintenance professionals include aircraft engineers and technicians who repair the type, model, and series of naval aircraft. An information scientist is someone who transforms data into information to decrease uncertainty by providing context. The decision maker then uses the information developed, often with the aid of the models or ML, to make actionable maintenance process decisions. On a naval maintenance staff, the decision makers are commanders, senior maintenance professionals, and members of the staff consisting of the officers, enlisted personnel, civilians, contractors, and other support workers.

Overcoming the technology challenges while maintaining data availability is critical for the success of extreme maintenance processes utilizing ML. Even with the diversity of the systems within the DOD, there is a demand for time-sensitive information (Miller et al., 2021). To merge ML engines, the DOD and Navy likely will have to implement data governance at the enterprise level. The overall reliability and availability of the ML will be gauged by the ability of maintenance technicians to access individual systems when required to migrate authoritative data into one location or a few corresponding locations where ML can act on the data, like a CIB. The ML, "gauge" for the extreme maintenance repair teams, is assisted by data standards, network science, and sharing problems. The repair process and infrastructure design have more potential than the described extreme maintenance application (i.e., AM, cybersecurity, and Internet of Things [IoT] modernization decisions). The end state is merging ML technology to take full advantage of extreme maintenance decision support with increased prediction reliability and technical repair data availability (i.e., access to AvPLM data). Predictability means that ML models are reliable, and the data are representatively complete enough for the repair teams to make accurate forecasting decisions on repairs and part information. This information architecture can offer a diffusion of knowledge in an adaptive learning environment (Schön, 1971), that can improve productivity and cycle time for the extreme maintenance repair teams.

Implementing ML across the DOD is an urgent necessity. Many of our cyber and defensive adversaries (e.g., Russia and China) are years ahead of the United States in making this transition and, therefore, are deploying much more sophisticated analytical capabilities (Hoadley & Lucas, 2018). It is often challenging to recognize that ML is being used, making analysis efforts difficult (Hoadley & Lucas, 2018). The DOD has invested billions of dollars in adopting rapidly evolving IoT or intelligent devices, exponentially increasing the volume of data points collected globally (Miller et al., 2019b). Without adopting ML engines, the significance of these data points can be lost along with any competitive edge we may have gained within extreme maintenance repair teams. To ensure aviation mission success, the DON should leverage new ML architectures for these extreme maintenance teams, including Future Knowledgebase System of Systems (FKSS) with technology like commercial off-the-shelf (COTS) AvPLM products, machine learning, and cloud computing with big data (Miller et al., 2019b). Frazier's (2022), research shows significant improvement in aircraft repair using ML technology. Based on his findings, it is likely that by using ML algorithms with existing aircraft data, we can expect at least a 31% increase in repair efficiency over traditional repair decision methods that do not employ ML-based algorithms.

E. ADDITIVE MANUFACTURING

Additive manufacturing for the extreme maintenance team provides the opportunity to make parts and tools locally without reliance on the supply system and chain. Certain subprocesses in the current extreme maintenance repair process will be positively impacted by AM in terms of cycle time if parts can be manufactured onsite, thus increasing overall productivity. The technical data AM machines use is often 3D high-fidelity drawings specific to certain devices. Aerospace and defense manufacturers typically require software modules (i.e., AvPLM) utilizing Siemens' Teamcenter, with unique data that require additional functionality when considering the risk requirements. Risk calculation tools could explore where AM machines and data provide the highest potential increase in productivity. Mun and Housel (2010) explain RO to estimate process forecasting based risk values, that process volatility (i.e., the riskiness of a process productivity estimate) can be simulated, which allows for a dynamic assessment of the volatility of a given process productivity. The current study uses this risk assessment method as a factor affecting the potential optimization of the extreme maintenance process. The risk parameter estimate is central to developing a portfolio of RO, in this case, the three IT artifacts of interest, to identify the optimal IT investment portfolio in terms of an efficient frontier where the optimal risk-to-return (productivity) estimate is calculated based on simulating a multitude of possible portfolios for the three IT artifacts.

Additive manufacturing requires reliable complex systems that take in technical data to create parts using the proper AM materials to ensure that the parts will be robust enough to handle the stress of aviation fatigue. AM systems that are portable and reliable will be critical for extreme maintenance processes. The technical 3D data can be significant in size for these AM machines, so locally storing the data in CIB would be ideal in a bandwidth-restrained environment. Huang et al. (2015) demonstrate that manual methods exist for calculating reliability, and a new process could augment this approach within an extreme maintenance AM context with limited or no network bandwidth.

When AM is applied early in the To-Be process design cycle and simulation modeling for potential risk and reward (productivity), the IRM methods used in the current research can estimate potential increases in productivity. This more general approach to predicting the effects of IT artifacts on productivity in a future operational context can be used in hypothesis generation efforts (Albert & Hayes, 2002). The IRM forecasted To-Be productivity modeling has been used to forecast the potential increases for ship maintenance processes in several prior studies (Housel et al., 2015; Housel & Mun, 2015). New technological innovations (e.g., AM) pave the way for less expensive products and services (Wooten, 2001).

AM relies heavily on computer-aided design (CAD) data that is often incomplete or of poor quality. The review of this CAD data is very manual and time-consuming. The data defects resulting from the use of CAD data, when applied to AM, can be expensive, increasing rework and repair cycle time. This is all part of the Industry 4.0 initiative with intelligent manufacturing, sustainable manufacturing, and resource optimization (Li et al., 2020). According to Schehl (2023), 3D printing is a way to shorten the supply chain and can produce components with the same material properties as ones produced via traditional methods as part of force design 2030. In Post et al. (2016), it is suggested that modern AM costs for time and material are equal to that of traditional manufacturing methods, but savings in supply chain costs and energy costs make the technology perfect for a niche use case such as extreme maintenance.

If a part must be refabricated due to poor CAD-based technical data, a quality control filter is required. This is where ML can be tested to see if it resolves the problem of poor data and thereby would assist by providing an automated quality control filter. The ML applications in the prior research on the effects of using ML and AM in various production contexts, utilize data manipulation and cleaning techniques for parameter optimization and defect detection of the CAD data (Meng et al., 2020). Some ML applications used in the AM space are unsupervised learning, supervised learning and image processing with neural networks (NN). Research using the ML models to facilitate more accurate AM outputs included ML models that used the Gaussian process, NN, regression trees, and vector regression. As with all ML approaches, sufficient data is required to fit the models properly for error detection and to minimize the loss function. There are also mathematical controls to ensure the ML models do not overfit, which could lead to type I and type II errors.

In the AM research space, the future for ML is very promising for teasing out the effects of combining these two IT artifacts on productivity by optimizing model parameter values through more correct AM data and by assisting with the cleaning and labeling of new data. The current study is designed, in part, to test the potential effects of these IT artifact combinations. The results of the current study should be applicable to using ML to optimize productivity in any manufacturing process, including subtractive manufacturing (i.e., machining by accelerating design; Aggour et al., 2019). While this research focused on AM, the results should be applicable to subtractive manufacturing. Federated big data storage and analytics data are critical to advances in ML for manufacturing (Aggour et al., 2019).

F. CLOUD IN A BOX

CIBs are small, durable, portable computing devices (i.e., mobile servers) that interface with commercial IT clouds to replicate data when disconnected for a period of time. The following CIB literature review informs the study in terms of the CIB artifact with gaps for the extreme maintenance case and sets the parameter value estimates for forecasting and hypotheses testing. Cloud technology is based on flexibility in computing, data availability, and virtual resources capability that provides value to the organization (Bounfour et al., 2022). The current research study does not focus on any CIB vendor specifically (e.g., AWS Snowball Edge). In this study, the location of the CIB devices on the edge of the network and their being easily dis-connectable is critical. The extreme maintenance teams use networks made up of organizations and resources (labor and materials) to repair the aircraft. The extreme maintenance network utilizes the supply chain and creates value by maintaining a product or system (i.e., aircraft; Lutkevich, 2021). "A supply chain consists of manufacturers, material delivery, and assistance in repair and delivery to a customer. A risk to the supply chain can impact maintenance risk. In aviation, maintenance and mission risk can be quantified" estimated using the IRM modeling techniques (Miller & Mun, 2023, p. 679). Risk determination is typically based on the technician's experience and intuition without the use of sophisticated estimation tools; however, IRM software can be used to find correlations and structural relationships that are not readily apparent to humans. Furthermore, all maintenance risks include a time dimension, and risk mitigation occurs by learning the behavior of systems through time, and as a result, uncertainty can be reduced (Mun, 2015). Figure 2 below shows examples of CIB technology ranging in size from Cloud-in-a-Toolbox to Cloud-in-a-Shoebox and Cloud-in-a-Pocket. The goal of CIB technology is to address the disconnected, denied, intermittent and/or limited bandwidth (DDIL) that Marines and extreme maintenance teams will encounter (Miller et al., 2021).

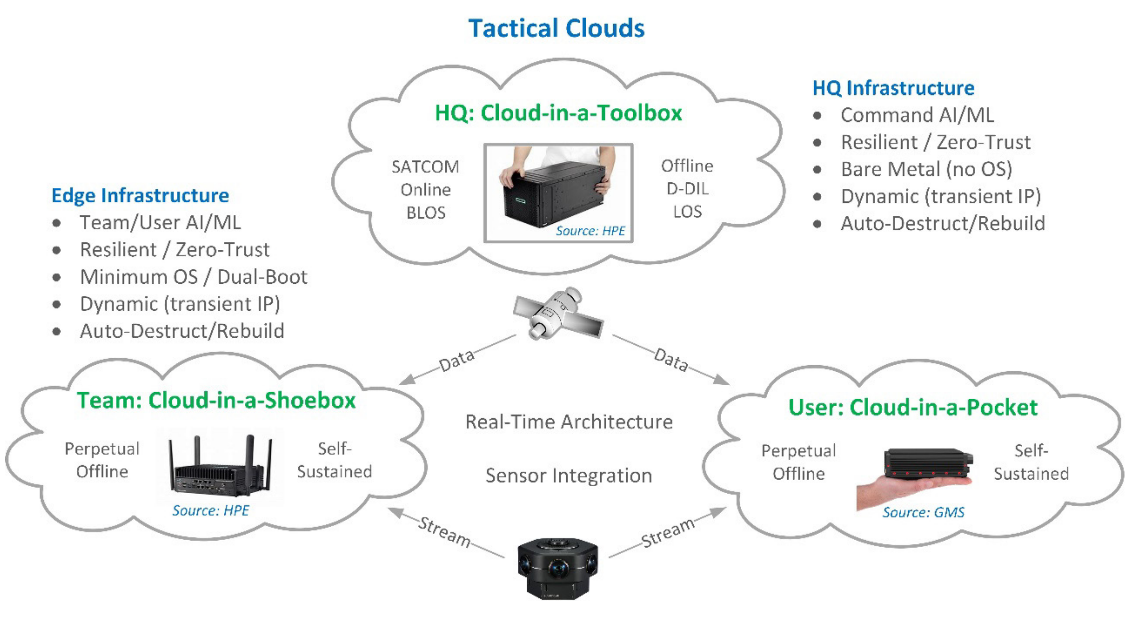

Figure 2. Cloud in a Box Technology

Additionally, CIB can store technical data needed to make repairs, and the ML artifact can help predict how to improve maintenance decision-making optimally. When combined with ML, the required technical maintenance data housed in the CIB would allow for a dynamic updating process that would be necessary due to rapidly changing missions in extreme maintenance settings. Feedback from maintenance personnel about how useful the ML was in maintenance decision-making would provide the changes required for extreme maintenance contexts. When applied early in the CIB design cycle and experimentation process, the methods presented in this research could increase productivity in an operational context and assist in hypothesis generation efforts (Albert & Hayes, 2002).

Parts of this paragraph were previously published by Springer Nature in *HCI for Cybersecurity, Privacy, and Trust* (Miller & Mun, 2023). Aviation cloud data sources and CIB in the DOD provide a Net-centric Data and Service Strategy (NCSS). According to Grimes (2006), NCSS makes "data assets visible, accessible, and understandable. This strategy also establishes services as preferred means by which data producers and capability providers can make their data assets and capabilities available" (p. i). When components fail, humans can discover correlations through manual analysis; however, this analysis is time-intensive and often incomplete (O'Connor & Kleyner, 2012). Inadequate static CIB models that do not take into account given environments and system integration challenges significantly overburden leadership (Nielsen et al., 2012). According to Jamshidi (2009), using Extensible Markup Language (XML) technology is preferred to exchange data between disparate systems. In the current study, the forecasted form of CIB would include this assumption. Cloud technology typically leverages big data and dockers with data pipelines of various sizes and scales (Stoica et al., 2017). Once the data pipelines exist, the simulations provide a means to model the complexity of those data connections. When the remote CIB has access to large data pipelines, the simulations provide a means to model the complexity of those data connections (McCarthy, 2020). (However, in the current study, the assumption is that the CIB used in the extreme maintenance context would not be able to leverage large data pipelines).

Ultimately, CIB technology provides the mechanism for the extreme maintenance teams to optimize subprocess leverage IT solutions in a degraded environment. CIB has the ability to house other technologies, such as technical data from AvPLM for repairs or AM and ML predictive decision-making tools. CIB, as a singular technology, has the potential for adequate impact, but as an enabling technology, it can radically change the extreme maintenance processes.

G. REVIEW OF RELEVANT THEORY, DEFINITIONS AND GAPS

Existing models and theories were used in the current study to help inform its central assumptions. The belief was that the current study would address a set of prior research gaps and thereby make unique contributions to the field of data science as well as information science. The review of existing theories focuses on the following theories and topics because they were deemed most relevant to the central purposes of the study.

- Economics of Information Technology (Jowett & Rothwell, 1986; Housel & Mun, 2015; Housel et al., 2008)
- Process Productivity Measurement (Housel & Bell, 2001; Castillo, 2011)
- Decision-Making Theory (Edwards, 1954; Simon et al., 1987)
- Sustainable Value Creation (Housel & Shives, 2022)
- ML for Predictive Maintenance (Susto et al., 2014)
- Research on Decision Support Systems for Maintenance (Liu et al., 2006)

The current study expanded and utilized the results of these theories and studies, and systems and applications would freely and securely exchange data and information in a CIB and provide insights to maintenance technicians and commanders. The research context diagram in Figure 3 shows commercial clouds and systems (i.e., AvPLM) with interconnections to a CIB tactical cloud.

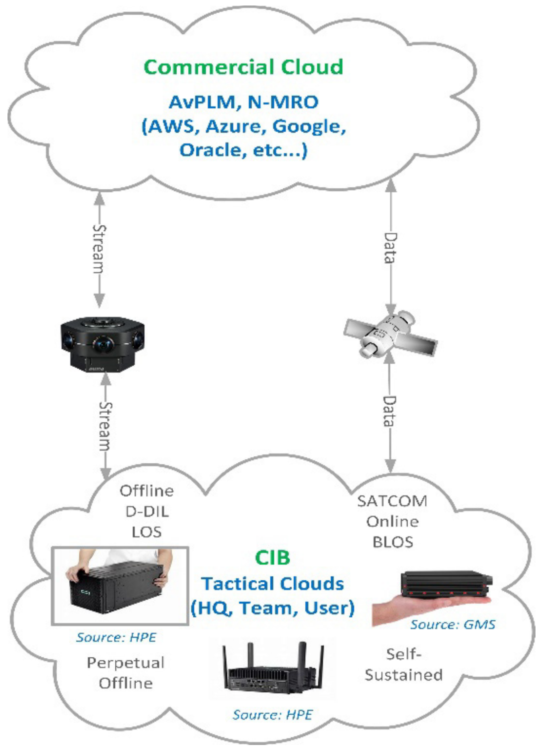

Figure 3. Research CIB Context Diagram

The current study can utilize the proposed strategy in Figure 3, and offers an NCSS model with gains in efficiency and security at a reduced cost. As discussed regarding the system architecture and CIB connections,

> expeditionary and interoperable exercises become increasingly reliant on technology, issues stemming from inabilities to synchronize and collaborate between garrison and deployed forces have necessitated more integrated and modernized networking tools. These critical issues of interoperability and access to technical data can only be rectified if the DOD recognizes and embraces the value of technological innovations to improve the dynamic capabilities of IT platforms. (Miller et al., 2019b, p. 78)

These modern capabilities shown in the context diagram (Figure 3) can provide CIB efficiency and leverage ML and AM. The knowledge management architecture in Figure 4 is a starting point for our inquiry, which builds on knowledge flow theory (Nissen, 2006).

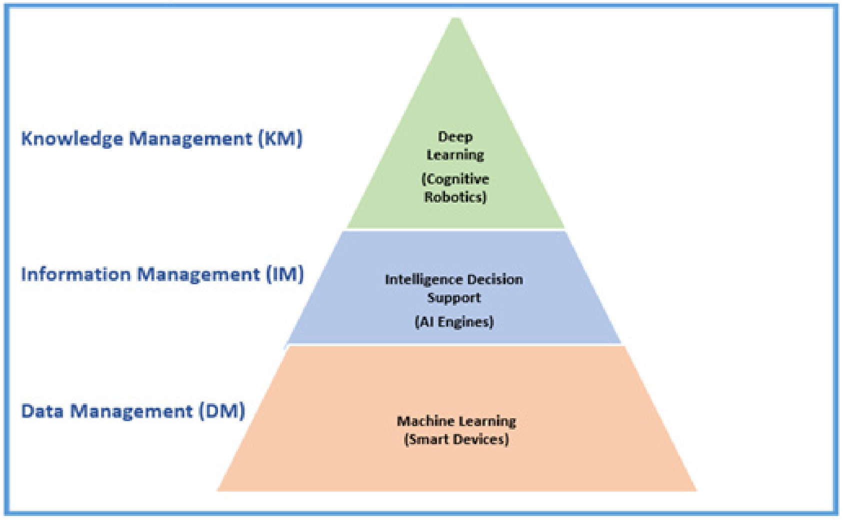

Figure 4. Knowledge Management Model. Source: Miller and Mun (2023, p. 681)

The proposed research addresses deficiencies in the current EOIT models and is based on the theoretical framework of Process Optimization Theory and BPR. The model in the current research utilizes information sciences approaches, for example, network science, which is primarily underpinned by the mathematics of graph theory. The deficiency or gap in prior EOIT research is with regard to edge computing devices, such as CIB, that are not addressed in an extreme maintenance context.

The current study's overall aim was to explore the relationship between the independent variables (IV; ML, AM, and CIB) and the dependent variables (DV; productivity and cycle time) by framing the problem as a comparison of the current extreme maintenance process (that does not use the three artifacts) to the To-Be forecasted process (that uses the three IT artifacts). In this vein, the research attempted to integrate ideas from EOIT theory in the context of the extreme maintenance process. The potential value of the research should be apparent in naval operations, especially when shaping the battlespace by optimizing the productivity and cycle time of the extreme maintenance process that is designed to preserve aircraft combat power by applying these three IT artifacts technologies.

III. RESEARCH METHODOLOGY

The current research used the EOIT branch of Information Sciences to measure the value added of new information technology in terms of optimizing extreme maintenance productivity and cycle time and expand on EOIT models by incorporating the extreme maintenance context. This research used modeling and simulation to forecast possible process improvements using emerging technology AM, CIB, and ML. Multiple simulations, including EOIT simulation, were applied to evaluate new approaches to extreme maintenance conditions, expanding on current methods.

The productivity in the extreme maintenance As-Is process was modeled and measured, and the To-Be process modeling and simulation provided defensible estimates of the value added of the three IT artifacts in terms of productivity and cycle time. In the As-Is modeling, the research presented the current extreme maintenance As-Is process model that was then compared to the forecasted To-Be extreme maintenance process model that included the potential impact of the three IT technologies. Because these three technologies are not currently used in this process, a robust modeling and simulation approach, that is, IRM, was used to estimate the potential value added of each of the technologies separately and in tandem. There was no guarantee that these technologies would be employed in the extreme maintenance context, so it was incumbent on the author of the current study to use modeling and simulation to estimate the potential value added to these IT artifacts. One of the goals of the current study was to evaluate emerging technology to enable the decision-maker to make informed adjustments to IT investment decisions in attempting to optimize the productivity and cycle time of the extreme maintenance processes.

This theoretical, quantitative study was conducted in two phases: analytical, i.e., As-Is modeling, and simulation, To-Be forecasting. The current study extended the existing maritime maintenance AI/ML research, based on current U.S. Fleet Forces Predictive Maintenance Naval Innovation Science & Engineering (NISE) research, to aviation maintenance processes; their study focused on the maritime domain (Wied et al., 2022), to aviation maintenance processes. In the current study, ML technology is also leveraged for predictive maintenance. The focus of this research was the aviation maintenance domain.

A. DESIGN OF THE EXPERIMENT

The extreme maintenance base case, the As-Is process without new technology (AM, CIB, ML), was documented based on a field experiment on an east coast island off the continental United States in the fall of 2022. The U.S. Navy (USN) then conducted a follow-up maritime extreme maintenance aviation experiment in the Pacific in the spring of 2023. After both limited experiments were conducted, the KVA extreme maintenance surveys discussed in detail later in this study were sent out to 90 combat repair team members involved in the experiments on both the island and on a naval vessel. The surveys were then collected 30 days later, in the spring of 2023. The completed surveys provided the data for the As-Is extreme maintenance process. The two field experiments were limited in duration and scope but provided a template for further field experiments and other process improvement endeavors. A full-fledged proof of concept model using the three IT artifacts for predicting improvements to extreme maintenance processes leading to improved aircraft readiness, given a limited amount of actual data, was a primary goal of the current study.

Simulations utilized in the current research included real options process optimization models (including risk parameters via Monte Carlo simulation) because they have proven useful in past naval maintenance process research (Mun & Housel, 2010) and were warranted in the context of the current study. The simulation and modeling provided metric parameter ranges to estimate the value added of the three technologies in the To-Be model to help assess the model's precision. The reliability of the As-Is extreme maintenance process model was estimated by obtaining parameter estimates from multiple extreme maintenance SMEs. The experimental design for the To-Be estimates can be visualized as a 2 × 4 factorial with before, As-Is parameter values without insertion of the three IT artifacts.

The experimental design considers the range of the effects of the IT artifacts as the IVs with the As-Is IV values represented as no IT artifacts. The models were deemed to have a strong goodness of fit, and it followed that regression analysis was applicable to test the effects of the IT artifacts. The data analysis was performed via Analysis of Variance (ANOVA), Parametric T-Test, Monte Carlo methods, and distributional curve fitting based on the Bayesian probability formula. Table 3 shows that DV productivity and cycle time were effected by the relationship between AM, ML, CIB, and AM + CIB + ML (Miller & Mun, 2023).

Table 3. Research Design Testable Framework

Research Design (2 x 4)		
IT Artifact	**As-Is (-)**	**To-Be (+)**
AM	DV Productivity / Cycle Time	DV Productivity / Cycle Time
CIB	DV Productivity / Cycle Time	DV Productivity / Cycle Time
ML	DV Productivity / Cycle Time	DV Productivity / Cycle Time
AM + CIB + ML	DV Productivity / Cycle Time	DV Productivity / Cycle Time

The researcher had to clean the survey data based on outliers, correlation, and reliability tests. In the data analysis section, data cleaning will be discussed in more detail. For example, more data can be gathered as part of naval extreme maintenance field experiments as part of follow-on research to validate the modeling results. Part of the goal of the research is to use the data gathered to make the Marines and Sailors more productive in making data-driven decisions pertaining to aircraft maintenance.

An example field experiment architecture demonstrating both the extreme maintenance repair teams, depot repair sites, cloud providers, and multiple Command and Control (C2) locations is shown in Figure 5. This concept diagram illustrates possible extreme maintenance experimental location ashore and at sea with a Marine Expeditionary

Force (MEF)-level battlefield context utilizing forward deployed repair teams with maintenance systems aided by emerging technology (AM, CIB, and ML). The cloud provider would house the maintenance data, both 2D and 3D, in a USN maintenance system (AvPLM). In this scenario, it was impossible to perform a field experiment using three IT artifacts for the current study because they had not yet been acquired. Because the fundamentals of any investment in IT must be a To-Be forecast to justify, or not, the acquisition of technology to optimize given processes such as the extreme maintenance process, in the current research, the focus was on forecasting the future value added of the three IT artifacts to optimize the extreme maintenance process.

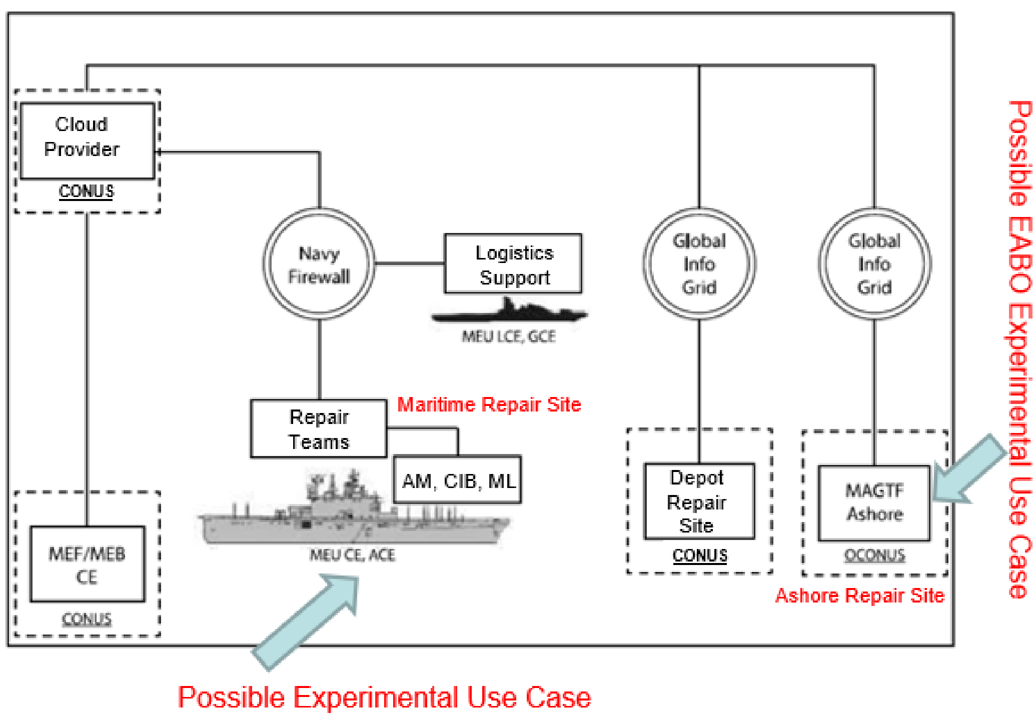

Figure 5. Aircraft-Depot Field Repair Use Case

Figure 5 was modified from previous research (Miller et al., 2021) and updated based on extreme maintenance aviation discussions with SMEs. The Aircraft-Depot Field Repair Use Case in the extreme maintenance context would support naval doctrine such as Expeditionary Advanced Base Operations (EABO) for combat aircraft repair (USMC, 2023).

The current research was built on an EOIT theoretical framework and tested eight hypotheses to determine the value added of the three IT artifacts in optimizing the productivity and cycle time of the extreme maintenance process reviewed in the study. The purpose was to determine whether investing in the three IT artifacts would be justified. The goal was to determine whether the artifacts should be implemented in the fleet as a result of the To-Be models developed by employing the concepts provided by the process optimization and BPR theoretical frameworks.

The research summarized the current As-Is process and employed theoretical framing from the EOIT literature to test the potential value added of using AM, ML, and CIB IT technologies to optimize the extreme maintenance process. Information sciences theoretical frameworks, i.e., Decision-Making Theory, Process Productivity Measurement, and ML for Predictive Maintenance, were used to test decision-making support options using the IT artifacts with the goal of adding to the body of knowledge concerning the extreme maintenance context. The models that employed advanced quantitative methods were designed to provide maintenance process decision-makers with the potential value added of IT artifacts with knowledge essential to making investments in IT naval maintenance decisions (Miller & Mun, 2023).

Decomposing the core extreme maintenance process into its constituent subprocesses was required to develop the As-Is extreme maintenance process model. Doing so, provided a baseline set of model parameter estimates that could be compared to the To-Be model projections. This approach allowed testing of process optimization IT investment decisions via the numerous simulations (over 10,000 simulations of the three process performance parameter estimates) that were conducted to see what future IT investment decisions would be necessary for the To-Be extreme maintenance process to be radically improved.

In the extreme maintenance As-Is core process model shown in Figure 6 (where AM, CIB and ML are currently not utilized), there are seven subprocesses. The As-Is current process analysis shows the inputs, process, and outputs of each subprocess. The outputs of the subprocesses are all different but can be made comparable using the KVA methodology. Making all process outputs comparable allows for determining the relative productivity of each subprocess. BPR is used to modify, replace, or create new subprocesses, and these potential improvements in productivity can be modeled using KVA at the subprocess level or any level of abstraction in a given organization. In this way, "KVA addresses a need long recognized by executives and manager-how to leverage and measure the knowledge resident in employees, information technology, and core processes" (Housel & Kanevsky, 1995, p. 91) when attempting to reengineer core processes (Housel & Bell, 2001; Mun & Housel 2010; Pavlou et. al., 2005; Shives & Housel, 2022).

A maintenance request for tactical repair of an aircraft, for example, includes an analysis of whether the repair can be done in the field or if it needs to be shipped back to the depot for repair. When possible, field repairs are done locally, and then the aircraft is inducted for maintenance. The technical manual and specifications are then reviewed during the field repair analysis to determine the required repairs, parts, and tools. In the extreme maintenance case, the inventory of parts is limited to the parts available in the repair PUK that are available locally. Parts may need to be acquired through the supply chain if they are not contained in the PUK. Once the parts come in through the supply chain, or if they are available in the PUK, the repair can be completed. After the repair is finished, the aircraft must be inspected and transported back to the flight deck or fleet unit to continue to fly missions.

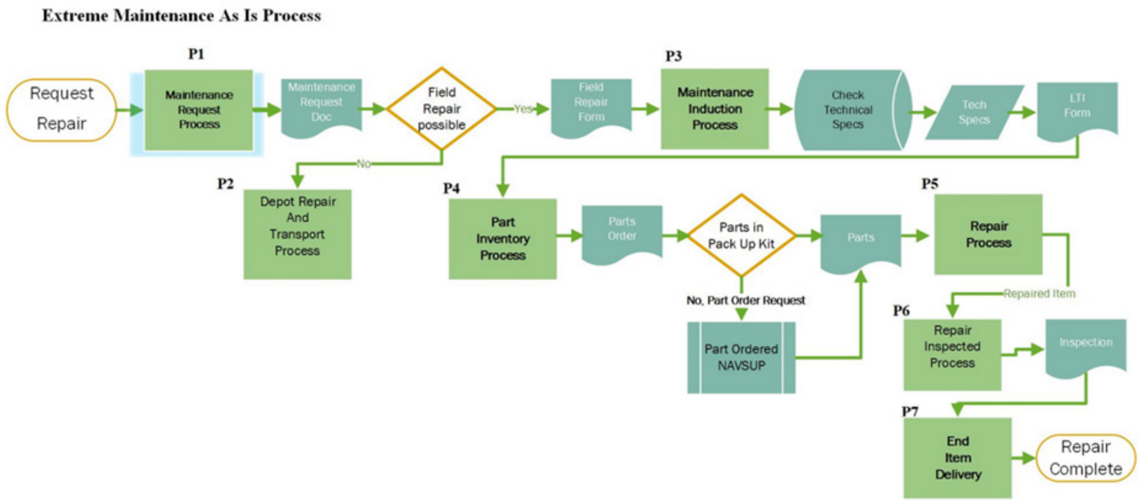

Figure 6. Extreme As-Is Maintenance Process

The KVA analysis results for the As-Is core process, and its subprocesses are provided in Table 4. The essence of KVA is that it takes knowledge utilized in the subprocesses (i.e., KVA describes all process outputs in common units of value) and translates it into a numerical form that allows allocation of units of value, e.g., revenue in for-profits and non-monetized units of value in non-profits, in proportion to the value-added by the process knowledge as well as provides the cost to use that knowledge. KVA analysis produces a ROK ratio that is 100% correlated with ROI estimates when revenue is distributed among core processes in for-profit organizations. A market-comparable valuation can be used to generate estimates of the monetized value of a given core process in a non-profit organization (Housel & Mun, 2015). Because ROK and ROI estimates are derived from the same parameter values, the two ratios are essentially the same. This allows the estimate of the value-added by given maintenance knowledge assets regardless of where they are used in the overall process or what the nature of the output is (e.g., repaired engine or part acquisition form). Tracking the conversion of knowledge into value while measuring its bottom line impacts optimization decisions and enables tactical managers to test ways to increase the overall productivity of these critical subprocesses (e.g., engine repairs or filling out an acquisition form).

Table 4. Extreme Maintenance As-Is Process

Sub-Process	Learning Time (hours)	Rank Order (In Complexity)	Cost (Work Time X the # Employees hours)	Average Time to Complete (hours)	IT Baseline Automation (% automation * output)	ROK	ROI
Maintenance Request	5.7	1	$1,162.93	7.78	26.7%	77.2%	10.7%
Depot Repair Decision	…	…	..	…	..	..	..
Maintenance Induction							
Part Inventory							
Repair							
Inspection							
End Item Delivery							

For Example

In Table 4, sub-process one, Maintenance Request, is displayed. The ROK is calculated by adding Learning Time to Automation and dividing by Average Time to Complete. Meanwhile, ROI is calculated by Ratio for Market Comp * LT – Time to Complete / Time to Complete. The general financial accounting formulas, correlations, and values for ROI (Revenue – Cost / Cost) are shown in Table 2. During the review of the As-Is maintenance process, the exiting minimal process IT automation is spread evenly across all subprocesses without using any of the three IT artifacts included in the To-Be forecasting models. Table 5 extends the example sub-process one from Table 4 for surrogate revenue time, which equals the ratio for Market Comps times the Cost.

Table 5. Formulas and Rough ROI in Using Market Comps

Formulas:	**Surrogate Revenue**
Return on Investment = (Surrogate Revenue -Cost) / Cost	$1,744.40
Return on Knowledge = (Learning Time + Automation) / Cost	**Cost**
Cost = Cost to use Resources to Produce Outputs	$1,162.93
Productivity = Output / Input	**Ratio for Market Comp.**
Value Estimate Reliability Check = Correlation between Learning Time & Rank Order of Complexity to Learn (Highly correlated)	
The correlation between ROK and ROI should always = 100%	1.50
IT Value Estimate = % Automation * Number of Outputs (in Subprocess)	

In Table 5, the revenue surrogate was assumed to be 150% of the existing price that the commercial market would pay to produce the same subprocess outputs. That is why the market comp revenue surrogate was assumed to be 150% of the price paid by the aggregate of the current subprocesses outputs in the Navy extreme maintenance context. Learning Time is the knowledge required to produce all the subprocess outputs. The correlations are between the two estimates of the knowledge Learning Time common units and Rank Order of Subprocess-Complexity to learn. The correlation of learning time common units and rank order learning time estimates were correlated among SMEs to estimate the reliability of their learning time input. An estimate of learning time is a logical surrogate for process knowledge because the more complex a process is to learn, the more knowledge is required to produce the output of a process. So, the complexity of knowledge and learning time are directly correlated; therefore, learning time is a sound representation (description) of the output of a process. Given that all outputs are described in comparable learning time ratio scale units, assigning a surrogate price, i.e., revenue per common unit of output, is possible. This estimate is calibrated in learning time ratio scale units simply by dividing the number of total core process learning time units into the surrogate market comp total revenue. Because all the units have the same value because they are common units of output, the price per unit is constant. It follows that the ROI estimates and ROK estimates among the subprocesses are not an issue with estimating the absolute values since the revenue is a surrogate revenue. Rather the concern is with the relative ROIs of the subprocesses so that we can compare the forecasted ROIs of the subprocesses in the To-Be Model with the ROIs in the As-Is model to calibrate the potential value added of the three technologies for the extreme maintenance processes.

B. OPERATIONALIZING THE VARIABLES

The variables used in the current study, experimental design, dependent variable DV, independent variables IV, and constraint space, are based on the foregoing literature review and shown in Table 6.

Table 6. Operational Variables and Constraint Space

Variables	Type	Scope	Constraints
Cycle Time	DV	Current Maintenance Subprocesses Cycle Times	Existing Data Sets, Surveys and Models
Productivity	DV	Labor and Automation, Learning Time	Repair Teams from Navy Regional Maintenance Centers using Automation
Additive Manufacturing	IV	Additive vs. Traditional Supply Chain Methods	Availability of Parts/ Supply Delivery
CIB	IV	Cloud vs. Legacy Networks	Simulation and Models
D2D ML Prediction	IV	CDR, Technician Focus	80/20 Rule, Maintenance and Bioinformatics Research

The Cycle Time DV is simply the time it takes to produce the subprocess outputs. The Productivity ratio is simply the number of common units of output, calibrated in learning time units divided by the cost of the resources (labor and automation, – not the actual equipment used in the repair). The ML operational definition is defined by previous maintenance research and bioinformatic algorithms versus traditional prediction methods. The prior studies defined AM as potentially beneficial (Housel et al., 2015; Housel & Mun, 2015; Wooten, 2020) that modeled the use of AM in maintenance processes. CIB is operationally defined as a stand-alone cloud server and software housing 2D/3D tactical data (AvPLM) information that can be updated when networking is available. Process optimization forecasting models and simulations are completed using the IRM methodology defined in the methods section that follows.

The variables were measured in the following ways, with D2D times being calibrated in days. Also, the potential effects of ML on D2D and productivity were based on the effects of IT technology in bioinformatics research. The mission risk estimates were based on the range of volatility around each subprocess productivity and cycle time estimate and were measured by the second moment with a probability estimate that was compared to the potential effects on the two DVs. The hypotheses listed shortly were assessed with statistical tests of significance. The productivity of the subprocesses and core process was measured using the KVA methodology with the number of subprocess outputs (calibrated in learning time units and monetized by price per common unit) divided by input (the cost of the resources required to produce the subprocess outputs), as specified in KVA research (Housel & Bell 2001; Housel & Shives, 2022). These tests depend on the parameter value distributions and the effects of the IT artifacts treated in the To-Be IRM analysis using RO analysis (each artifact represents an IT real option). The results of the RO analysis were based on 10,000 simulations around each subprocess productivity parameter and cycle time parameter (representing the volatility or riskiness of using each IT artifact in the subprocesses). The results were then submitted to a portfolio analysis to determine the optimum, risk-to-reward (i.e., Sharpe ratio analysis), portfolio of the IT artifacts in the To-Be models.

In RO analysis, simulation and optimization were used to model volatility and measure the risk (i.e., upside as well as to hedge against downside risks) to the value of the IT artifact real options. The use of these modeling and simulation capabilities allows extreme maintenance executives to make IT acquisitions that will strategically position them to take advantage of these potential upside risks as well as to hedge against the downside risks that are a result of fluctuations in the productivity and cycle time of the core process and its subprocesses. As such, these models and simulations can help deal with the complexity and uncertainty of investing in IT options and provide options and trigger points for optimal timing of investments in the IT artifacts. Modeling tools for real options include the development of a lattice solver technique using an American or custom option and the Black-Scholes algorithm to model and calculate a potential investment in IT expansion option using the parameter inputs discussed in the foregoing in the productivity and cycle time-DV. The result of this analysis was a value estimate for the IT expansion option for a potential investment decision (Mun, 2015).

The real options analysis provides a way to analyze risk and measure the value of the IT options and is useful in making informed IT investment decisions. Using real options, you can defer, accept, mitigate, and avoid risk (Mun, 2015). Real options are used for longer-term IT investments, such as those evaluated in the current study. Real options analysis is used for evaluating risks in investments in real physical or intangible assets, such as IT options that the DOD leadership must constantly make to stay ahead of enemy competition. In contrast, financial options are used in the capital asset markets where the investments are short in maturity, and the values are usually relatively small. In these investments, for example, in the equity markets such as the New York Stock Exchange, equities (stocks) are marketable and traded securely with comparable pricing information. The net present value analysis used in these cases does not provide a means in the real options cases to make complex option strategy trees based on models and markets with the flexibility to manage complex risks appropriately. However, because ROI estimates are used in the current study to evaluate current and potential investments in IT real options, leadership can make informed investments in IT decisions including ways to mitigate investment risks.

The IT investment strategies that provide real options help mitigate risk and allow decision-makers to take advantage of potential value upside risk while mitigating potential downside risks. Often, the strategies are displayed in a strategy tree that explores the options for stakeholders. Execution types include American options, Asian options, Bermudan options, and European options. The American option can be executed at any time up to and including the maturity date. The Asian option is based on historical trends and is time-specific. The Bermudan option can be used at any time except during blackout periods. The European option can only be used at maturity. There is always the call option with zero dividends. Real options offer methods to explore each hypothesis below:

- 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 reach-back methods.
- Hypothesis 8: AM + CIB + ML improves extreme maintenance process productivity compared to traditional depot-level reach-back methods.

C. ASSUMPTIONS OF THE CURRENT RESEARCH

In this research, the domain of analysis is based on financial accounting principles within the context of the extreme maintenance case, where rapid repair with limited resources is required. The focus was on how the three IT artifacts could be used to optimize the extreme maintenance core process, and subprocesses. SMEs were asked to provide feedback to support modeling or simulation parameter projections based on the assumed effects of the three IT artifacts. The common reference point learner for the KVA estimates was assumed to be an engineer who had the knowledge necessary to run the extreme repair process in the As-Is model. The SMEs were asked to assume that this common reference point learner was a basic engineer with the required process knowledge so that all biases in estimates would be evenly distributed among all the As-Is parameter estimates to reduce the potential for biased estimates. The required engineering skills are covered under the DOD 0800 career field requirements.

D. DATA COLLECTION

This quantitative study was conducted in two phases: analytical and simulation. The simulation included elements of the extreme maintenance condition, each as a process. Each subprocess data parameter estimation for the existing As-Is aviation core and its subprocesses model was based on estimates from process SMEs. The use case was a forward-deployed combat repair team. The To-Be process model was based on the potential use of AM, CIB, and ML as used in bioinformatics integrated with cloud technology to help generate optimal decisions and strategies that informed To-Be processes in extreme maintenance conditions (e.g., naval tactical field repair).

This research will make theoretical contributions to information sciences through process optimization by gauging the ability to affect productivity and decrease cycle time. The current research tested the To-Be model hypotheses using a simulation of real options modeling based on standard practices used in prior economics of information technology real options research (Mun & Housel, 2010).

1. SAMPLING METHOD

The KVA survey used in the current study to collect the As-Is parameter values focused on the SMEs' parameter estimates and validation of the process model. The surveys provided opportunities for the SMEs to supply the model parameter values and estimated volatility (i.e., the riskiness of the IT artifacts that could potentially be used to optimize the core extreme maintenance process) that would be required in the probabilistic forecasting To-Be model.

The surveys were provided to leadership and SMEs who had the background (those who typically conducted the extreme maintenance process or were in the leadership over the process) to supply the parameter estimates for the extreme maintenance As-Is model. The surveys were sent to a random sampling of the targeted SMEs, as has been done in many previous studies that used the same basic methodology (Housel & Mun, 2015) and has been suggested by previous research (Fowler, 2002). Over the course of a month, the individually completed surveys were submitted directly to the Primary Investigator (PI). The participants were instructed not to discuss or collaborate with each other during the execution of the survey. Any questions on the results of the survey were directed to the PI for clarification. The PI was able to talk to the survey participants if required. The participants' identities were kept anonymous, and completing the survey was voluntary.

2. DESCRIPTION OF COLUMN DATA

The following is a description of the Excel entry points for the column data that was given to the participants of the survey (see the Survey Template Table 7).

(1) Learning Time

Learning time is the time the single point of reference "learner" needs to learn how to perform a particular set of tasks (not the amount of time to actually perform those tasks, which is captured in the cost estimates). For example, the learning time of a Ph.D. to perform the job of a secretary or janitor would be the same as that of anyone else because the learning time estimate simply equals the time to learn all the duties of a secretary or janitor, and how to perform them correctly and does not take into account the level of education. Note that the learning time estimates do not equal the cost of training. It is not a cost estimate. It is only an estimate of the amount of common units of knowledge (i.e., units of learning time) in use to produce the given outputs of a given subprocess.

(2) Relative Learning Time

Using a relative learning time value of 100 hours (i.e., to acquire 100% of the knowledge required to produce a subprocess output), weeks, or months (the most appropriate unit of time for estimating learning time for this entire process was hours) of learning time and this amount is distributed among the subprocesses. The analysis assumes a "naïve average single reference point learner" will learn all he or she needs to know to successfully complete all the tasks in each subprocess within this total of 100 units of time. The learning time estimate for the automation would be the equivalent of the time it would take the same "naïve average learner" to learn how to produce the same output that the automation (e.g., IT artifacts) produces. The distribution of the 100-hour learning period is according to how complex the areas are for the "average person" to learn. The purpose is to determine relative learning times for each subprocess given the 100-hour total. In the current analysis, the subprocess Total blocks at the bottom of this column are verified for consistency. The learning time number for all the subprocesses totaled 100. Rough estimates were sufficient in this step of the process.

(3) Rank Order of Complexity (Difficulty to Learn)

Instructions to the participant: Please rank order processes and sub-processes in terms of their difficulty to learn (1 = easiest to learn and 7 = the most difficult to learn). Remember, please complete the entire column to the best of your ability; rough estimates are sufficient.

(4) Number of Employees

Instructions to the participant: Provide an estimate of the total number of employees working in each area.

(5) Corresponding Pay Grades

Instructions to the participant: Please provide a range of the government pay grades corresponding to the number of employees involved in each process, and please be as detailed as possible.

(6) Times Performing the Task

Instructions to the participant: Please provide the estimated number of times that each subprocess is performed in a 10-day time period.

(7) Average Time to Complete

Instructions to the participant: Please provide the estimated time it takes whoever is completing the sub-process to produce the output of the subprocess.

(8) Average Actual Training Period

Instructions to the participant: Please indicate what the actual average training time in hours is for the "average person" for each subprocess. This would be for a new employee (possessing an engineering degree) with no background who would be required to learn everything necessary to produce the outputs of the given subprocesses.

(9) Percentage Automation

Instructions to the participant: Please give an estimate of the percentage of automation that is used for each subprocess.

(10) Automation Tools

Instructions to the participant: Please list the automation tools that aid in the completion of each subprocess.

(11) Notes/Comments

Instructions to the participant: Please feel free to make any notes or comments regarding your methodology or reasoning for making a certain entry.

(12) General Comments

Instructions to the participant: Use this field to provide any general comments that don't apply specifically to the processes above. For instance, if you feel that there is a missing or improperly named process, please comment on that here and provide the requisite information.

E. KVA SURVEY FOR EXTREME MAINTENANCE

The KVA survey was given to SMEs to provide the range parameter values for the As-Is Extreme Maintenance Process before any new technology is inserted into the process. A military organization that focuses on military aircraft repair was selected to provide SMEs to complete the survey. A detailed instruction document was given to provide context for the variables being measured, with examples of sample subprocesses being provided to the SMEs. The survey went through the NPS IRB process and was approved prior to being sent to the SMEs. The following are the components of the survey.

1. SURVEY GOAL

This is part of my dissertation research, and I need your help. Your input is necessary to provide accurate estimates because you are the Subject Matter Expert (SME) on this process and its' various subprocesses. I believe your input will make this research more accurate and precise to ensure the validity and reliability of my conclusions. The results of this research should make a difference in a DOD context because failure to make correct repairs to battle-damaged equipment can make the difference between winning and losing a conflict.

The purpose of this survey is to obtain baseline performance data in extreme maintenance conditions, i.e., Forward Deployed Combat Repair maintenance process with tactical aircraft repair. In this scenario, there may be no access to depot repair resources. The SMEs provide inputs to the As-Is baseline model parameters. The results of these surveys will establish a baseline "As-Is" model to explore the value added of using three emerging technologies (i.e., Additive Manufacturing [AM], Machine Learning [ML] resource requirement prediction, and Cloud "in a box" [CIB]) to support and improve the performance of this unique maintenance process.

2. SURVEY METHOD

I will accomplish this goal by utilizing the knowledge value added (KVA) methodology and other Economics of Information Technology (EoIT) performance measurement approaches that estimate and forecast the improvements to the productivity of core process resources (i.e., human and automation assets). KVA can be used to objectively describe all process outputs in common units (using learning time as a surrogate for a common unit of output). This approach establishes a value and cost per unit of output for all processes and subprocesses. This allows the allocation of value to processes throughout the organization at any level of aggregation or detail. This approach provides objective performance information for management and has been in use in the DOD, Navy, and industry for the past 30 years.

3. SURVEY BENEFITS

The benefits of the survey and methodology are to objectively measure the EOIT parameters and explore decision-making options using the three target technologies for extreme maintenance conditions.

- Objective Return on Investment (ROI) and Return on Knowledge (ROK) estimates the contributions of IT and human resources in core subprocess and functional areas.
- The KVA data will feed a Real Options and portfolio optimization analysis that estimates the value of improving core processes using the three technology options as well as providing several possible paths to re-engineering those processes.

4. SURVEY REQUIREMENTS

The requirements of the participants of the study are as follows:

- The completion of the template is below.
- The templates' completion instructions are below, including detailed descriptions of how to fill in the blanks. The PI will help the participants complete this template via a meeting or phone interview. The PI's contact information is provided.

- Please answer to the best of your ability, but remember only rough estimates are necessary; do not waste your time attempting to answer with extreme accuracy. Otherwise, only complete the sections that are within your expertise.
- Therefore, depending on the respondent's understanding of the process, the whole template can be completed in 1.5 hours (or less).

5. SURVEY QUESTIONS

Instructions to the participant: Please answer these questions in the allotted spaces:

- Job Title: Please enter your job title.
- Job Description: Please provide a brief job description.
- All individual responses will remain anonymous. The contact information is just for informational purposes only and if I need to contact you with questions.
- Name: (Optional)
- Government Pay Grade:
- Please enter your government pay grade. If you are a contractor, please estimate the equivalent government pay grade for the position in which you serve, if possible. If you cannot make such an estimate, enter "N/A."
- Notes:
- General Comments:

Table 7. Extreme Maintenance As Is Processes Survey

Sub-Process #	Sub-Process	Rank Order (In Complexity)	Learning Time (hours)	Number of Employees	Corresponding Pay Grades	Times Performing Task (# of Executions)	Average Time to Complete (hours)	Average Actual Training time (hours)	IT Baseline Automation (% automation * output)	Automation Tools
1	Maintenance Request	1	14	5	(3 GS-9s, 2 GS-12s)	5	20	15	0.3	Advanced Software
2	Depot Repair Decision									
3	Maintenance Induction									
4	Part Inventory									
5	Repair									
6	Inspection									
7	End Item Delivery									

For Example

F. QUANTITATIVE METHODS AND SIMULATION

The quantitative methods discussed in this section cover terminology and analysis methods used in the research and include any exploratory data methods and forecasts with simulations that are real options. Some assumptions and limitations are included to set the boundary conditions for the research analysis section. Certain charts are used in EOIT to provide insights to the data, including tornado charts and sensitivity analysis to analyze the emerging technology in extreme maintenance conditions. A tornado chart is an analytical tool that measures the impact of variables on the model's outcome. The model displays the results from the most significant perturbation to the least. The tornado chart, therefore, identifies which variables are best suited for simulation. A sensitivity analysis applies dynamic perturbations after the simulation run (Mun, 2015). Sensitivity charts display the impact of the result when multiple interacting variables are simulated together in the model.

The models for the To-Be processes are broken down by each emerging technology— AM, CIB, and ML—and all the technologies in combination AM + CIB + ML. The one current As Is model and the four forecast To-Be models' parameters were run over 10,000 trials, with individual data points being tested in intervals between the parameters in the models. The models' charts show representations of the data in various scenarios; for example, the simulation might be needed for forecasting, estimation, and risk analysis. Simulations can handle data that is skewed, where the average does not work, and the median may be better. Simulation can also handle thousands of possible permutations and non-parametric data.

Optimization works to find the best combination or permutation of decision variables. It is often used for project selection, configuration, and stock portfolio. An optimization model is used to find the optimal values for the control or decision variables. An optimization model has three major elements: decision variables, constraints, and objectives (Mun, 2019). Optimization often uses smart heuristics and algorithms with decision variables being adjusted to meet the objects and stay within the constraints set. Multiple optimization types can match the given data, including linear, nonlinear, discrete, binary, and continuous. The overall goal of optimization is to find the best configuration possible.

The data collection and models generated are built considering the following traits: accuracy, precision, probability, consistency, correlation, goodness-of-fit, P-value and significance levels, predictability, reliability, and validity. These traits distinguish the quality or characteristics of the data and tests where the degree to which the result of a measurement, calculation, or specification conforms to a range estimate, correct value, or a KVA and EOIT standard.

The following are basic definitions of some of the traits mentioned above and other pertinent terms. Accuracy is how close a given data set is to the true value. This trait is usually displayed in measurement. Precision is how close the data is to other data points and is a measure of statistical variability. Both accuracy and precision are sought in this study's modeling efforts. In this research, forecast relies on probability theory: when a particular event happens, and another event follows that event, repeatedly. Bayesian probability is a conditional probability situation, meaning the probability of an event occurring given that another event has already happened. In these process optimization models, you know a fact or event affecting another future event's probability. Bayesian probabilities are often written as follows: the probability of a Hypothesis, H conditional on a new piece of Evidence, E or $P(H|E) = P(E|H) * P(H) / P(E)$. Bayesian probability and data analytic tools provide a path forward in dealing with complex and seemingly unsolvable models.

Hypothesis testing statistically evaluates the hypothesis against an alternate hypothesis given a data set. The test tells the scientists if they should accept or reject their hypothesis in favor of the alternative hypothesis. The hypothesis test checks to see how likely the tested data set represents the overall population. The central limit theorem is often used when more than 30 samples are involved to allow the hypothesis testing to use a normal distribution. Levels of confidence for the hypothesis test can be set. Normal levels of confidence or acceptance are 90%, 95%, and 99% for the null hypothesis (Babu, 2017). This means the corresponding range for the alternative hypothesis is 10%, 5%, and 1%. In the two-tailed test (see Figure 11), the acceptance range of the null hypothesis is between 5% and 95%. The higher the confidence level, the more likely the null hypothesis will be accepted in favor of the alternative hypothesis. Hypothesis testing allows the researchers to infer if their hypothesis is supported statistically or not by the data within the confidence level they set.

The goodness-of-fit of the tests can determine if the hypothesis H0: is from the sample of the specified distribution or else the Ha: The sample is not from the specified distribution. The p-value is calculated and compared against some predefined level of significance (the standard alpha significance levels of 0.10, 0.05, and 0.01). If the p-value is below these significance levels, the null hypothesis is rejected, and the alternate hypothesis is accepted. The precision and statistic test measurements are working as intended within a certain threshold (i.e., control charts). The predictability of these measurements provides the ability to forecast the portfolio as Real Options and whether the emerging technologies are worth the investments and increase the productivity of the subprocess or reduce cycle time for the repairs. The investment portfolio view in Real Options uses methods like ARIMA, Econometrics, Monte Carlo Simulation, and Regression.

Real options that lower risk are contraction, abandonment, and barrier options. Risk reduction occurs in the real options approach by analyzing the first-moment central tendency (mean, median, and mode) and the second-moment variance (Standard Deviation, Range, VaR). Adjustments to the first and second moments happen through the IRM process with value enhancement. Uncertainty is limited by reducing, if possible, the variance or spread (Second moment). Risk reduction is accomplished by cutting off the left tail and adjusting the variance, limiting the downside. This adjustment affects the first moment as well. In short, IRM reduces uncertainty by changing the first and second moments, and risk is reduced through a lower downside, timely events, and actions.

The data collected are subjected to basic statistics and visualization. The underlying assumptions for a parametric test are of a known underlying population distribution from which the sample was collected. The first moment has many types of parametric theoretical hypothesis tests such as t-test, z-test, F-test, and other tests of significance or differences. The ANOVA for the second moment is parametric as well. The third moment, or skewness, is a measure of the symmetry, or lack thereof, of a distribution, while kurtosis, the fourth moment, is a measure of the extreme tails of the probability distribution of a real-valued random variable. Both the third and fourth moments require solely nonparametric empirical tests, such as bootstrap simulations, that can test the first and second moments on their confidence intervals, precision levels, and statistical significance. Some of the most common nonparametric tests are the Runs test for randomness, the Wilcoxon test, the Lilliefors test, the Kruskal–Wallis test, and Friedman's test (Mun, 2019). Spearman's nonlinear nonparametric correlation coefficient test is essential as well.

Simulation offers a way to model the complexity of the real world to make an informed decision. It is efficient to test a theory using simulations before making significant decisions like in real options. Simulations can be used for forecasting, estimation, and risk analysis. Simulations can handle skewed data where the average does not work, and the median may be better. They can also run thousands of possible permutations and non-parametric data. Monte Carlo simulation is a primary method of simulation for parametric data where a historical record exists. The Monte Carlo Simulation generates thousands or more possible outcomes and analyzes their characteristics. These compiled results are then used to explore options and make decisions. If forecasting models over time have low volatility, then the model has homoskedasticity and can forecast further. If the forecast has high volatility, there is a risk of heteroskedasticity, and the forecast model should limit the predicted years. For these To-Be models, we are comfortable forecasting three years out.

G. RISK MANAGEMENT AND REAL OPTIONS

Integrated risk management (IRM) starts with identifying the risk, forecasting prediction modeling, the base case static model, using dynamic Monte Carlo risk simulation, real options problem framing, real options valuation and modeling, portfolio and resource optimization, and reports, presentations, and updates. The analysis section will explore the IRM process based on the data and forecast of the emerging technologies in the extreme maintenance case. The IRM process is displayed in Figure 7.

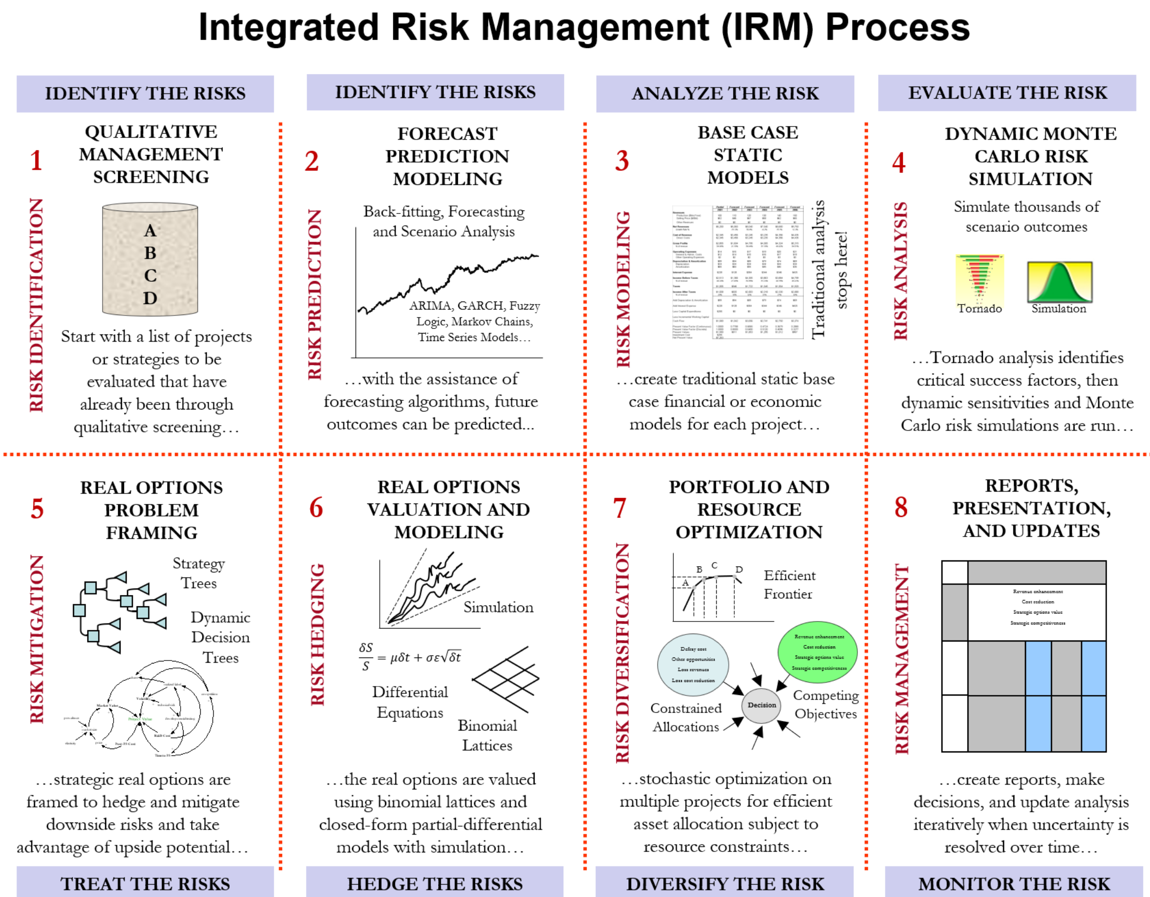

Figure 7. IRM Overview. Source: Mun (2015)

Using risk management (RM) and RO, strategy trees can be created to model options and lower the downside risk. The wait and defer/execute option will provide proof of concept to determine better extreme maintenance's cost, profitability, and schedule risks. It gives the ability to wait for valuable information to arrive before deciding to execute the new technology AM, CIB, ML, and AM+ CIB + ML.

A non-parametric bootstrap simulation estimates the reliability or accuracy of forecast statistics and answers confidence and precision questions. The bootstrap method analyzes the skewness, tails for excess kurtosis, correlation between variables, and accuracy with R2. A parametric simulation would be used first, and when the simulation is done, a bootstrap is usually run to analyze the statistics.

RM includes many tools for making decisions through analysis using sensitivity charts and tornado diagrams. These tools are valuable in determining the critical drives, for example, in inventory decisions. Tools such as the Risk Simulator (RS) allow modeling and forecasting of future needs. Through modeling, you can forecast part failure. For example, the Mean Time Between Failure (MTBF) utilizes a Weibull distribution. RS can determine thresholds such as a reorder point and part on hand with what-if analysis methods.

Real options provide a way to analyze risk, defer, accept, mitigate, and avoid risk, measure the market, and make informed decisions. Real options are used for longer maturity ventures, usually measured in years with significant million or billion-dollar assets and decisions. The types of firms that use RO are often not traded and are proprietary, like nuclear power plants, the DOD, and science and technology companies. In contrast, financial options are short in maturity, and the values are usually small. The companies are marketable and traded with comparable pricing information. In contrast, net present value does not provide a means to make these complex strategies tree based on models and markets with the flexibility to manage complex risks appropriately.

Real options help in risk mitigation and taking advantage of potential upsides, and they include abandonment, expansion, contraction, wait and defer, and executing options of using these three IT artifacts. Execution types are based on accounting rules and financial laws governed by countries, including American options, Asian options, Bermudan options, and European options. The American option can be executed at any time, including the maturity date. The Asian option is backward-looking and time-specific. The Bermudan option can be used at any time except during blackout periods. The European option can only be used at maturity. There is always the call option with zero dividends.

The current research utilizes IRM (Figure 7) to forecast the effects of using the three IT artifacts to optimize extreme maintenance subprocesses that have been optimized using BPR techniques. The analysis section will explore the IRM process based on the data and forecast of the emerging technologies in the extreme maintenance case.

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IV. ANALYSIS

Much of the research analysis was conducted as described in Chapter III. 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.

A. DATA OVERVIEW

The data analytics in this section 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 Inter Class Correlation [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 nonprofit 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.

B. EXPLORATORY DATA ANALYSIS

This subsection provides an exploratory data analysis of the data collected to include statistical tests described in Chapter III. 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 8 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 8. 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 in Table 9 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 described in Chapter III. We can also set up a basic statistical test based on the information listed in Table 9 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 9. 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 8 to give a spatial visual of the descriptive data. Figure 8 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.

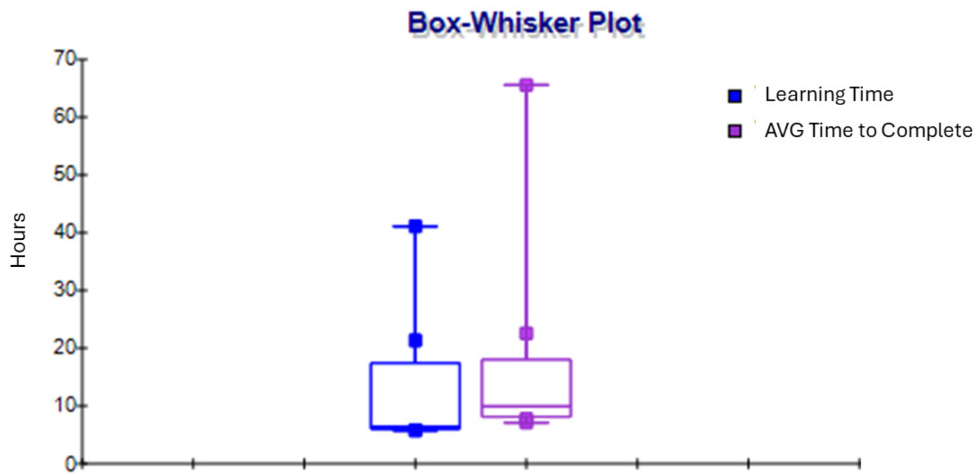

Figure 8. Learning Time and AVG Time to Complete by Sub-Process

The As-Is Expected Project Schedule shown in Figure 9 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.

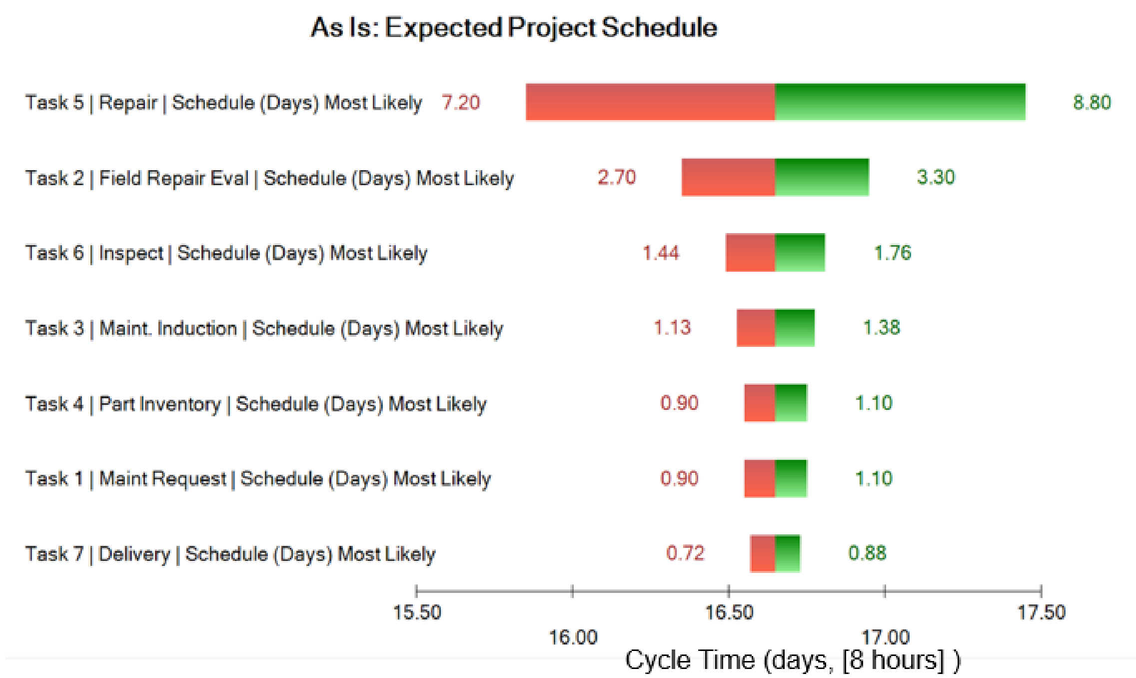

Figure 9. The As Is Project Schedule for Subprocesses

The focus up to this point has been on the complexity of the subprocess and learning time, which provide value to understanding key subprocesses that create the thing of value. At the corporate level, the repaired aircraft is the output and the item of value. Still, at the subprocess level, the work and output vary from subprocess to subprocess but can be measured throughout with KVA as common units.

Table 10 shows the cost information and number of executions of the subprocess to get to the output for that subprocess. It also shows the average time to complete each subprocess. The average time to complete the repair and repair request delivery takes the least time, while the repair and field evaluation or depot repair decisions are the most time-consuming. The induction, parts inventory, and inspection subprocess are comparable with the duration to complete those tasks. Also, the most expensive subprocess for labor is the field evaluation or repair decision concerning whether the item can be repaired on-site. At the same time, the cheapest labor category was the part inventory required for the repair.

Table 10. As Is Process Employees, Executions, and Time to Complete Data

Sub-Process #	Sub-Process	Number of Employees Avg	Corresponding Pay Grades Avg Hourly Rate	Number of Executions Avg	Average Time to Complete (hours)
1	Maintenance Request	1.4	$36.83	2.9	7.8
2	Depot Repair Decision	3.0	$42.76	3.0	22.6
3	Maintenance Induction	2.0	$34.80	2.6	9.9
4	Part Inventory	1.8	$23.81	3.0	8.4
5	Repair	3.3	$33.34	4.1	65.6
6	Inspection	1.7	$33.12	4.4	13.5
7	End Item Delivery	2.0	$30.75	2.6	7.1

Table 11 shows the total cost of the work performed per subprocess, with the most expensive subprocess being repair and the least costly subprocesses being delivery of the repaired item and the requests to conduct the repair. Furthermore, the table shows actual training hours, and the current automation per subprocess with individual systems and technologies listed under automation tools are listed. ROK and ROI are also listed. The highest ROKs in the current As-Is process are the tactical repair evaluation/depot repair decision and inspection, while the lowest ROKs are the actual repair. For ROI, similar subprocesses have high values (inspection and depot repair decision), with the lowest ROI subprocesses being repair and maintenance induction. As expected, ROI and ROK are highly correlated as they both measure the value of the subprocess.

Table 11. As Is Process Cost, Training, Current Automation, ROK and ROI

Sub-Process #	Sub-Process	Cost (Work Time X the # Employees hours)	Average Actual Training time (hours)	IT Baseline Automation (% automation * output)	ROK	ROI	Automation Tools
1	Maintenance Request	$1,162.93	14.0	26.7%	77.2%	10.7%	System S/W, JDRS, Microsoft, Message S/W, Web
2	Depot Repair Decision	$8,536.34	24.0	14.2%	95.3%	42.0%	System S/W, WMS, JEDMICS/AvPLM, MRO, Message S/W, Spreadsheets (Custom or FST approved)
3	Maintenance Induction	$1,789.64	12.0	22.5%	66.4%	-3.8%	System S/W, MRO, NALCOMIS, Web
4	Part Inventory	$1,055.63	43.5	15.0%	70.9%	3.8%	Supply S/W & MOD Kit Tracker, MRO, Supply S/W
5	Repair	$28,770.86	206.0	8.3%	62.8%	-6.0%	WMS for Emergent Engineering Instructions, MRO, AM
6	Inspection	$3,306.93	160.6	7.5%	100.4%	49.8%	Advanced H/W and S/W, Tech Pub Library, MRO, Wed Video, Pictures, email, visual
7	End Item Delivery	$1,087.38	18.0	15.8%	88.6%	29.5%	System S/W, MRO, Web
				Correlation	ROK/ROI	99.7%	

Statistical tests, including reliability tests, are run on the individual SME inputs. The first run test is a basic linear correlation test on the subprocess's complexity (rank order) and the learning time, as seen in Table 12. When we run the basic linear correlation test on these variables, we find four SMEs in the acceptable range: SME5 at 0.827, SME9 at 0.827, SME10 at 0.887, and SME11 at 0.798.

Table 12. Individual SME Correlation between LT and RO

	Correlation (Rank Order and Learning Time)	Notes
SME1	0.6294	Not Acceptable
SME2	-0.7974	Negative Correlation
SME3	0.0000	Not enough data points
SME4	-0.6897	Negative Correlation
SME5	0.8268	Acceptable
SME6	0.0000	Ranges Provided
SME7	0.4559	Not Acceptable
SME8	0.5457	Not Acceptable
SME9	0.8271	Acceptable
SME10	0.8869	Acceptable
SME11	0.7978	Acceptable
SME12	0.1905	Not Acceptable

With a simple correlation between the SMEs' rank order and learning time conducted, a more complex reliability test is run on the SMEs' data. The ICC in Table 13 test assesses the consistency, or conformity, of measurements made by multiple observers measuring the same quantity. For example, the SMEs were asked to provide the complexity of the subprocesses, and we can measure how consistent the scores are with each other. A high ICC indicates a high level of reliability, while low correlations mean low reliability and low consistency.

Table 13. ICC Test Learning Time with All SMEs

ICC Model Inputs:					
SME1 LT, SME2 LT, SME4 LT, SME5 LT, SME7 LT, SME8 LT, SME9 LT, SME10 LT, SME11 LT, SME12 LT					
Inter Class Correlation for Inter-rater Reliability Test					
	DF	Adj SS	Adj MS	F-Stat	P-Value

Subprocesses	6	10431.63	18.95106	18.95106	0
Unique Process Variables	9	0	0	0	1
Error	54	4954.06	91.74		
Total	69	15385.69			
Inter Class Correlation					0.68

In looking at the learning time data for the four identified SMEs to see if it improves, we see the ICC has improved slightly in Table 14.

Table 14. ICC Test Learning Time with four targeted SMEs

ICC Model Inputs:					
SME2 LT, SME5 LT, SME9 LT, SME10 LT					
Inter Class Correlation for Inter-rater Reliability Test					
	DF	Adj SS	Adj MS	F-Stat	P-Value
Subprocess	6	5222.71	870.45	9.0515	0.00012
Unique Process Variables	3	0	0	0	1
Error	18	1731	96.17		
Total	27	6953.71			
Inter Class Correlation					0.70135

Control charts in Figure 10 show how the study compared the subprocesses and their learning time. The data are plotted in subprocess order, starting with the maintenance request as process one and ending with the delivery of the repaired item as process seven. The Central Line (CL) is the average learning time (14.2 hours), the upper line is for the Upper Control Limit (UCL; 25.6 hours), while the lower line is for the Lower Control Limit (LCL; is 2.9 hours). These lines are determined from historical data from the SMEs. As expected, the repair process is outside what we see with the other subprocesses, and the depot repair decision is close to the UCL.

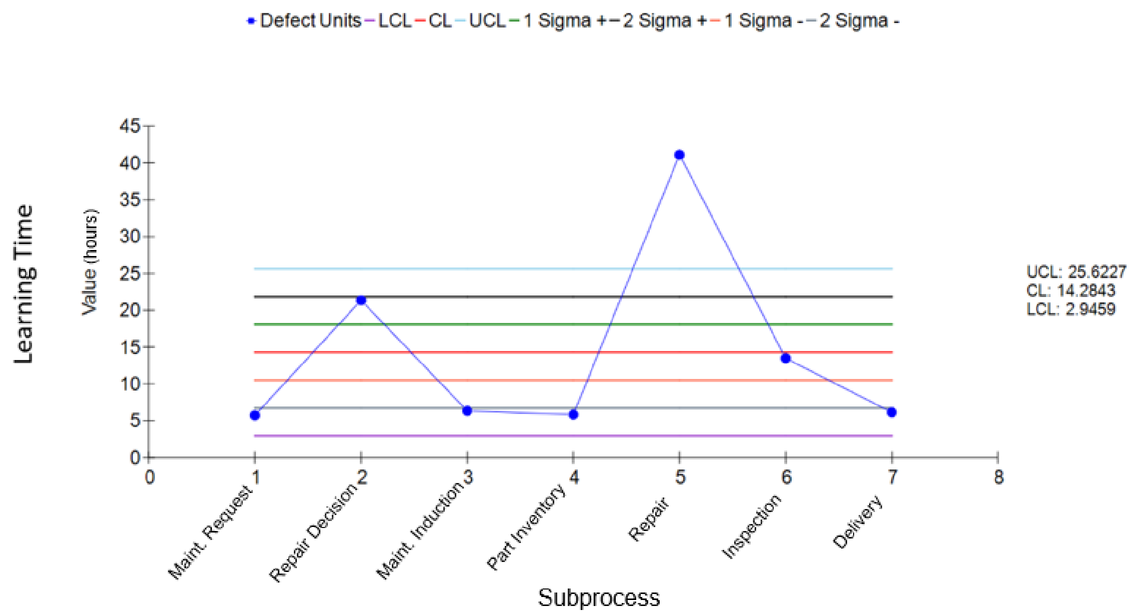

Figure 10. Learning Time Control Chart by Subprocess

Grubbs' method identifies an outlier by calculating the difference between the value and the mean and dividing that difference by the standard deviation (Mun, 2019). The value is defined as an outlier when that ratio is too large. The null hypothesis is that all data values are from the same normal population with no outliers. In Table 15, the repair subprocess is shown to have the largest learning time, with 41.1 hours, compared to the average learning time for the subprocesses, which is 14.3 hours. All the subprocesses are critical to the aircraft's overall repair; the subprocess will not be removed.

Table 15. Grubbs Outlier Test for Learning Time

Grubbs Test for Outliers
Model Inputs:
Learning Time
Grubbs Stat (Smallest Data): 0.647925
Grubbs Stat (Largest Data): 2.033473
G Critical @ 0.01: 2.097304
G Critical @ 0.05: 1.938135
G Critical @ 0.10: 1.827976
Minimum: 5.740000
Average: 14.284286
Maximum: 41.100000
Outlier: 41.100000

C. STATISTICAL INFERENCES

This subsection explores simulation and modeling with emerging technology to present options to leadership on investment by technology and subprocess. The content covers the statistical inferences of the simulation and the results of the hypothesis tests presented in the research methodology chapter.

1. AS-IS BASE MODEL

The base case assumes no new technology (AM, CIB, or ML). The labor cost of extreme maintenance teams for over two weeks without any new technology, given the As-Is case, is shown in Figure 11. As such, the As Is Repair Team Labor costs between $39,394.77 and $51,145.08, with a 90% confidence level.

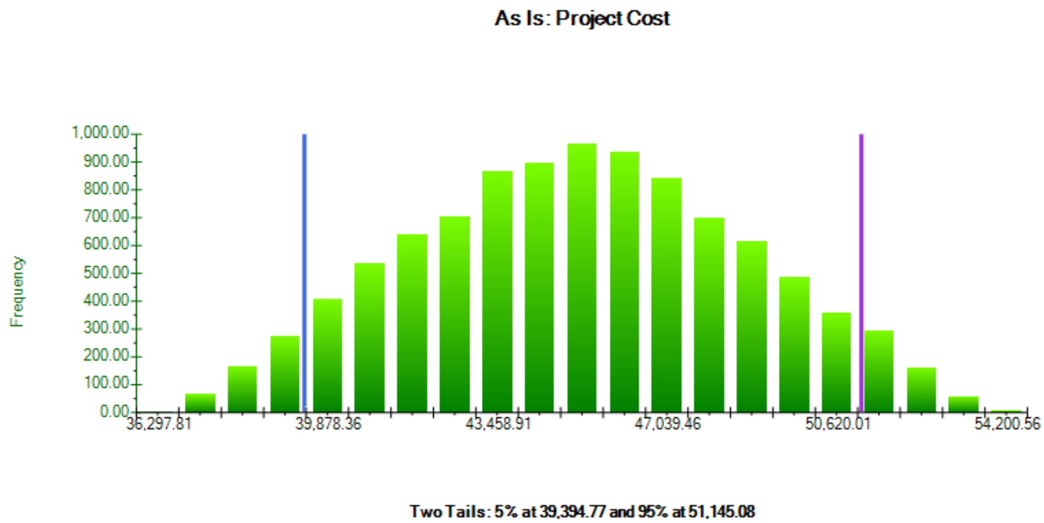

Figure 11. Two Tail As-Is Project Cost

When building forecasting models with new technologies, it is important to consult SMEs in the area of interest or technology judgment on realistic adjustments to the parameters of the models. The parameter adjustments on the following models are based on work groups, SME input, and researcher experience. The As-Is Process model is shown in Figure 5 in the research methodology section. As a reminder, the As-Is process is the base process that is adjusted to create the To-Be models (AM, CIB, ML, AM+ML+CIB). As collected from the survey data, the As-Is cost parameters in the base models are listed in Table 16. The technician's maintenance cost is a result of the number of employees and the number of executions required for each subprocess to produce its desired output. The most likely total labor cost of the repair is approximately $45K.

Table 16. As Is Model Cost Parameters

As-Is Model Parameters
Cost

Subprocess	Minimum	Most Likely	Maximum	Computed
Maint. Request	900.00	1,100.00	1,300.00	1,101.50
Field Repair Eval	7,500.00	8,500.00	9,500.00	8,504.50
Maint. Induction	1,500.00	1,800.00	2,100.00	1,801.88
Part Inventory	800.00	1,000.00	1,200.00	1,001.50
Repair	20,000.00	28,500.00	37,000.00	28,512.00
Inspect	2,900.00	3,300.00	3,700.00	3,302.40
Delivery	800.00	1,000.00	1,200.00	1,001.20
Project Total	**34,400.00**	**45,200.00**	**56,000.00**	**45,224.97**

The schedule of the extreme repair based on days for the As-Is process is shown in Table 17. The schedule utilizes a triangular distribution with minimum, most likely, and maximum values to include possible overrun for each subprocess. The most likely repair will be completed in slightly less than 17 days from the maintenance request to delivery of the aircraft to the requesting organization.

Table 17. As Is Extreme Maintenance Schedule Parameters

As-Is Model Parameters
Time Schedule (Days)

Subprocess	Minimum	Most Likely	Maximum	Daily Cost
Maint Request	0.50	1.00	1.50	1.50
Field Repair Eval	2.00	3.00	4.00	1.50
Maint. Induction	1.00	1.25	1.50	1.50
Part Inventory	0.90	1.00	1.10	1.50
Repair	6.00	8.00	10.00	1.50
Inspect	1.00	1.60	2.20	1.50
Delivery	0.60	0.80	1.00	1.50
Project Total	**12.00**	**16.65**	**21.30**	**24.97**

2. TO-BE AM PROCESS MODEL

The forecasting parameters for the To-Be AM model were based on the diagram in Figure 12, which was derived from talking to SMEs familiar with the AM technology and its application in extreme maintenance. Factors that were considered include power, security, technical part data, and space available to make the parts. AM provides value in extreme maintenance in the part-ordering subprocess (P4) with its ability to generate parts on-site. While parts can still be ordered through the traditional supply system, doing so can be problematic in the extreme maintenance context due to logistics limitations.

Figure 12 shows an option for parts required in the repair that are not part of the PUK besides using the supply chain to order and transport parts to remote locations, which stresses the capabilities of logistical support. Waiting for the part to be delivered to the extreme maintenance site extends the repair time.

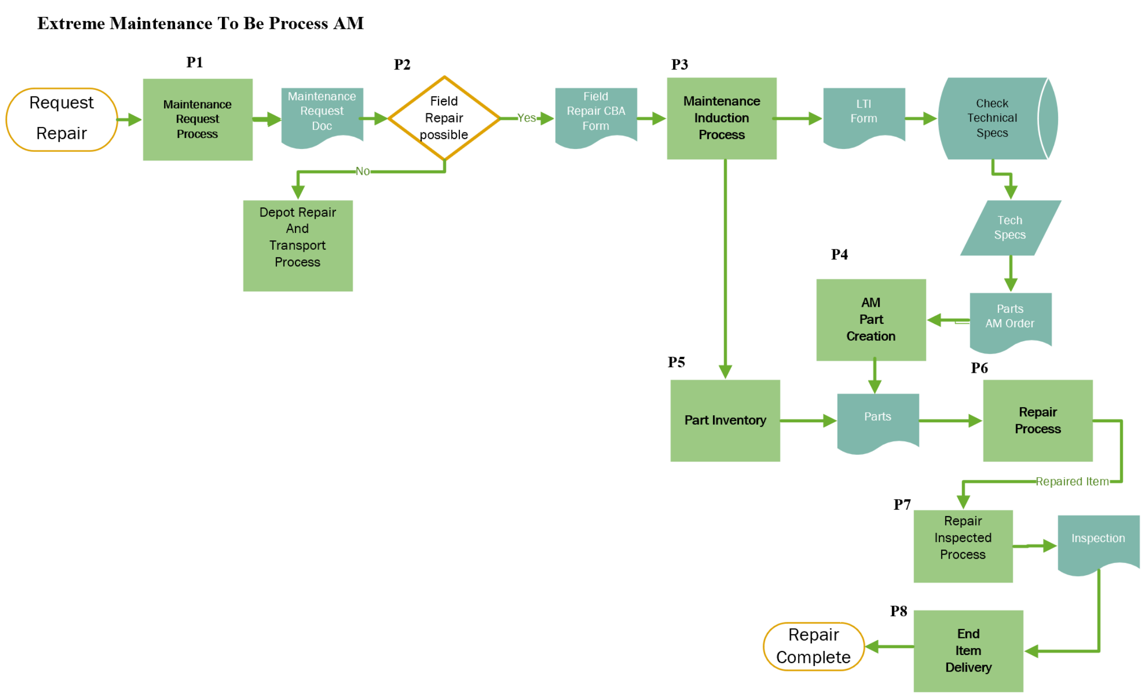

Figure 12. Forecasting AM To-Be Process Diagram

The option offered by AM technology allows for branching and critical path analysis (Figure 13) in the process optimization. After the maintenance induction subprocess (P3), parts can come from the PUK via the supply chain or be generated on-site through AM technology. The repair subprocess is the merger point for the AM Part Creation and traditional part inventory subprocess.

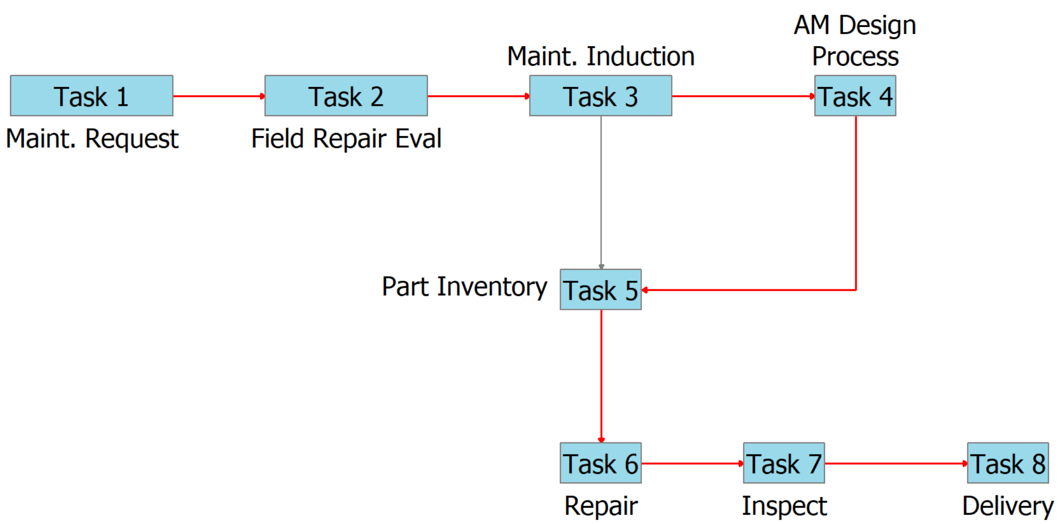

Figure 13. Critical Path for AM To-Be Process.

The AM forecast parameters for the model are shown in Table 18 below. The cost is reduced by adding an extra subprocess with the AM design and creation subprocess. The reason that cost is decreased by adding an extra subprocess is the branch that gives the repair artisan another way to acquire parts shown in the network path. The most likely cost for the repair with AM technology added is $42.3K. This cost reflects reduced labor and part inventory wait time. These adjustments were based on SME input and a literature review (Post et al., 2016).

Table 18. Cost Parameters for AM To-Be Process Model

AM Model Parameters Cost

Subprocess	Minimum	Most Likely	Maximum	Computed
Maint. Request	900.00	1,100.00	1,300.00	1,101.50
Field Repair Eval	7,500.00	8,500.00	9,500.00	8,504.50
Maint. Induction	1,500.00	1,800.00	2,100.00	1,801.88
AM Design Process	400.00	600.00	800.00	600.75
Part Inventory	800.00	1,000.00	1,200.00	1,001.50
Repair	20,000.00	25,000.00	30,000.00	25,010.50
Inspect	2,900.00	3,300.00	3,700.00	3,302.40
Delivery	800.00	1,000.00	1,200.00	1,001.20
Projected Total	**34,800.00**	**42,300.00**	**49,800.00**	**42,324.22**

The schedule parameters for the AM model are included in Table 19. We can see the overall savings are projected at half a day to 16.15 days (if multiple repairs are conducted, overtime can add up). The daily cost column represents the possibility of cost overruns and is figured into the worst-case projection of the repair schedule. The AM parameter adjustments were estimated based on SME input and literature review (Schehl, 2023).

Table 19. Schedule Parameter for AM To-Be Process Model

AM Model Parameters Time Schedule (Days)				
Subprocess	**Minimum**	**Most Likely**	**Maximum**	**Daily Cost**
Maint. Request	0.50	1.00	1.50	1.50
Field Repair Eval	2.00	3.00	4.00	1.50
Maint. Induction	1.00	1.25	1.50	1.50
AM Design Process	0.40	0.50	0.60	1.50
Part Inventory	0.90	1.00	1.10	1.50
Repair	6.00	7.00	8.00	1.50
Inspect	1.00	1.60	2.20	1.50
Delivery	0.60	0.80	1.00	1.50
Projected Total	**12.4**	**16.15**	**19.9**	**24.22**

3. TO-BE CIB PROCESS MODEL

The CIB forecasting model in Figure 14 provides added capability to the extreme maintenance team by allowing the teams to work onsite in austere conditions. CIB added to the subprocess provides the technician with onsite automation.

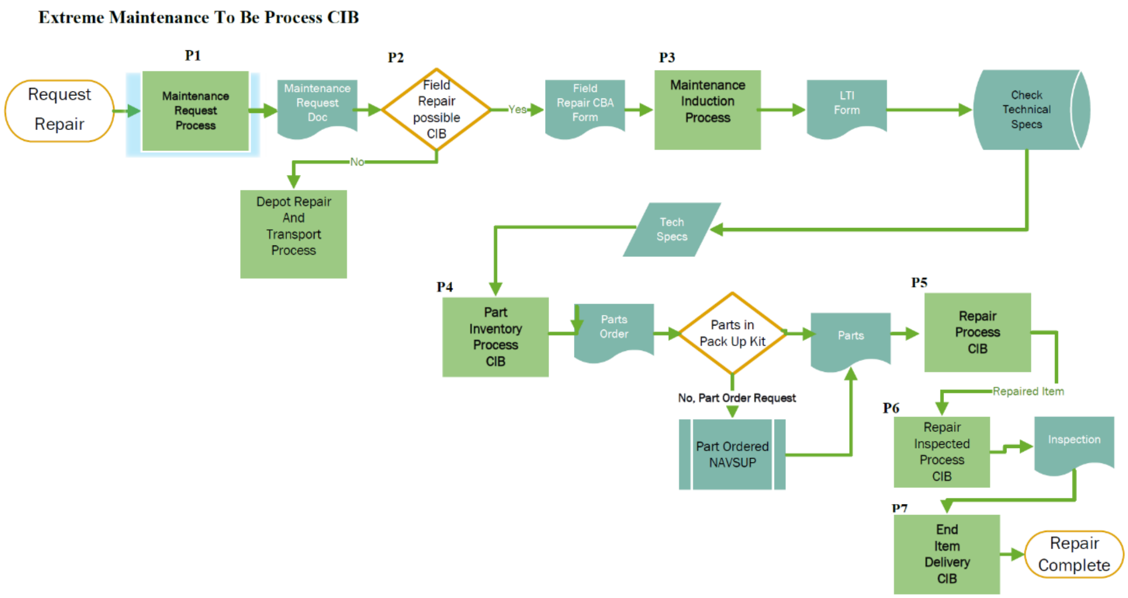

Figure 14. Forecasting CIB To-Be Process Diagram

The CIB To-Be process offers significant process automation and critical path analysis Figure 15, to multiple subprocesses. The subprocesses that benefit from CIB technology are Part Inventory, Repair, Inspection, and Delivery.

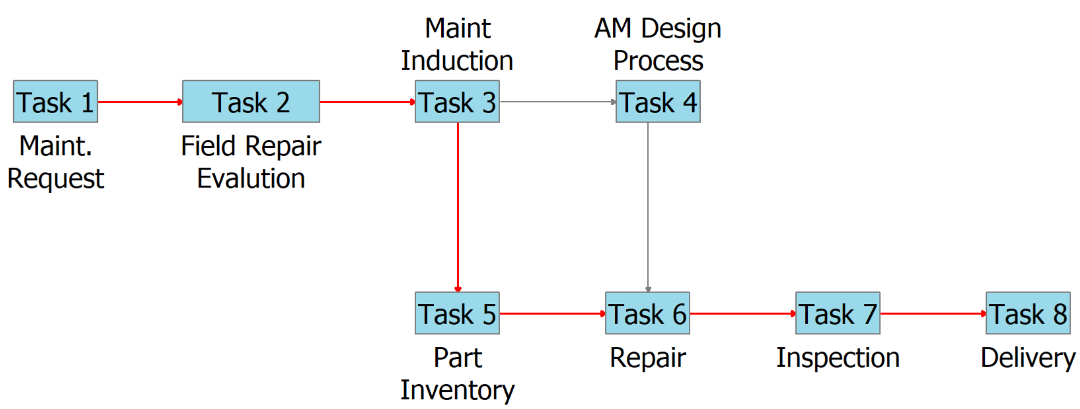

Figure 15. Critical Path for CIB To-Be Process

The To-Be CIB model parameters in Table 20 include AM possibility for reach-back but not necessarily onsite AM capability. The subprocesses that CIB impacted were the maintenance induction, repair, and delivery subprocesses.

Table 20. Model Cost Parameters for To-Be CIB Model

CIB Model Parameter Cost

Subprocess	Minimum	Most Likely	Maximum	Computed
Maint. Request	900	1,100	1,300	1,101.50
Field Repair Evaluation	7,500	8,500	9,500	8,504.50
Maint Induction	1,400	1,600	1,800	1,601.65
AM Design Process	300	400	500	400.6
Part Inventory	800	1,000	1,200	1,001.50
Repair	20,000	27,000	35,000	27,012.00
Inspection	2,900	3,300	3,700	3,302.40
Delivery	700	800	900	801.05
Project Total	**34,500.00**	**43,700.00**	**53,900.00**	**43,725.20**

The CIB impacts on specific subprocesses provide more schedule improvement in Table 21, impacting some subprocesses than others. The subprocess that is impacted is the overall most likely repair schedule time, which is reduced to 16.40 days.

Table 21. Schedule Parameters for CIB To-Be Process

CIB Model Parameter
Time Schedule (Days)

Subprocess	Minimum	Most Likely	Maximum	Daily Cost
Maint. Request	0.50	1.00	1.50	1.50
Field Repair Evaluation	2.00	3.00	4.00	1.50
Maint Induction	0.90	1.10	1.20	1.50
AM Design Process	0.30	0.40	0.50	1.50
Part Inventory	0.90	1.00	1.10	1.50
Repair	6.00	8.00	10.00	1.50
Inspection	1.00	1.60	2.20	1.50
Delivery	0.60	0.70	0.80	1.50
Project Total	**11.90**	**16.40**	**20.80**	**25.20**

4. TO-BE ML PROCESS MODEL

The forecasting parameter adjustments made on the ML model are based on Fraizer's (2022) and Zhao's (2016) research. ML Aviation technology focuses on maintenance conditions with ML used for prediction using ML algorithms often seen in bioinformatics. Figure 16 shows the subprocesses that benefit from this emerging technology. ML impacts all the subprocesses to some degree, but it has a minimal impact on the delivery subprocess.

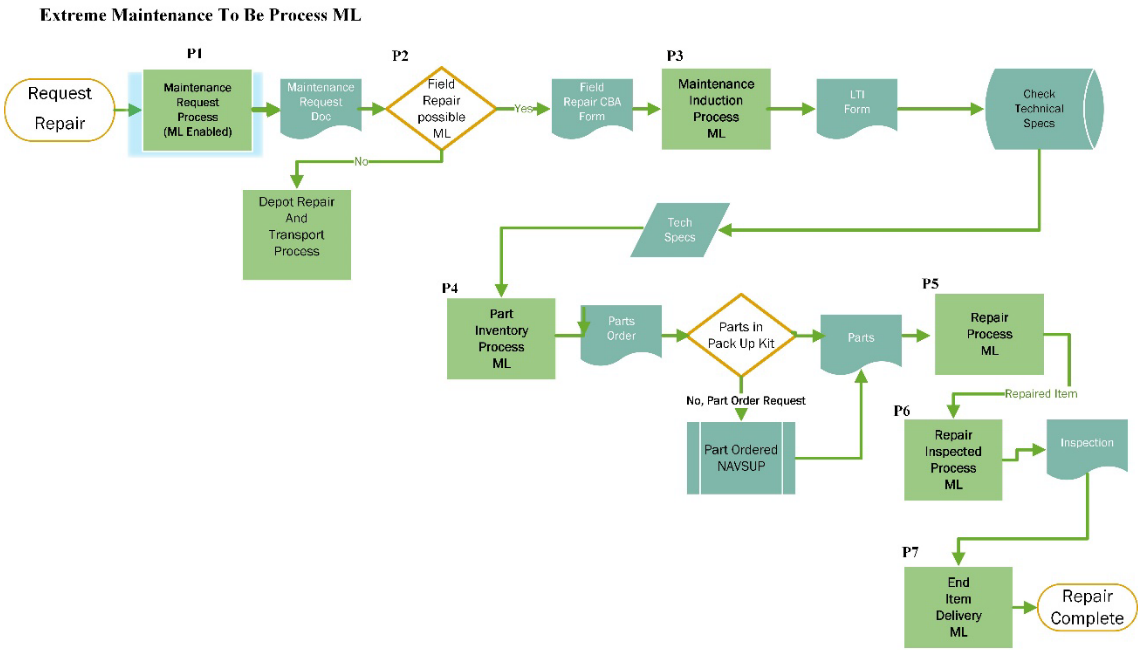

Figure 16. Forecasting ML To-Be Process Model

The parameters used for ML forecasting cost are listed in Table 22. These figures were derived from the baseline numbers with adjustments made for ML subprocess improvements, prior research, and SME input. The labor cost improves to 28.9K from 45.2K for the As-IS model in two to three weeks.

Table 22. ML Model Cost Parameter

ML Model Parameter Cost

Subprocess	Minimum	Most Likely	Maximum	Computed
Maintenance Request	800	900	1,000	900.99
Field Repair	6,000	7,000	8,000	7,004.50
Maintenance Induction	1,200	1,500	1,800	1,501.50
Part Inventory	600	800	1,000	801.2
Repair	18,000	22,000	27,000	25,009.00
Inspection	2,500.00	2,900.00	3,200.00	2,901.80
Delivery	700.00	800.00	1,100.00	801.05
Project Total Cost	**31,800.00**	**38,900.00**	**46,100.00**	**38,920.04**

The ML schedule parameters are included in Table 23. We can see a considerable time decrease to 12.16 days, saving over three days compared to traditional repair methods. Across the subprocesses, there is an impact on the overall cycle time. ML can speed up almost every subprocess in the extreme maintenance case, offering a significant impact on the overall performance metric. The depot repair decision and the repair itself incur the most net change.

Table 23. Schedule Parameters for To-Be ML Model

ML Model Parameter Time Schedule (Days)				
Subprocess	**Minimum**	**Most Likely**	**Maximum**	**Daily Cost**
Maintenance Request	0.50	0.86	1.40	1.50
Field Repair Evaluation	2.23	2.50	2.90	1.50
Maintenance Induction	1.00	1.20	1.50	1.50
Part Inventory	0.90	1.00	1.10	1.50
Repair	6.20	7.40	8.90	1.50
Inspection	1.00	1.50	2.20	1.50
Delivery	0.60	0.70	1.00	1.50
Project Total Cost	12.43	15.16	19.00	24.84

5. TO-BE AM + CIB + ML PROCESS MODEL

Figure 17 illustrates the forecasting model with all the technologies implemented together (AM + CIB + ML). With all the technologies, the extreme maintenance process automation increases productivity and cycle time for most subprocesses.

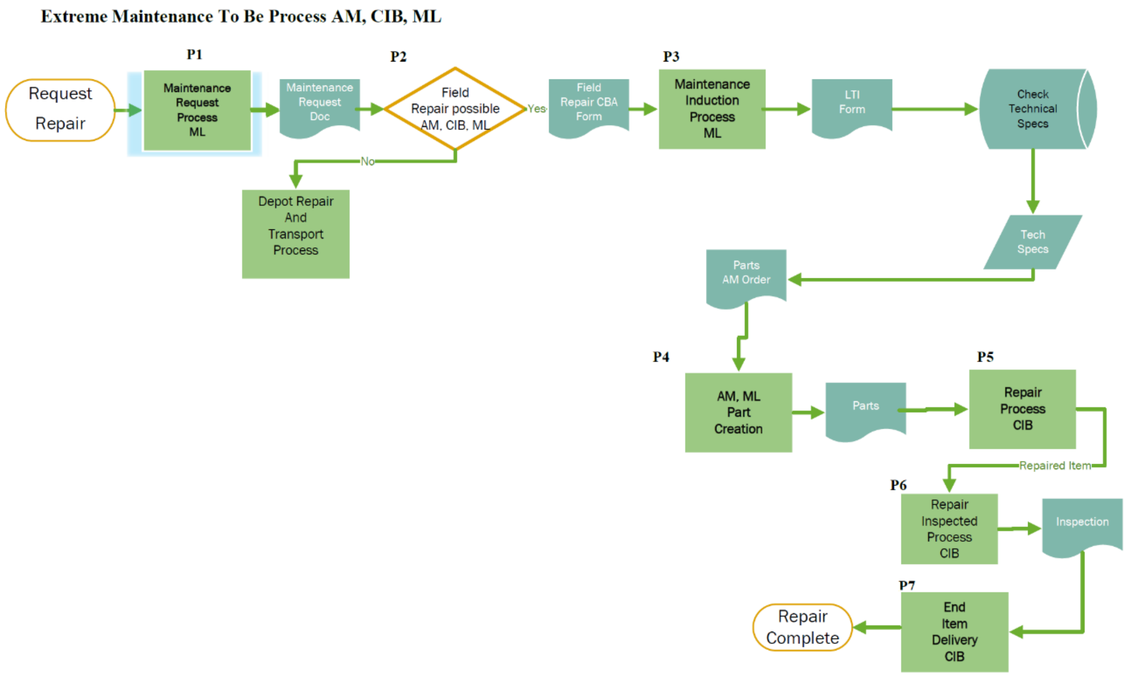

Figure 17. To-Be AM + CIB + ML Diagram

Table 24 lists cost parameters for the AM + CIB + ML To-Be Process Model. As with the other models, the cost focuses on labor. The relationship between the three technologies provides ample cost savings on labor. Any additional infrastructure cost for the technologies (AM + CIB + ML) is not factored into the total cost of the new technology and will need to be amortized over ten years.

Table 24. Cost Parameters for To-Be AM + CIB + ML Model

AM + CIB+ ML Model Parameter
Cost

Subprocess	Minimum	Most Likely	Maximum	Computed
Maintenance Request	800	900	1,000	900.99
Field Repair Evaluation	7,500	8,500	9,500	8,504.50
Maintenance Induction	1,400	1,500	1,600	1,501.20
AM Design Process	300	400	500	400.6
Part Inventory	700	800	900	801.2
Repair	19,000	24,000	29,000	24,010.50
Inspection	2,500	3,000	3,300	3,001.80
Delivery	600	700	800	700.9
Project Total Cost	**32,800.00**	**39,800.00**	**46,600.00**	**39,821.69**

Table 25 shows the To-Be AM + CIB + ML model schedule. The critical path of the subprocess is not linear, and the new technology offers branches for part ordering or making the parts on-site with the AM technology. The To-Be cost saving is realized over days, with a total cost saving of over two days on the total aircraft repair.

Table 25. Schedule Parameters for AM + CIB + ML To-Be Model

AM + CIB+ ML Model Parameter
Time Schedule (Days)

Subprocess	Minimum	Most Likely	Maximum	Daily Cost
Maintenance Request	0.53	0.80	1.20	1.50
Field Repair Evaluation	2.20	3.20	4.10	1.50
Maintenance Induction	0.70	0.90	1.20	1.50
AM Design Process	0.60	0.70	0.80	1.50
Part Inventory	1.00	1.10	1.30	1.50
Repair	6.20	7.16	7.80	1.50
Inspection	1.00	1.40	1.60	1.50
Delivery	0.60	0.70	0.90	1.50
Project Total Cost	12.83	15.96	18.90	23.94

The investment portfolio for the five models (As-Is, AM, CIB, ML, and AM + CIB + ML) is displayed in Figure 18 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 eight thousand dollars 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.

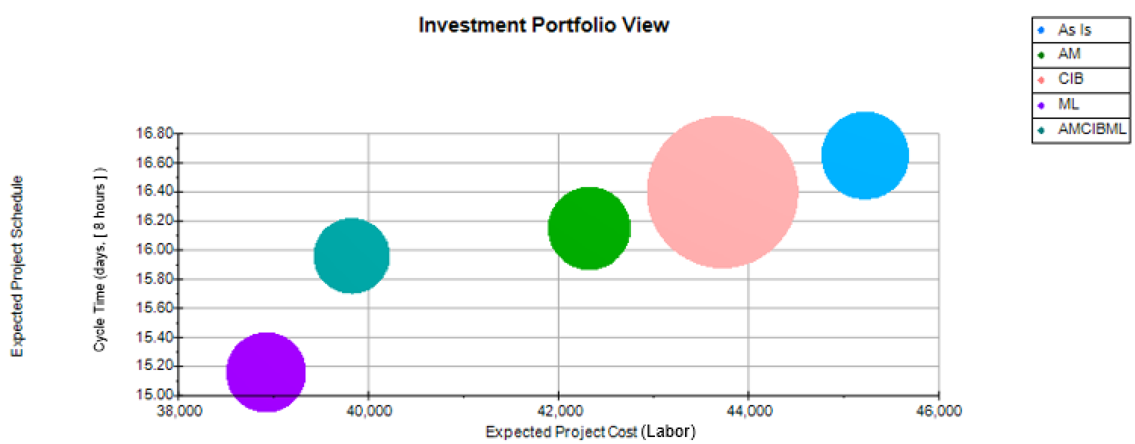

Figure 18. New Technology Investment Portfolio

Based on Monte Carlo simulation, Figure 19 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 20 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.

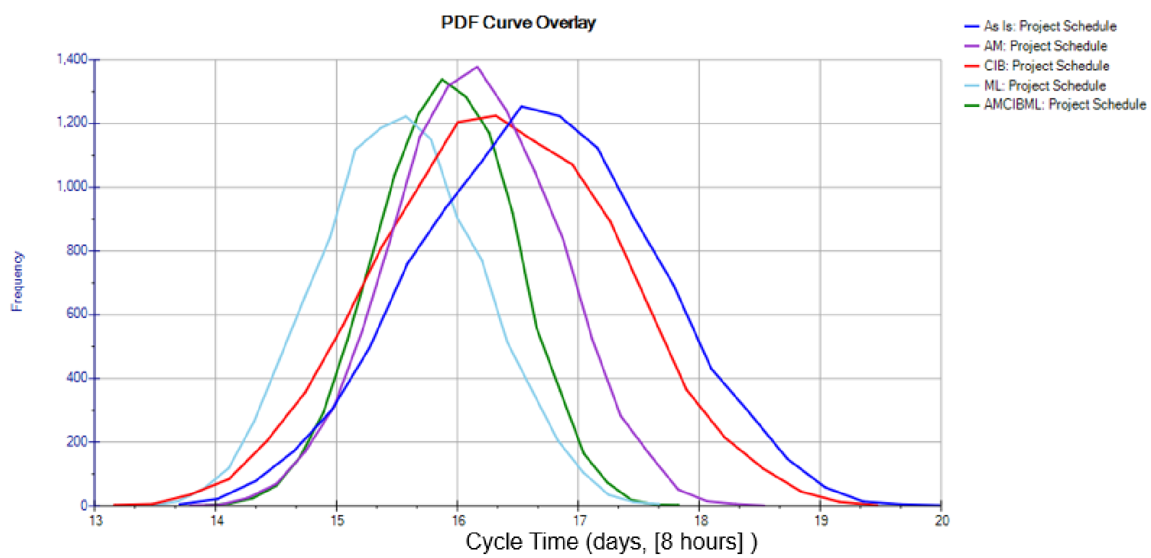

Figure 19. Predicted Schedule Saving of the Emerging Technology

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V. TESTING AND RISK MANAGEMENT

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 20, 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 20.

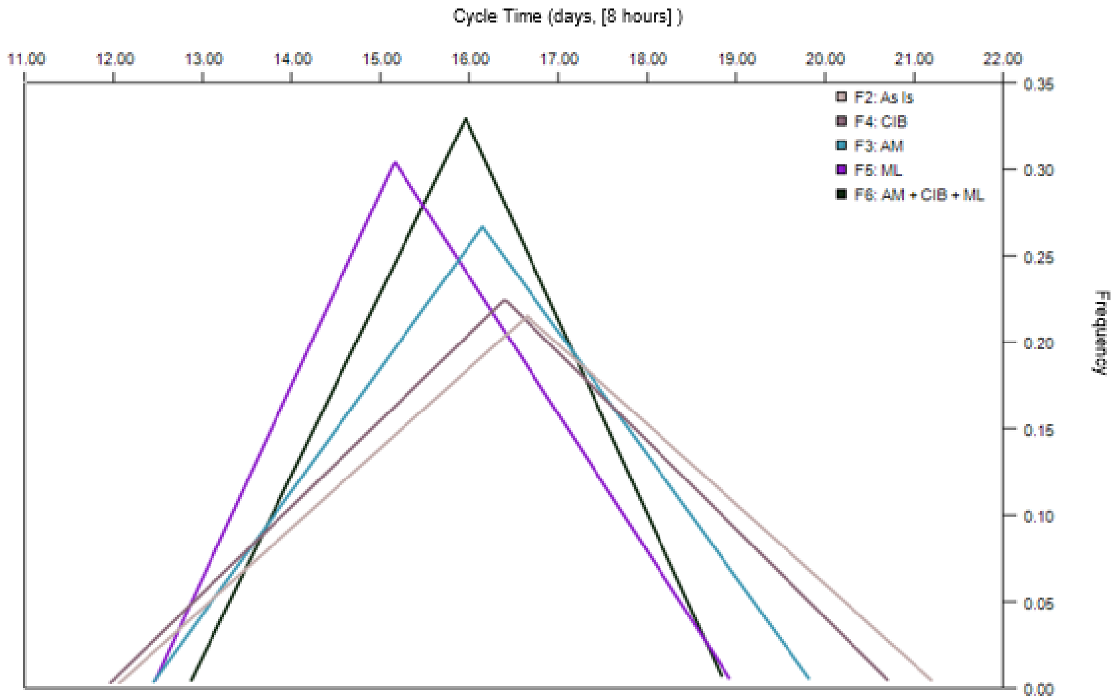

Figure 20. Cycle Time Triangle Distribution

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 21, and the simulation results obtained are utilized in the hypotheses tests.

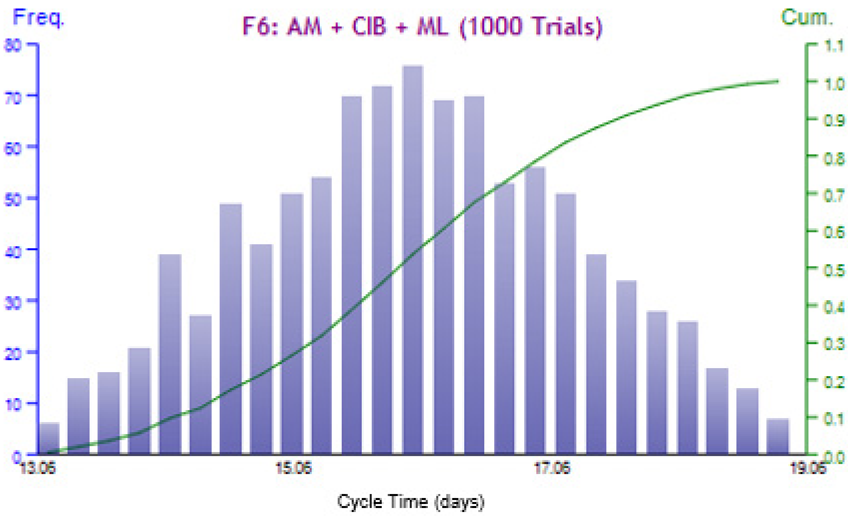

Figure 21. Hypothesis Distribution Simulation Data

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 1 states that ML improves cycle time compared to traditional prediction methods; Hypothesis 3 states that AM increases cycle time compared to traditional supply chain parts acquisition methods; and Hypothesis 5 states that CIB technology improves cycle time compared to traditional reach-back methods; Hypothesis 7 states AM + CIB + ML technology improves extreme maintenance process cycle time compared to traditional methods. Table 26 shows a directional main effects hypothesis. The CIB, Hypothesis 5, is that p-values are less definitive but can still reject the null hypotheses. Finally, Hypothesis 7 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 26 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 percent of the time at the significant level of 0.05 and 0.01.

Table 26. 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 27 demonstrates that one or more technologies have a statistically significant effect at Alpha 1% on at least one of the levels.

Table 27. 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 ten samples of a hundred, for the T-test (Figure 22). 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%.

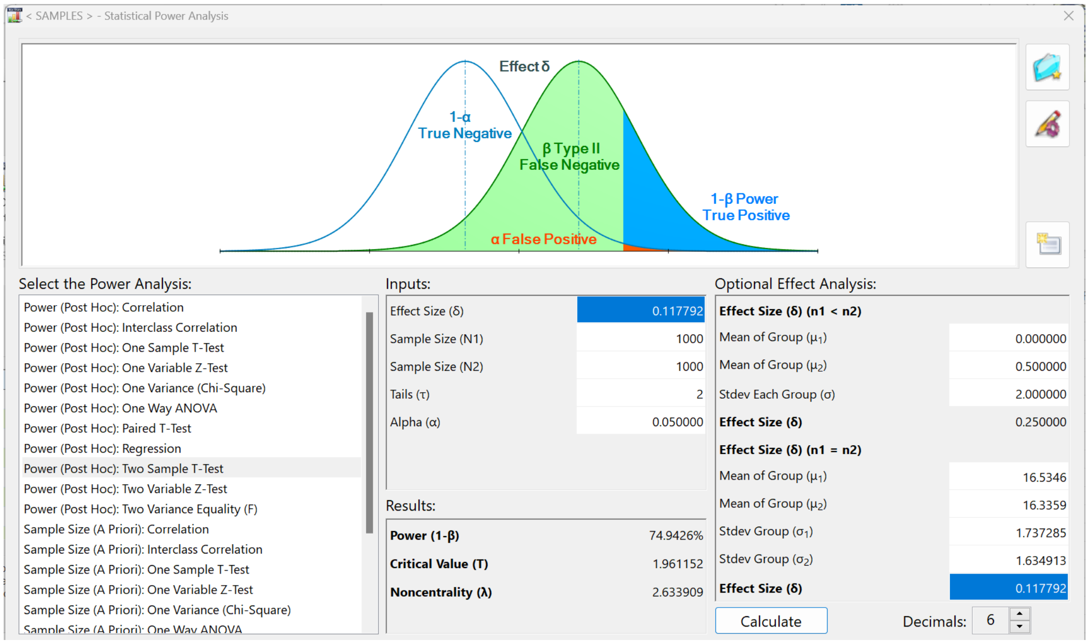

Figure 22. Power Analysis for Hypotheses Tests

At the corporate level, ROI and ROK are productivity ratios in accounting, as seen in Table 28. ROI is based on revenue in the extreme maintenance case for a nonprofit 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 28. 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 29 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 29. 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 30.

Table 30. 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%

B. INTEGRATED RISK MANAGEMENT

As previously noted, the current research utilized IRM to forecast the effects of using the three IT artifacts to optimize extreme maintenance subprocesses that have been optimized using BPR techniques. Figure 6 illustrates its eight-step process: identifying the risk, forecasting prediction modeling, the base case static model, using dynamic Monte Carlo risk simulation, RO problem framing, RO valuation and modeling, portfolio and resource optimization, and reports, presentations, and updates. Here, details are provided about the application of that process utilizing data and forecasts of the emerging technologies in the extreme maintenance realm.

1. RISK IDENTIFICATION

Risk identification from the extreme maintenance repair team has been conducted over the last year. There have been multiple meetings, exercises, and screenings by management to discuss the possible risks to the extreme maintenance teams. The organization has reviewed the risk and decided that the opportunity the extreme maintenance teams provide to the U.S. Navy is well worth that risk. This chapter will focus on the risk of process optimization of the extreme maintenance team. While the organization will deal with the greater risk at the enterprise level, additional research and deployment development are required to reduce the risk. The identified risks in the extreme maintenance environment include:

- Lack of resources in both labor and materials, i.e., parts and equipment
- Lack of technical data (2D/3D maintenance information)
- Degraded network connectivity, communications, and maintenance system access
- Bottlenecks due to inefficient extreme maintenance processes and subprocesses
- Lack of experience on extreme maintenance teams due to new aircraft and retiring personnel

2. RISK PREDICTION

The As-Is extreme maintenance forecasting and prediction modeling of schedule and cost in this study was based on two- to three-week field and tabletop exercises. The data gained from the surveys were simulated over 10,000 trials. The schedule has a mean of 16.65 days in the current As-Is process and 18.83 days with a 99th percentile value. This means that using a single-point estimate of 16.65 days would yield a completely incorrect assessment of the actual schedule risk. On average, there could be a two-day schedule slip in a two-week period. In Figure 23, the absolute worst-case scenario, we are still sure that, 99% of the time, repairs to the aircraft will be completed in 18.83 days. The To-Be extreme maintenance team schedule modeled with all the new technology (AM, CIB, ML) is presented later in the risk diversification subsection.

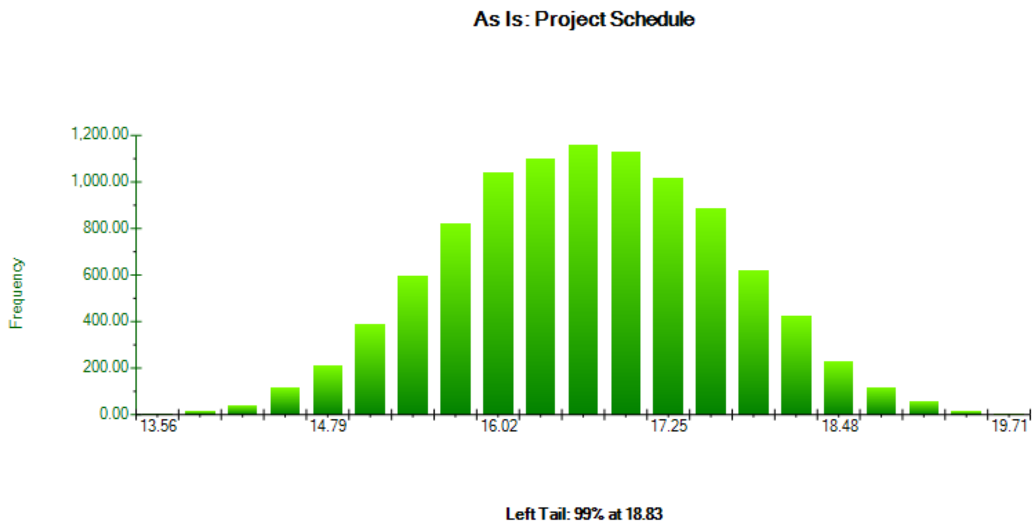

Figure 23. As Is Project Schedule Risk Prediction

Figure 24 shows the simulated cost of labor over a two-week period, where the extreme maintenance team could be 12 to 15 employees with a mean cost of $45,196.06 with a 90% confidence interval that the cost will be between $39,394.77 and $51,145.08. This means that there is a 5% chance that the cost will be below $39,394.77 and a 5% chance it will exceed $51,145.08. This is a far cry from the $45,196.06 single-point estimate. In this case, there could be, biweekly, an average $5,000 budget overrun. If simulation were not applied, the project could be significantly over budget, late, or both, based on projections.

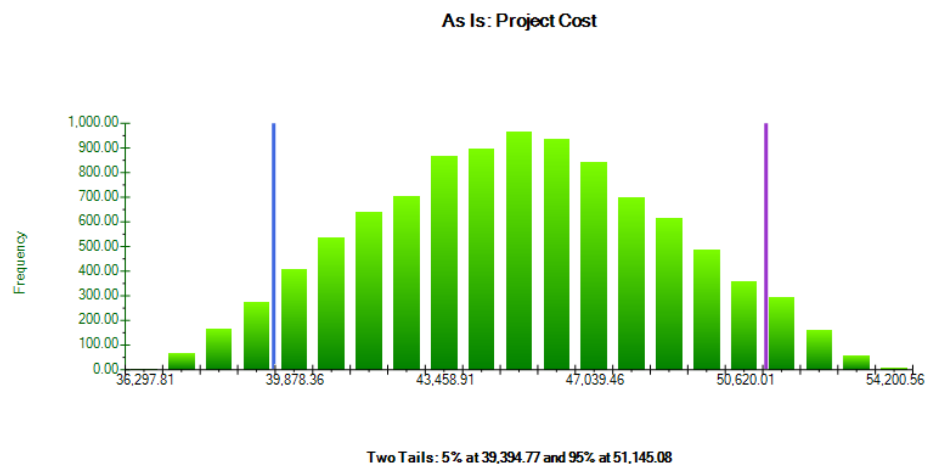

Figure 24. Two Tail As-Is Extreme Maintenance Labor Cost Two Week

3. RISK MODELING

This study's risk model is a mathematical representation of the schedule and cost of the extreme maintenance teams, incorporating probability distributions for process optimization. The models employed relevant survey data as well as SME input from technicians and management versed in extreme maintenance conditions to provide an understanding of the probability of an extreme maintenance event to repair an aircraft and the potential upside of using emerging technology. For example, the cycle time over a two-week period for the As-Is base case is shown in Figure 25 along with the To-Be models of emerging technologies (AM, CIB, ML, AM + CIB + ML) Over a two-week period, it can be seen that ML can save over one day of cycle time over the As-Is case.

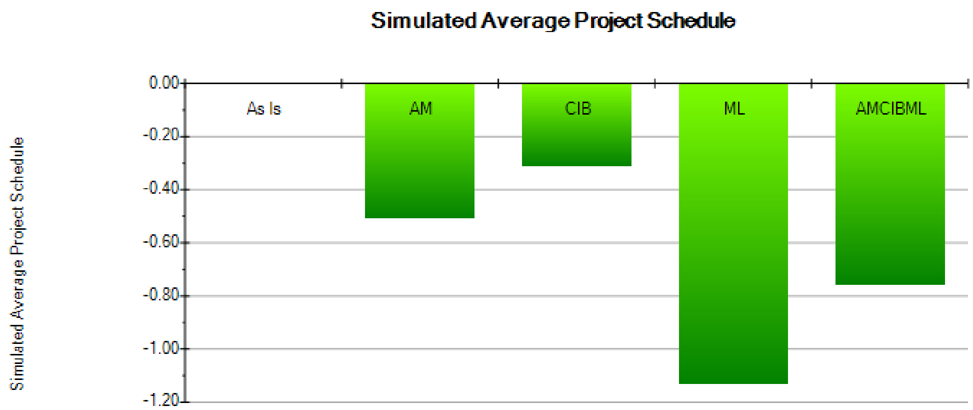

Figure 25. Cycle Time Model for Extreme Maintenance

4. RISK ANALYSIS

Performing a risk analysis includes considering the possibility of optimization of the process by adding technology and changing the existing As-Is subprocesses, such as adding branches for creating parts with AM and CIB technology to mitigate limited communications. Further, a review of battlefield conditions to identify adverse events caused by extreme maintenance conditions or adversary activities are required. An important part of risk analysis is identifying the potential for harm from these events and the likelihood of their occurrence. All the technologies AM, CIB, and ML were chosen to assist with extreme maintenance conditions and the risk identified previously.

5. RISK MITIGATION

The RO problem framing As-Is base case static model illustrated in Figure 26 is an activity-on-node diagram representing a complex schedule network model for the project shown to the right with seven tasks or nodes. The arrows in the diagram indicate the precedence relationships between the tasks. A scheduling model can be developed by assigning an input assumption for each task representing the likelihood of completing the particular task over a specific duration.

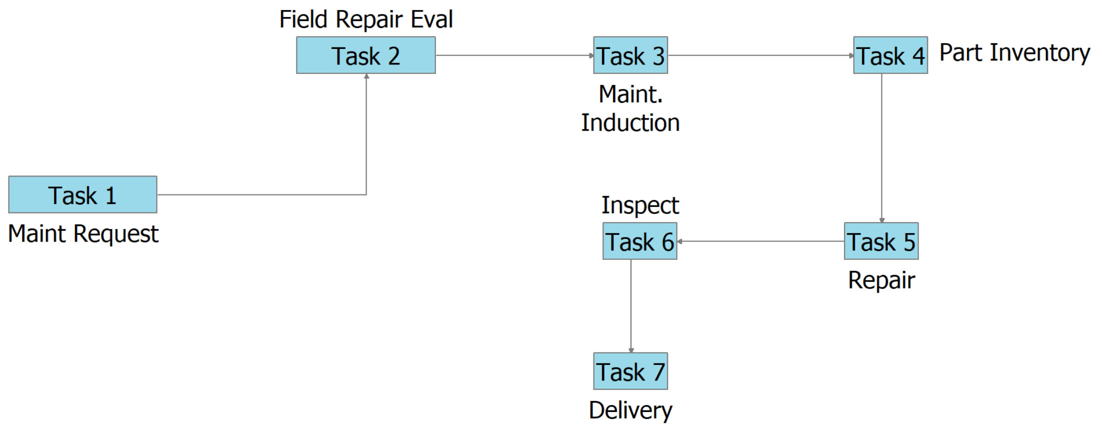

Figure 26. As-Is Network Path Diagram

Typically, a triangular distribution is assigned to each activity using three parameters:

1. The minimum time to complete an activity,
2. The most likely time to complete an activity.
3. The expected maximum time to complete an activity.

Next, one must determine the beginning of the network, the end of the network, and any merger points. The merger points are where different paths come together. Task 3 and Task 4 have a merge point at Task 5. The beginning and end can be considered pseudo-merge points. Then, formulas to calculate the durations of the various paths from merge point to merge point need to be created, and the longest (maximum) duration path is the subtotal duration for that part of the network.

Monte Carlo risk simulation of 10,000 trials was run, and the critical path probabilities can be seen in Figure 27. There are only two probable critical paths: 1–8, and 1–3, 5–8. This indicates that the two critical paths are highly similar, except for Tasks 3 and 4. Further, we see that the most likely schedule is 14.46 days, and the total estimated cost is $39,821.69.

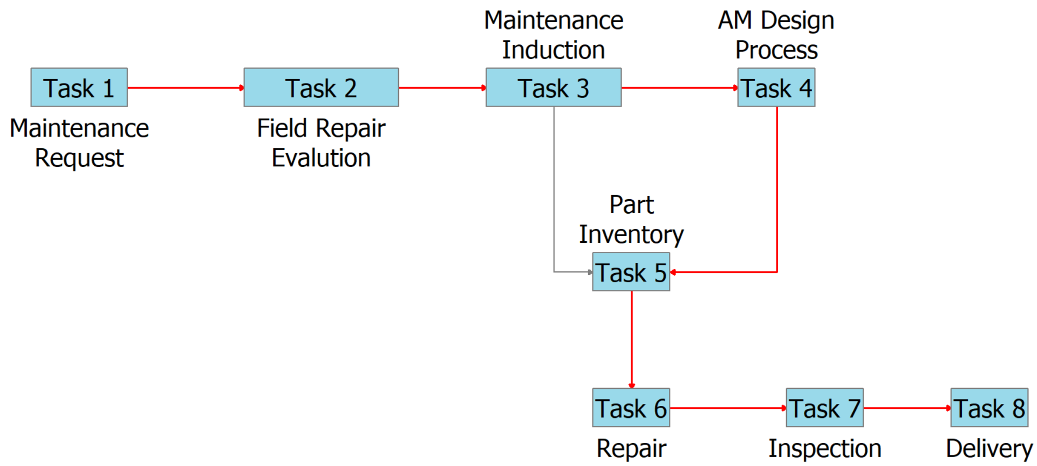

Figure 27. To-Be Network Diagram for AM, CIB and ML

6. RISK HEDGING

Risk-hedging encompasses supply chain strategies that aim to secure resources for parts and materials, thereby reducing supply uncertainty. This approach aligns with situations with high supply uncertainty, high productivity, and low cycle time demand. To achieve this, real options valuation and modeling are employed. Additionally, the risk-hedging efforts of extreme maintenance teams are supported through the use of distributed CIB for cloud-edge collaborative maintenance, AM to reduce part availability risk, and ML to assist with forecasting. This includes sharing technical data and systems for repair in the extreme maintenance environment.

7. RISK DIVERSIFICATION

Figure 28 shows the simulated schedule has a mean of 15.9 days with a 99th percentile value of 17.14 days. This means that a single-point estimate of 14 days would yield a completely incorrect assessment of the actual schedule risk. On average, there will be a 1.9-day schedule slip. In the absolute worst-case scenario, we are sure that the repair will be complete 99% of the time in 17.14 days.

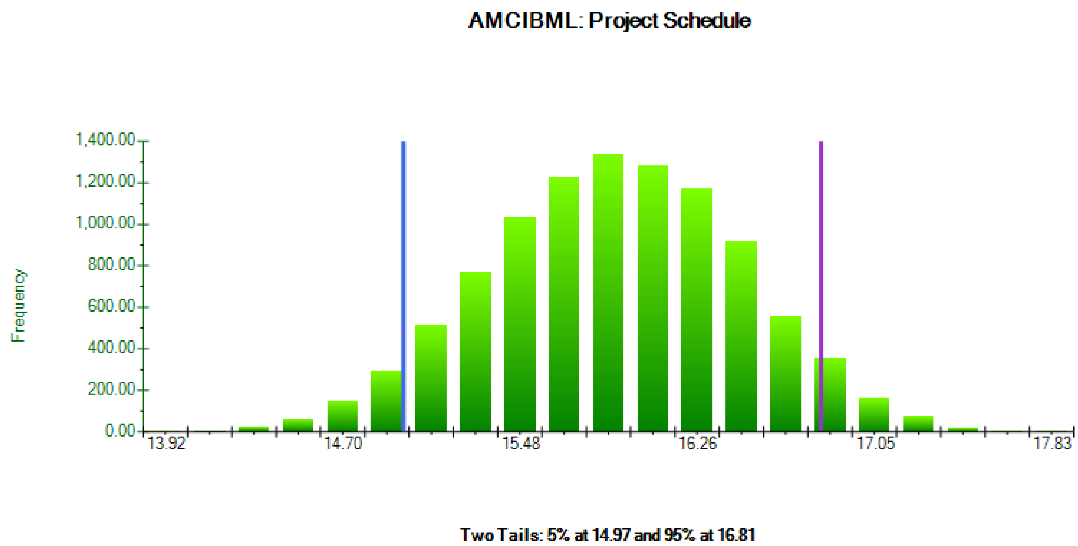

Figure 28. AM CIB ML Repair Schedule

Figure 29 shows the simulated cost, where the mean is $39,766.76, with a 90% confidence interval that the cost will be between $36,341.20 and $43,285.81. This means that there is a 5% chance the cost will be below $36,341.20 and a 5% chance it will exceed $43,285.81. This is a far cry from the $45,000 single-point estimate. In this case, there will be an average $5,000 budget overrun. If simulation were not applied, the repair would be projected to be both significantly over budget and late.

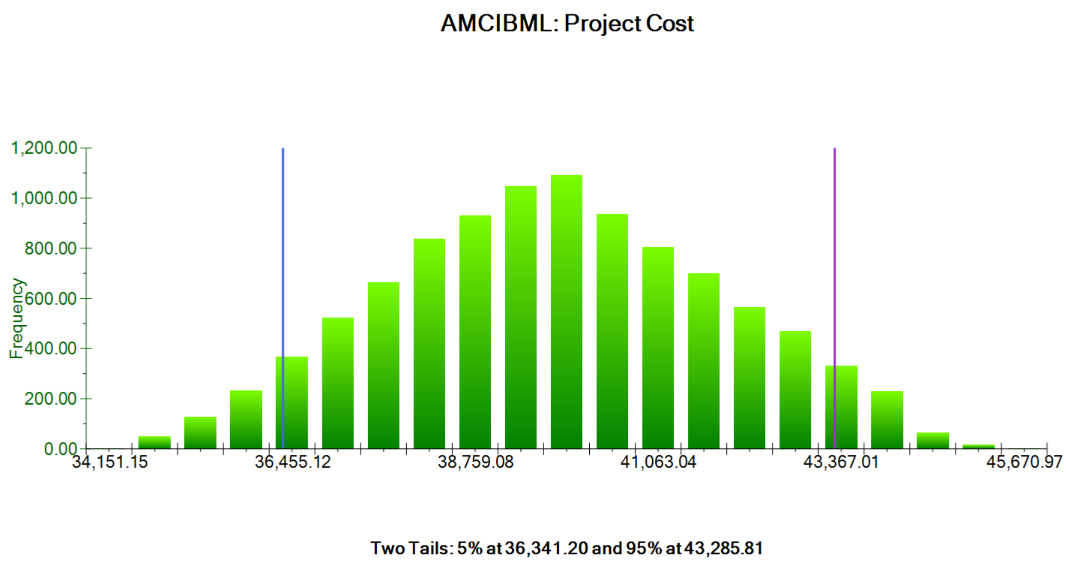

Figure 29. AM CIB ML Repair Cost

8. RISK MANAGEMENT

Risk management for extreme maintenance is the continuing process of identifying, analyzing, evaluating, and treating loss exposures and monitoring risk control and financial resources to mitigate the adverse effects of loss. For this study, a loss may result from battlefield conditions, repair team training, and complexity of the repair. The fielding of the emerging technologies (AM, CIB, ML) in an extreme maintenance environment, for example RO is shown as a two-phase approach in Figure 30.

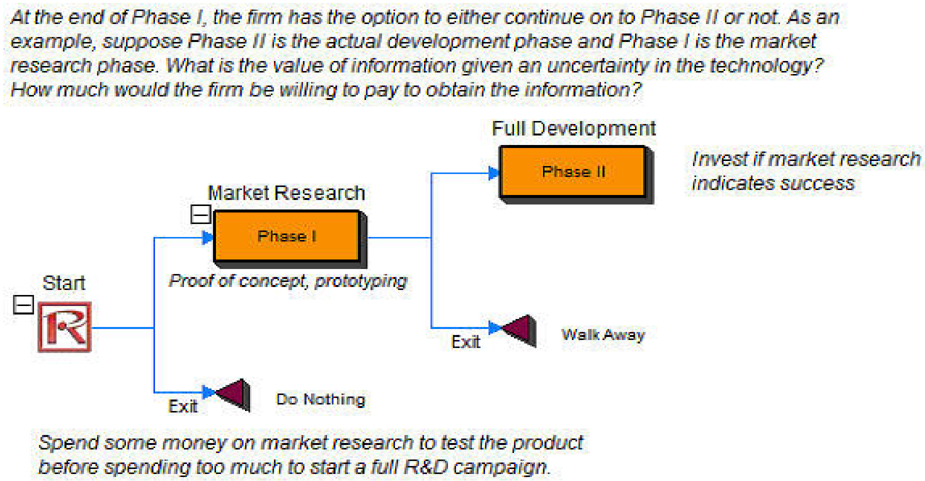

Figure 30. Real Option Prototype for AM, CIB, and ML

Real options in RM compute the value of a two-phased sequential compound option. That is, it values the stage-gate implementation of high-risk project development with early prototyping, low-rate initial production, technical feasibility tests, technology demonstration, or valuing contracts with multiple stages with the option to exit at any time with the built-in flexibility to execute different courses of action at specific stages of development, milestones, or research and development programs executed in phases, using the present value of implementation costs at each phase and the maturity of each phase (i.e., time zero until the end of each phase) in years. At each phase, the option exists to exit and walk away from the extreme maintenance project or emerging technology (AM, CIB, and ML). The financial critical factors to field AM, CIB, and ML can be seen, in Figure 31.

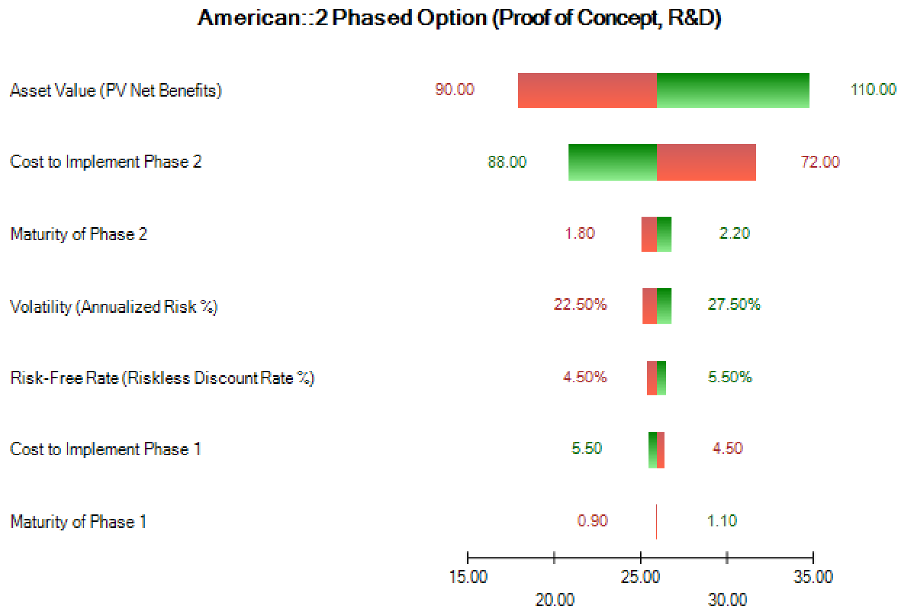

Figure 31. Proof of Concept RO Analysis for AM, CIB, and ML

VI. CONCLUSION

A. CONCLUSION AND RECOMMENDATIONS

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 Machine Learning (ML), Additive Manufacturing (AM), and Cloud In a Box (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 31.

Table 31. 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, Highly 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).

In the BPR research domain, that is most often viewed as a subset of the broader EOIT and process optimization research domains, the findings of this study offer new ways to calibrate the potential ROI improvement estimates when new IT technologies are used to optimize any core process. In this context, it is essential to note that BPR is not just another approach to incremental optimization but a unique and valuable perspective with its focus on radically improving the productivity of core processes that can be significantly improved by using the process analysis techniques and tools used in the current study to estimate the effects of IT technologies on process productivity and cycle time.

CIB technology could provide a means to store required AM parts data. The technical 3D data can be significant in size for these AM machines, so locally storing the data in CIB would be ideal in a bandwidth-restrained environment. AM and ML technologies are combined to improve performance in various industries. ML technologies are well suited for repeatable manual tasks that rely on underlining mathematics and data; therefore, when ML and AM are combined, process optimization is more likely. Hypotheses seven and eight were included in the current study to model the potential effects of using all the IT artifacts in combination and individually to tease out the benefits of combining the multiple technologies over using them alone. These hypotheses represent a partial replication and extension using an extreme maintenance context. The Monte Carlo simulation gives the volatility metrics that feed into the portfolio optimization process.

The potential contribution of this research is significant, particularly given the complexity of process optimization theory with extreme maintenance conditions with IT artifacts that integrate edge networks with data science to increase information availability. The current research results demonstrate that the three IT technologies should speed up the D2D times and productivity, which will also reduce risk (e.g., aircraft downtime). As such, the current research results should apply to process productivity assessment and improvement beyond extreme maintenance conditions. The methodology presented in this research is repeatable and offers potential benefits in extreme maintenance and other contexts.

In conclusion, this research addressed the use of emerging information technology in extreme maintenance conditions (e.g., aircraft maintenance) and applies to other supply chain management areas (e.g., ground or maritime maintenance) through an information sciences approach and provides a pathway to make the much-needed process optimizations to forward deployed combat repair teams.

B. RESEARCH LIMITATIONS

One of the issues is that the potential emerging technologies (AM, CIB, ML) have not been tested in extreme maintenance conditions. This dissertation is not testing 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.

C. 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, that is, 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.

D. AUTHOR STATEMENT

The views expressed in this dissertation 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 dissertation is not a product of NAVAIR.

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APPENDIX A. GRUBBS TEST SUBPROCESS COMPLEXITY

A Grubbs test for outliers was conducted on the roll-up of the complexity of the subprocesses (Table 32). The repair subprocess is considered an outlier compared to the other subprocesses.

Table 32. Grubbs Test for Outliers Subprocess Complexity

Grubbs Test for Outliers
Model Inputs:
RO Complexity
Grubbs Stat (Smallest Data): 1.185668
Grubbs Stat (Largest Data): 1.832397
G Critical @ 0.01: 2.097304
G Critical @ 0.05: 1.938135
G Critical @ 0.10: 1.827976
Minimum: 2.910000
Average: 3.947143
Maximum: 5.550000
Outlier: 5.550000
Null Hypothesis: All data values are from the same normal population (no outliers)

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APPENDIX B. ANOVA RESULTS

Model Inputs:						
VAR1; VAR2; VAR3						
As Is, AM, CIB						
One Way ANOVA with Randomized Multiple Treatments						
		DF	Adj SS	Adj MS	F-Stat	P-Value
Treatment Factor (Column)		2	123.282	61.6408	20.363	0
Error	2997	9072.13	3.0271			
Total	2999	9195.41	3.0662			
R-Square		0.0134%				
Adj R-Square		0.0127%				
Std Error		1.7398				
F Critical at 10% : 2.304355						
F Critical at 5% : 2.998729						
F Critical at 1% : 4.612253						
Eta-Square:	0.013407					
Omega-Square:	0.012744					
One or more of the treatments has statistically significant effect at Alpha 1% on at least one of the levels						

Tukey HSD Kramer

Alpha 0.05

Treatment	Mean	N	Sum of Squares	DF	Q-Crit
VAR1	16.6521	1,000	3,461.0778		
VAR2	16.1749	1,000	2,326.4654		
VAR3	16.2947	1,000	3,284.5879		
		3,000	9,072.1311	2,997	3.3140

Comparative Q-Test

Alpha 0.05

Treatment 1	Treatment 2	Mean	Std Error	Q-Stat	Lower
VAR1	VAR2	0.4772	0.0550	8.6741	0.2949
VAR1	VAR3	0.3574	0.0550	6.4956	0.1750
VAR2	VAR3	0.1199	0.0550	2.1785	-0.0625

Treatment 1	Treatment 2	Upper	P-Value	Mean-Crit	Cohen D
VAR1	VAR2	0.6596	0.0000	0.1823	0.2743
VAR1	VAR3	0.5397	0.0000	0.1823	0.2054
VAR2	VAR3	0.3022	0.2722	0.1823	0.0689

DUNNETT'S TEST

Alpha 0.05

Treatment	Mean	N	Sum of Squares	DF	D-Crit
VAR1	16.6521	1,000	3,461.0778		
VAR2	16.1749	1,000	2,326.4654		
VAR3	16.2947	1,000	3,284.5879		
		3,000	9,072.1311	2,997	2.2120

D-TEST

Alpha 0.05

Treatment	Mean	Std Error	D-Stat	Lower	Upper	P-Value
VAR2	0.4772	0.0778	6.1335	0.3051	0.6494	0.0000
VAR3	0.3574	0.0778	4.5931	0.1853	0.5295	0.0000

Treatment	Mean-Crit	Cohen D
VAR2	0.1721	0.2743
VAR3	0.1721	0.2054

GAMES HOWELL

Alpha 0.05

Treatment	Mean	N	Variance
VAR1	16.6521	1,000	3.4645
VAR2	16.1749	1,000	2.3288
VAR3	16.2947	1,000	3.2879

Model Inputs: **VAR1; VAR2; VAR3; VAR4; VAR5** **As Is, AM, CIB, ML, AM + CIB + ML**					
One Way ANOVA with Randomized Multiple Treatments					
	DF	**Adj SS**	**Adj MS**	**F-Stat**	**P-Value**
Treatment Factor	4.00	12069.61	3017.40	1203.20	0.00
Error	4995.00	12526.65	2.51		
Total	4999.00	24596.18	4.92		
R-Square	49.07%				
Adj R-Square	49.03%				
Std Error	1.58				
F Critical at 10% :	1.945986				
F Critical at 5% :	2.373711				
F Critical at 1% :	3.322926				
Eta-Square :	0.49071				
Omega-Square :	0.490253				
One or more of the treatments has statistically significant effect at Alpha 1% on at least one of the levels.					

Tukey HSD Kramer

Alpha 0.05

Treatment	Mean	N	Sum of Squares	DF	Q-Crit
VAR1	16.6521	1,000	3,461.0778		
VAR2	16.1749	1,000	2,326.4654		
VAR3	16.2947	1,000	3,284.5879		
VAR4	12.5303	1,000	1,859.8886		
VAR5	14.3725	1,000	1,594.5417		

	5,000	12,526.5614	4,995	3.8580

Comparative Q-Test

Alpha	0.05

Treatment 1	Treatment 2	Mean	Std Error	Q-Stat	Lower
VAR1	VAR2	0.4772	0.0501	9.5299	0.2840
VAR1	VAR3	0.3574	0.0501	7.1364	0.1642
VAR1	VAR4	4.1219	0.0501	82.3086	3.9287
VAR1	VAR5	2.2796	0.0501	45.5209	2.0864
VAR2	VAR3	0.1199	0.0501	2.3935	-0.0733
VAR2	VAR4	3.6446	0.0501	72.7787	3.4514
VAR2	VAR5	1.8024	0.0501	35.9910	1.6092
VAR3	VAR4	3.7645	0.0501	75.1721	3.5713
VAR3	VAR5	1.9222	0.0501	38.3844	1.7290
VAR4	VAR5	1.8423	0.0501	36.7877	1.6491

Treatment 1	Treatment 2	Upper	P-Value	Mean-Crit	Cohen D
VAR1	VAR2	0.6704	0.0000	0.1932	0.3014
VAR1	VAR3	0.5506	0.0000	0.1932	0.2257
VAR1	VAR4	4.3151	0.0000	0.1932	2.6028
VAR1	VAR5	2.4728	0.0000	0.1932	1.4395
VAR2	VAR3	0.3131	0.4387	0.1932	0.0757
VAR2	VAR4	3.8378	0.0000	0.1932	2.3015
VAR2	VAR5	1.9956	0.0000	0.1932	1.1381
VAR3	VAR4	3.9577	0.0000	0.1932	2.3772
VAR3	VAR5	2.1154	0.0000	0.1932	1.2138
VAR4	VAR5	2.0355	0.0000	0.1932	1.1633

DUNNETT'S TEST

Alpha	0.05

Treatment	Mean	N	Sum of Squares	DF	D-Crit
VAR1	16.6521	1,000	3,461.0778		
VAR2	16.1749	1,000	2,326.4654		
VAR3	16.2947	1,000	3,284.5879		
VAR4	12.5303	1,000	1,859.8886		
VAR5	14.3725	1,000	1,594.5417		

	5,000	12,526.5614	4,995	2.4420

D-TEST

Alpha 0.05

Treatment	Mean	Std Error	D-Stat	Lower	Upper	P-Value
VAR2	0.4772	0.0708	6.7387	0.3043	0.6502	0.0000
VAR3	0.3574	0.0708	5.0462	0.1844	0.5303	0.0000
VAR4	4.1219	0.0708	58.2009	3.9489	4.2948	0.0000
VAR5	2.2796	0.0708	32.1881	2.1067	2.4525	0.0000

Treatment	Mean-Crit	Cohen D
VAR2	0.1729	0.3014
VAR3	0.1729	0.2257
VAR4	0.1729	2.6028
VAR5	0.1729	1.4395

GAMES HOWELL

Alpha 0.05

Treatment	Mean	N	Variance
VAR1	16.6521	1,000	3.4645
VAR2	16.1749	1,000	2.3288
VAR3	16.2947	1,000	3.2879
VAR4	12.5303	1,000	1.8618
VAR5	14.3725	1,000	1.5961

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APPENDIX C. PRODUCTIVITY TRIANGLE DISTRIBUTION

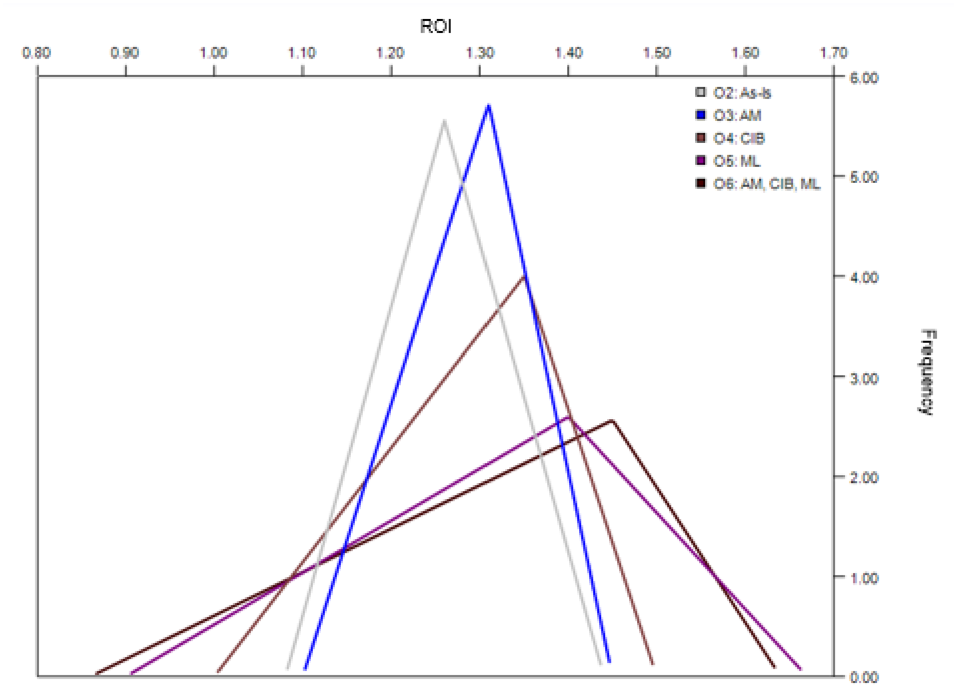

Figure 32. Productivity Triangle Distribution

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APPENDIX D. ROI AND ROK SUB-PROCESS ANALYSIS

Table 33. ROI/ROK Sub-Process Analysis

Sub-Process #	Sub-Process	Learning Time (hours)	Rank Order (In Complexity)	Cost (Work Time X the # Employees hours)	Average Time to Complete (hours)	IT Baseline Automation (% automation * output)	ROK	ROI
1	Maintenance Request	5.7	1	$1,162.93	7.78	26.7%	77.2%	10.7%
2	Depot Repair Decision	21.3	6	$8,536.34	22.56	14.2%	95.3%	42.0%
3	Maintenance Induction	6.3	4	$1,789.64	9.89	22.5%	66.4%	-3.8%
4	Part Inventory	5.8	3	$1,055.63	8.44	15.0%	70.9%	3.7%
5	Repair	41.1	7	$28,770.86	65.56	8.3%	62.8%	-6.0%
6	Inspection	13.5	5	$3,306.93	13.50	7.5%	100.4%	49.8%
7	End Item Delivery	6.1	2	$1,087.38	7.11	15.8%	88.6%	29.5%
	Correlation		**84.3%**					**99.7%**

Formulas:	**Surrogate Revenue**
Return on Investment = (Revenue - Cost) / Cost	$68,564.55
Return on Knowledge = Learning Time (K) / Cost	**Total Cost**
Rank order = how hard it is to learn (Complex)	$45,709.70
Productivity = Output / Input	**Ratio for**
Correlation between learning time & rank order based in complexit	**Market Comp.**
Correlation between ROK and ROI	1.50
IT Baseline = % automation * output	

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APPENDIX E. CYCLE TIME HYPOTHESES DATA

As Is	*AM*	*CIB*	*ML*	*AM + CIB + ML*
15.28	*14.16*	*16.22*	*16.60*	*16.43*
16.33	*15.56*	*19.32*	*13.78*	*16.37*
13.11	*15.04*	*15.48*	*18.49*	*16.52*
17.44	*15.22*	*16.92*	*16.27*	*16.59*
19.83	*14.02*	*14.44*	*15.05*	*17.00*
14.71	*17.49*	*15.41*	*16.89*	*17.48*
16.92	*17.08*	*17.37*	*12.92*	*18.52*
18.41	*17.91*	*13.48*	*15.50*	*15.99*
15.43	*19.48*	*17.32*	*15.06*	*15.70*
17.55	*16.89*	*16.25*	*14.52*	*15.42*
16.77	*14.58*	*15.63*	*16.21*	*15.57*
14.59	*18.71*	*13.75*	*18.18*	*15.88*
17.35	*13.55*	*14.10*	*14.39*	*14.11*
15.67	*16.34*	*15.40*	*18.77*	*17.41*
18.33	*14.89*	*13.91*	*14.22*	*15.68*
19.92	*15.76*	*17.83*	*17.85*	*14.36*
16.61	*15.40*	*13.48*	*15.34*	*15.45*
16.09	*15.63*	*12.45*	*15.90*	*17.19*
18.81	*17.38*	*13.79*	*13.12*	*17.48*
15.13	*18.01*	*16.27*	*14.75*	*14.36*
14.34	*15.63*	*16.26*	*15.00*	*16.09*
15.64	*13.79*	*14.49*	*14.60*	*15.72*
18.03	*14.62*	*14.25*	*17.06*	*18.63*
15.71	*19.23*	*17.10*	*17.08*	*16.58*
19.71	*16.31*	*17.30*	*14.13*	*13.44*
12.99	*14.32*	*13.63*	*14.72*	*14.79*
13.89	*18.46*	*16.26*	*16.90*	*18.63*
14.29	*17.82*	*17.34*	*17.51*	*13.84*
15.71	*14.79*	*17.64*	*14.22*	*14.09*
17.59	*16.70*	*14.99*	*13.17*	*16.12*
15.23	*14.90*	*16.95*	*15.83*	*14.68*
17.07	*16.91*	*15.44*	*14.93*	*16.02*
14.75	*19.48*	*18.59*	*13.46*	*15.43*
18.56	*17.00*	*15.44*	*17.09*	*17.41*
16.52	*15.26*	*17.60*	*16.76*	*15.52*
17.94	*17.51*	*16.41*	*13.61*	*15.37*
16.09	*18.17*	*13.23*	*16.36*	*18.07*

18.85	*15.33*	*18.57*	*16.01*	*15.62*
16.35	*16.27*	*15.62*	*15.03*	*17.43*
15.75	*15.44*	*17.29*	*16.89*	*15.04*
20.35	*15.42*	*15.81*	*14.10*	*14.18*
19.85	*16.08*	*18.15*	*14.42*	*15.73*
18.28	*14.61*	*14.97*	*12.87*	*14.51*
15.49	*18.71*	*14.35*	*13.76*	*15.90*
16.76	*17.71*	*17.19*	*15.26*	*15.71*
19.69	*18.66*	*15.71*	*17.59*	*13.86*
16.22	*14.17*	*17.29*	*16.88*	*15.44*
13.64	*16.19*	*18.71*	*15.94*	*13.25*
16.05	*16.09*	*17.11*	*14.34*	*16.30*
15.38	*15.29*	*15.56*	*14.45*	*16.22*
16.03	*14.63*	*16.78*	*14.86*	*16.72*
14.55	*16.79*	*19.24*	*16.34*	*14.55*
12.52	*14.24*	*18.83*	*14.14*	*13.58*
17.57	*16.11*	*15.98*	*16.04*	*14.11*
18.15	*13.71*	*16.47*	*13.69*	*14.31*
13.31	*14.63*	*16.21*	*16.89*	*14.64*
17.37	*16.60*	*14.21*	*14.83*	*16.52*
15.18	*16.24*	*15.68*	*13.68*	*14.82*
16.19	*16.44*	*14.51*	*15.35*	*13.08*
15.34	*16.47*	*16.32*	*14.19*	*17.89*
18.18	*18.07*	*17.27*	*14.02*	*17.15*
15.68	*16.79*	*16.36*	*14.38*	*16.56*
20.23	*14.72*	*14.03*	*15.62*	*15.95*
16.13	*19.31*	*16.74*	*15.39*	*16.99*
14.58	*14.32*	*15.52*	*15.25*	*16.51*
14.91	*18.15*	*13.30*	*13.67*	*17.31*
16.45	*16.94*	*15.32*	*17.27*	*15.58*
18.09	*18.49*	*20.22*	*15.43*	*15.47*
17.03	*13.27*	*14.31*	*15.09*	*14.95*
15.04	*16.00*	*16.96*	*18.00*	*16.26*
15.42	*12.75*	*12.38*	*15.03*	*16.96*
17.38	*16.36*	*15.00*	*15.31*	*16.34*
16.27	*16.57*	*15.96*	*14.95*	*14.95*
15.51	*18.23*	*14.95*	*14.07*	*16.79*
16.48	*19.57*	*13.74*	*13.87*	*14.86*
14.34	*19.29*	*19.20*	*14.36*	*15.81*
17.92	*15.15*	*13.79*	*15.37*	*16.19*
16.43	*16.91*	*18.97*	*13.71*	*16.80*

15.00	16.95	16.51	17.13	17.91
20.20	16.61	17.94	14.11	17.96
15.68	14.93	16.25	14.37	14.48
15.44	18.40	18.73	14.12	16.45
17.45	16.63	13.04	18.59	17.54
14.57	16.22	19.20	16.57	16.93
17.15	19.28	14.28	15.10	16.04
18.18	16.02	14.89	14.18	14.99
16.70	14.75	17.85	14.57	14.54
16.69	17.51	18.62	14.87	15.27
16.81	17.48	17.70	15.21	14.17
17.08	16.80	16.54	18.06	16.97
16.43	16.90	12.88	15.02	15.40
15.76	13.96	13.63	16.11	15.48
18.42	16.98	17.49	17.53	14.52
16.47	17.79	17.84	16.99	15.54
15.93	16.71	16.85	15.29	15.01
18.44	14.95	17.44	14.76	17.98
14.25	18.48	15.12	15.03	16.97
18.60	14.60	15.92	17.48	17.14
16.28	17.11	14.80	18.05	15.93
18.65	13.81	18.30	14.67	16.34
17.99	18.07	17.36	15.74	15.71
18.48	13.89	16.70	13.92	16.03
14.03	15.65	17.81	16.32	15.02
19.03	15.91	15.61	13.92	15.29
15.54	15.91	18.53	12.91	18.10
17.32	15.87	17.03	17.86	15.63
17.95	15.72	16.06	16.11	14.81
15.20	14.94	17.26	17.80	18.22
18.03	16.55	15.25	15.01	16.71
13.44	18.72	16.35	16.31	16.31
16.16	17.13	17.46	17.98	15.39
15.65	13.00	17.29	15.88	17.02
16.10	15.93	16.96	16.30	17.00
17.72	18.63	13.92	15.48	13.36
17.41	17.29	15.91	14.07	16.12
17.63	14.51	16.36	14.68	17.68
17.60	18.52	19.08	14.84	13.33
12.74	16.88	16.26	14.85	17.55
15.11	16.32	13.52	14.02	16.18

15.66	*19.12*	*16.69*	*15.72*	*13.55*
14.14	*17.84*	*20.03*	*16.24*	*18.21*
17.36	*15.43*	*16.68*	*15.08*	*16.42*
14.55	*16.21*	*15.92*	*16.24*	*14.33*
16.44	*16.22*	*15.35*	*16.24*	*16.94*
13.09	*16.03*	*17.84*	*15.87*	*16.97*
14.15	*16.96*	*15.12*	*15.69*	*15.04*
17.76	*16.50*	*19.07*	*14.56*	*17.06*
18.62	*18.69*	*14.91*	*14.94*	*15.49*
17.61	*14.16*	*13.71*	*16.12*	*16.78*
17.75	*14.39*	*15.74*	*13.07*	*14.39*
18.30	*16.90*	*18.55*	*16.70*	*12.91*
17.34	*13.83*	*15.76*	*17.46*	*17.36*
19.82	*13.78*	*20.76*	*13.98*	*17.91*
16.94	*16.51*	*14.35*	*17.32*	*15.15*
16.69	*15.26*	*19.35*	*14.85*	*14.20*
19.40	*15.70*	*13.96*	*17.16*	*14.08*
20.08	*15.42*	*14.98*	*15.23*	*15.80*
13.13	*17.09*	*14.22*	*14.56*	*14.64*
18.09	*16.45*	*15.48*	*15.40*	*15.66*
17.24	*14.16*	*19.38*	*16.37*	*14.71*
14.25	*19.39*	*16.28*	*16.43*	*16.29*
16.65	*17.16*	*16.58*	*16.21*	*14.09*
15.29	*18.93*	*16.40*	*16.89*	*17.57*
17.27	*17.72*	*16.66*	*16.11*	*17.67*
18.69	*15.99*	*18.78*	*16.32*	*15.98*
19.59	*19.01*	*16.20*	*17.44*	*15.85*
18.40	*15.91*	*15.81*	*16.15*	*18.12*
20.26	*17.81*	*16.37*	*16.86*	*18.10*
15.58	*14.61*	*16.11*	*14.18*	*17.72*
18.33	*13.80*	*16.36*	*15.76*	*17.00*
18.27	*16.34*	*15.25*	*16.81*	*15.39*
17.46	*14.03*	*17.77*	*14.40*	*16.54*
16.79	*15.17*	*17.05*	*14.37*	*15.13*
18.46	*16.49*	*18.20*	*17.11*	*17.75*
18.21	*15.46*	*17.64*	*16.27*	*16.29*
17.51	*13.03*	*17.53*	*16.71*	*16.69*
18.87	*16.06*	*18.61*	*13.81*	*16.56*
15.34	*14.51*	*16.70*	*14.88*	*15.24*
19.03	*13.90*	*15.26*	*13.96*	*15.71*
13.00	*16.28*	*14.95*	*17.35*	*14.27*

15.01	*15.01*	*17.03*	*16.06*	*13.42*
16.44	*17.55*	*16.72*	*14.28*	*16.50*
17.38	*15.62*	*19.77*	*15.41*	*17.13*
13.52	*15.74*	*16.53*	*15.51*	*13.45*
17.43	*13.04*	*16.34*	*15.64*	*13.76*
17.70	*13.60*	*16.91*	*14.63*	*16.22*
14.41	*17.42*	*18.25*	*16.17*	*15.96*
17.25	*17.77*	*14.86*	*13.68*	*14.95*
16.43	*16.48*	*15.81*	*16.07*	*16.44*
16.71	*14.14*	*17.94*	*14.78*	*15.52*
17.29	*19.67*	*17.46*	*17.20*	*15.77*
14.91	*17.25*	*13.75*	*15.88*	*15.29*
16.18	*14.72*	*15.40*	*15.80*	*16.04*
18.88	*16.28*	*15.31*	*18.18*	*14.79*
15.05	*14.63*	*16.13*	*14.68*	*16.12*
13.75	*16.69*	*18.25*	*17.34*	*16.01*
17.10	*15.10*	*15.40*	*17.31*	*18.16*
14.43	*13.77*	*19.58*	*14.45*	*15.30*
18.94	*17.26*	*16.87*	*16.59*	*17.17*
15.37	*15.19*	*17.92*	*13.88*	*17.00*
20.32	*17.64*	*18.13*	*13.80*	*14.61*
16.41	*16.34*	*16.06*	*14.77*	*15.53*
16.95	*18.36*	*14.69*	*13.63*	*16.69*
14.50	*18.10*	*16.00*	*15.92*	*15.60*
18.34	*16.43*	*13.47*	*16.04*	*15.34*
16.47	*16.43*	*17.25*	*15.27*	*15.23*
18.31	*17.82*	*17.47*	*13.73*	*16.08*
18.18	*15.92*	*14.74*	*16.34*	*15.97*
17.07	*16.69*	*17.14*	*17.02*	*16.82*
19.91	*16.38*	*16.49*	*13.31*	*16.54*
16.04	*17.90*	*14.46*	*16.31*	*18.82*
16.19	*17.28*	*14.47*	*16.60*	*16.61*
19.01	*18.00*	*20.02*	*12.57*	*16.20*
17.80	*14.77*	*13.90*	*15.54*	*17.96*
17.72	*16.91*	*17.37*	*13.81*	*17.10*
14.66	*18.35*	*14.85*	*17.37*	*15.51*
19.26	*13.54*	*17.02*	*16.54*	*17.75*
19.63	*16.91*	*12.28*	*13.74*	*14.52*
12.91	*15.19*	*16.05*	*12.94*	*16.37*
17.79	*16.76*	*17.13*	*14.56*	*13.72*
18.05	*15.99*	*12.13*	*13.72*	*18.38*

17.67	*14.51*	*13.42*	*17.37*	*17.19*
16.61	*16.30*	*15.19*	*15.09*	*17.02*
18.61	*14.98*	*14.89*	*13.59*	*16.42*
13.23	*14.75*	*12.34*	*15.02*	*17.79*
16.29	*15.07*	*17.29*	*15.33*	*14.23*
16.71	*15.10*	*19.61*	*17.07*	*16.30*
16.39	*13.53*	*16.57*	*16.62*	*14.92*
18.19	*16.65*	*13.99*	*14.58*	*16.43*
16.56	*12.80*	*13.08*	*14.39*	*17.05*
16.55	*15.86*	*16.75*	*15.82*	*13.17*
16.94	*15.97*	*16.98*	*14.13*	*16.09*
16.38	*16.05*	*16.81*	*16.71*	*15.31*
15.16	*16.44*	*15.99*	*16.61*	*15.43*
18.27	*16.96*	*16.14*	*17.02*	*17.43*
16.22	*13.96*	*17.65*	*16.32*	*15.76*
16.27	*14.88*	*16.25*	*16.06*	*16.31*
13.95	*16.89*	*15.73*	*17.03*	*13.91*
20.71	*15.83*	*15.81*	*14.40*	*16.96*
15.62	*13.34*	*15.47*	*17.73*	*15.68*
19.27	*16.50*	*15.13*	*17.10*	*13.46*
18.25	*19.11*	*17.59*	*16.34*	*16.21*
16.52	*17.03*	*18.94*	*16.30*	*14.45*
15.12	*12.54*	*19.21*	*14.16*	*14.94*
16.90	*14.83*	*16.70*	*16.31*	*15.46*
15.99	*15.36*	*14.94*	*13.44*	*16.15*
16.05	*17.35*	*18.08*	*14.70*	*16.05*
18.61	*18.81*	*16.92*	*15.97*	*17.20*
14.19	*18.62*	*17.07*	*14.55*	*16.19*
15.51	*16.17*	*17.21*	*13.63*	*16.11*
15.62	*14.04*	*14.35*	*16.25*	*17.40*
17.67	*13.09*	*16.59*	*15.43*	*16.41*
16.52	*17.23*	*17.26*	*14.04*	*14.85*
17.72	*18.19*	*16.96*	*14.14*	*15.24*
15.40	*15.69*	*15.36*	*14.86*	*14.36*
17.20	*16.40*	*15.48*	*13.93*	*14.05*
18.86	*16.72*	*14.36*	*15.42*	*15.10*
15.50	*16.63*	*14.00*	*15.15*	*17.27*
18.48	*15.80*	*14.10*	*18.36*	*15.47*
15.97	*15.12*	*16.38*	*13.24*	*17.46*
16.10	*18.08*	*16.41*	*16.62*	*15.20*
19.41	*17.51*	*18.15*	*15.73*	*15.07*

14.38	*16.99*	*16.01*	*15.16*	*16.96*
18.60	*16.53*	*14.63*	*17.21*	*17.80*
13.91	*17.45*	*14.80*	*14.80*	*15.88*
18.81	*15.13*	*15.45*	*18.03*	*16.83*
15.88	*13.74*	*15.27*	*14.51*	*16.55*
20.37	*14.34*	*15.78*	*14.31*	*15.43*
16.59	*17.52*	*16.52*	*14.07*	*16.66*
14.26	*19.35*	*17.40*	*14.30*	*16.02*
18.13	*13.86*	*16.98*	*13.80*	*17.01*
17.15	*16.86*	*14.69*	*14.70*	*15.72*
17.42	*16.08*	*18.44*	*16.85*	*17.67*
13.71	*15.82*	*14.58*	*16.37*	*17.06*
17.68	*14.89*	*20.16*	*15.52*	*15.73*
15.52	*15.07*	*13.46*	*15.80*	*15.49*
18.91	*16.38*	*14.10*	*15.20*	*18.53*
15.44	*15.91*	*14.57*	*15.25*	*14.13*
15.65	*18.61*	*13.80*	*16.53*	*16.60*
12.54	*18.61*	*17.46*	*14.49*	*16.41*
17.72	*17.59*	*19.91*	*15.06*	*17.20*
16.88	*13.96*	*13.98*	*16.07*	*15.95*
15.88	*16.59*	*16.84*	*17.54*	*16.14*
13.99	*15.58*	*16.05*	*16.89*	*16.37*
17.30	*14.98*	*17.59*	*15.97*	*15.92*
18.05	*14.31*	*14.95*	*16.85*	*15.71*
15.86	*16.30*	*18.18*	*17.79*	*16.47*
13.59	*16.46*	*17.59*	*15.79*	*15.74*
14.84	*15.44*	*16.46*	*17.66*	*16.75*
17.68	*15.50*	*14.55*	*14.26*	*16.26*
17.39	*16.19*	*18.74*	*15.80*	*13.47*
16.49	*13.82*	*15.60*	*17.28*	*14.07*
16.25	*17.87*	*15.32*	*14.43*	*14.62*
18.43	*17.45*	*17.14*	*14.53*	*15.95*
16.70	*16.64*	*18.29*	*15.04*	*15.77*
15.61	*17.08*	*18.06*	*17.38*	*17.04*
16.24	*18.78*	*13.26*	*14.35*	*16.96*
18.63	*16.75*	*14.94*	*17.58*	*14.79*
20.53	*14.99*	*18.42*	*15.48*	*13.54*
15.79	*13.42*	*15.34*	*16.54*	*17.79*
19.32	*16.91*	*19.12*	*16.12*	*14.20*
13.04	*16.86*	*16.43*	*14.01*	*16.67*
18.00	*15.12*	*16.13*	*13.60*	*16.46*

16.47	*17.57*	*13.76*	*15.22*	*15.35*
14.65	*16.37*	*17.60*	*13.33*	*16.00*
15.44	*17.34*	*15.53*	*14.95*	*14.35*
15.38	*15.85*	*13.30*	*18.07*	*17.54*
17.90	*13.27*	*15.77*	*13.81*	*16.85*
14.65	*14.35*	*13.82*	*14.32*	*15.76*
17.84	*17.48*	*17.85*	*17.01*	*16.11*
16.77	*18.73*	*18.48*	*15.19*	*16.87*
15.91	*18.64*	*18.65*	*14.04*	*17.13*
15.34	*15.51*	*14.42*	*12.98*	*15.77*
15.75	*14.85*	*16.29*	*14.23*	*17.80*
16.34	*15.89*	*19.89*	*16.11*	*14.63*
13.10	*16.01*	*16.55*	*15.79*	*17.03*
16.57	*19.36*	*16.31*	*16.69*	*16.22*
15.68	*16.39*	*16.96*	*14.31*	*16.04*
18.29	*14.42*	*14.93*	*14.68*	*15.94*
18.51	*19.08*	*13.63*	*16.46*	*14.39*
16.69	*15.36*	*16.83*	*17.50*	*14.39*
13.99	*19.01*	*14.69*	*14.57*	*16.75*
19.11	*15.77*	*15.31*	*14.90*	*15.38*
15.40	*17.90*	*15.75*	*15.18*	*14.47*
18.11	*16.51*	*15.27*	*15.98*	*14.47*
15.55	*14.80*	*17.36*	*14.13*	*15.42*
13.50	*15.71*	*17.97*	*15.32*	*15.20*
14.72	*15.72*	*16.72*	*16.08*	*15.93*
15.84	*15.61*	*15.74*	*15.30*	*16.41*
16.09	*17.88*	*18.71*	*17.76*	*14.96*
20.03	*16.57*	*17.12*	*15.83*	*15.46*
19.41	*13.29*	*19.55*	*16.59*	*17.20*
19.09	*15.18*	*13.06*	*17.43*	*16.54*
16.65	*16.58*	*18.19*	*13.33*	*14.64*
18.99	*15.22*	*17.42*	*17.54*	*17.01*
16.15	*14.90*	*18.19*	*18.37*	*16.81*
16.34	*15.38*	*17.72*	*17.58*	*15.55*
16.39	*17.17*	*14.68*	*13.77*	*15.51*
14.49	*15.89*	*18.04*	*16.89*	*16.29*
13.70	*15.46*	*16.22*	*16.59*	*14.54*
18.20	*13.30*	*18.32*	*16.57*	*15.46*
17.58	*18.21*	*17.61*	*16.77*	*18.12*
17.67	*14.78*	*19.82*	*12.91*	*15.59*
16.99	*16.21*	*14.03*	*15.50*	*14.98*

18.11	*15.82*	*17.52*	*16.10*	*13.58*
16.38	*16.06*	*18.68*	*14.74*	*16.72*
13.67	*17.29*	*13.41*	*16.93*	*18.28*
16.20	*16.05*	*20.23*	*15.66*	*16.62*
16.88	*19.56*	*15.86*	*13.98*	*16.52*
19.70	*15.98*	*17.95*	*15.18*	*13.78*
16.89	*14.89*	*19.43*	*15.54*	*15.55*
15.96	*15.32*	*14.55*	*16.43*	*17.70*
14.96	*13.00*	*16.11*	*13.54*	*17.58*
19.66	*14.42*	*14.31*	*13.22*	*18.57*
14.06	*16.24*	*16.63*	*16.77*	*16.57*
18.14	*13.23*	*16.80*	*18.38*	*14.13*
20.58	*16.92*	*16.21*	*14.55*	*14.70*
18.71	*17.56*	*16.51*	*15.24*	*16.28*
14.12	*15.29*	*15.09*	*15.98*	*15.94*
16.81	*16.36*	*15.49*	*14.47*	*16.77*
18.33	*15.36*	*17.72*	*15.20*	*17.95*
13.05	*16.82*	*14.34*	*16.93*	*16.30*
15.82	*17.06*	*14.66*	*16.02*	*17.79*
16.73	*16.34*	*14.68*	*17.30*	*13.87*
14.40	*16.61*	*17.40*	*15.17*	*17.50*
18.37	*15.16*	*19.02*	*14.74*	*14.58*
15.05	*17.00*	*15.68*	*14.51*	*15.19*
17.56	*18.46*	*13.09*	*14.75*	*14.56*
14.80	*16.79*	*17.37*	*16.86*	*15.13*
16.11	*14.13*	*16.87*	*16.28*	*18.48*
20.49	*15.58*	*16.08*	*14.21*	*16.27*
14.80	*16.57*	*15.59*	*15.58*	*14.51*
18.05	*17.22*	*18.39*	*16.11*	*15.61*
17.33	*15.56*	*19.41*	*14.96*	*15.03*
17.09	*16.20*	*18.75*	*16.38*	*17.41*
16.54	*18.35*	*18.69*	*14.02*	*15.91*
17.67	*16.83*	*14.82*	*14.77*	*14.66*
18.79	*15.13*	*14.59*	*15.94*	*14.28*
13.75	*16.49*	*16.36*	*14.08*	*15.59*
16.35	*17.56*	*12.99*	*15.15*	*16.37*
13.21	*14.49*	*15.06*	*15.28*	*15.58*
16.51	*16.03*	*17.42*	*14.75*	*14.44*
15.40	*17.09*	*14.72*	*13.24*	*15.77*
13.98	*16.27*	*16.58*	*15.43*	*16.07*
16.01	*14.62*	*15.49*	*14.53*	*14.70*

12.40	*13.09*	*17.62*	*14.85*	*15.71*
17.53	*18.10*	*16.25*	*15.44*	*15.81*
16.83	*15.82*	*17.74*	*17.47*	*16.61*
16.09	*16.37*	*18.63*	*15.42*	*17.23*
15.90	*15.71*	*16.20*	*16.24*	*15.26*
19.28	*15.10*	*16.54*	*17.13*	*15.10*
18.84	*17.74*	*12.29*	*14.62*	*15.57*
16.43	*17.13*	*15.82*	*17.14*	*15.80*
16.06	*15.03*	*17.37*	*15.71*	*17.67*
17.56	*17.36*	*17.04*	*16.69*	*14.60*
18.47	*15.28*	*18.22*	*15.11*	*17.17*
17.22	*16.37*	*13.22*	*12.94*	*16.01*
16.22	*15.54*	*16.90*	*14.45*	*16.25*
17.73	*15.80*	*16.34*	*15.49*	*15.02*
17.47	*14.61*	*12.72*	*13.12*	*15.79*
14.13	*16.94*	*18.72*	*16.66*	*16.35*
14.42	*16.64*	*17.65*	*16.24*	*15.77*
16.96	*12.72*	*16.85*	*15.23*	*16.92*
19.19	*16.91*	*15.74*	*14.87*	*13.84*
13.18	*16.69*	*16.25*	*18.04*	*14.83*
15.38	*15.19*	*14.15*	*15.58*	*15.92*
17.36	*15.19*	*18.02*	*17.77*	*16.69*
19.52	*16.84*	*15.13*	*15.04*	*15.58*
18.29	*16.55*	*18.97*	*16.60*	*13.72*
17.71	*17.58*	*13.41*	*16.40*	*15.43*
20.32	*17.55*	*17.29*	*18.17*	*15.69*
16.51	*14.87*	*19.10*	*15.71*	*15.48*
18.82	*16.13*	*14.81*	*14.30*	*17.08*
15.53	*14.77*	*17.16*	*16.29*	*17.28*
15.16	*15.84*	*20.16*	*17.70*	*15.07*
16.31	*17.09*	*17.37*	*17.60*	*15.94*
16.44	*14.89*	*15.88*	*14.23*	*15.99*
18.65	*16.51*	*18.23*	*15.48*	*15.04*
17.76	*17.20*	*17.31*	*12.82*	*16.04*
15.58	*15.72*	*17.49*	*17.96*	*16.81*
16.65	*14.43*	*15.64*	*17.25*	*14.37*
16.92	*17.62*	*17.69*	*16.29*	*18.84*
18.02	*16.21*	*12.32*	*13.49*	*17.67*
17.34	*14.07*	*13.00*	*16.11*	*18.26*
17.68	*15.62*	*14.37*	*15.28*	*14.48*
16.61	*17.16*	*19.94*	*15.09*	*18.14*

13.30	*19.79*	*17.63*	*14.16*	*13.22*
15.65	*18.00*	*16.45*	*13.44*	*18.15*
12.99	*17.77*	*14.11*	*15.48*	*15.93*
14.90	*17.17*	*16.97*	*13.72*	*17.59*
14.91	*15.58*	*13.33*	*18.30*	*13.88*
14.38	*19.51*	*18.79*	*16.41*	*16.34*
18.54	*17.74*	*15.70*	*16.44*	*18.06*
18.02	*17.37*	*18.27*	*13.42*	*16.25*
18.11	*16.48*	*19.78*	*16.25*	*18.00*
18.82	*15.04*	*17.06*	*17.83*	*17.95*
18.05	*14.13*	*18.70*	*15.41*	*16.88*
17.57	*18.70*	*17.75*	*13.83*	*17.42*
15.68	*19.07*	*17.88*	*15.19*	*14.49*
14.86	*16.07*	*15.81*	*15.63*	*16.81*
16.27	*18.21*	*16.70*	*15.40*	*14.45*
17.21	*15.70*	*15.65*	*13.11*	*14.78*
19.06	*15.55*	*19.41*	*16.68*	*17.42*
17.81	*18.67*	*18.55*	*18.12*	*15.14*
18.38	*12.95*	*17.53*	*14.22*	*15.19*
18.28	*17.53*	*16.60*	*15.65*	*16.86*
16.05	*17.96*	*13.83*	*14.28*	*16.00*
18.81	*16.28*	*15.91*	*14.94*	*14.56*
15.55	*16.54*	*17.59*	*17.49*	*18.54*
20.01	*13.24*	*20.40*	*15.62*	*15.68*
15.24	*16.58*	*15.96*	*14.62*	*17.98*
16.21	*14.60*	*15.87*	*14.29*	*15.41*
18.45	*17.77*	*17.97*	*14.59*	*17.11*
12.85	*15.10*	*17.74*	*14.58*	*13.47*
14.81	*16.32*	*16.46*	*16.82*	*18.50*
14.97	*15.18*	*18.13*	*14.26*	*15.34*
18.11	*17.56*	*12.27*	*13.94*	*15.98*
18.15	*15.98*	*18.19*	*14.50*	*14.33*
17.60	*14.40*	*14.78*	*12.56*	*15.39*
16.43	*17.54*	*16.27*	*13.69*	*18.24*
17.71	*15.13*	*17.60*	*15.54*	*14.99*
17.69	*13.98*	*16.84*	*14.66*	*16.78*
14.42	*15.56*	*14.78*	*17.14*	*16.18*
12.55	*17.74*	*17.19*	*16.42*	*13.80*
16.94	*15.89*	*16.47*	*14.02*	*15.36*
13.32	*15.48*	*16.46*	*15.33*	*16.03*
16.17	*17.52*	*17.54*	*14.37*	*16.33*

16.65	*13.77*	*16.28*	*17.28*	*17.13*
17.59	*17.88*	*16.60*	*15.41*	*18.33*
15.78	*18.55*	*15.62*	*15.16*	*15.37*
17.24	*14.35*	*17.60*	*13.27*	*15.64*
15.41	*17.21*	*16.83*	*14.26*	*14.80*
15.95	*16.42*	*14.23*	*16.43*	*15.39*
15.82	*16.66*	*20.47*	*14.48*	*14.11*
19.69	*15.56*	*17.90*	*17.51*	*15.47*
17.74	*18.10*	*13.02*	*14.11*	*13.22*
14.13	*19.44*	*13.93*	*13.93*	*17.70*
15.40	*13.68*	*17.31*	*16.73*	*15.44*
18.06	*16.03*	*15.32*	*16.15*	*15.80*
14.20	*17.09*	*18.08*	*14.04*	*16.38*
17.72	*18.58*	*14.01*	*14.86*	*15.58*
15.37	*15.53*	*18.20*	*16.12*	*16.62*
16.08	*17.05*	*16.10*	*14.22*	*14.20*
15.99	*16.02*	*12.53*	*16.86*	*14.05*
15.48	*18.57*	*14.74*	*17.22*	*15.33*
16.51	*13.73*	*13.97*	*15.26*	*15.03*
20.54	*13.85*	*18.69*	*15.50*	*15.23*
14.69	*18.07*	*17.83*	*16.37*	*16.42*
19.42	*14.95*	*12.74*	*13.68*	*18.24*
13.40	*13.31*	*14.03*	*15.74*	*14.19*
17.38	*17.04*	*20.21*	*13.52*	*15.46*
18.12	*17.18*	*14.98*	*18.88*	*17.77*
14.95	*15.01*	*15.80*	*15.16*	*16.67*
15.66	*17.68*	*19.09*	*17.22*	*17.80*
16.59	*16.96*	*15.27*	*14.14*	*14.57*
13.45	*18.39*	*14.04*	*17.40*	*15.15*
16.37	*18.70*	*16.50*	*14.94*	*16.26*
15.46	*13.93*	*18.15*	*14.07*	*16.03*
16.32	*16.74*	*17.83*	*16.75*	*15.77*
17.56	*17.85*	*16.85*	*14.99*	*16.46*
15.09	*14.11*	*15.00*	*16.01*	*16.26*
19.87	*15.86*	*18.20*	*17.46*	*15.28*
18.73	*16.64*	*15.58*	*16.32*	*15.87*
15.30	*17.06*	*13.01*	*16.78*	*15.74*
15.13	*12.75*	*17.83*	*14.89*	*15.91*
18.68	*18.38*	*16.31*	*16.28*	*15.86*
14.93	*15.39*	*17.67*	*14.47*	*13.93*
15.82	*17.04*	*18.65*	*16.43*	*16.43*

18.75	15.08	18.96	16.96	16.55
18.43	15.33	13.45	14.80	14.80
20.02	17.65	17.98	17.59	15.72
15.06	15.44	18.84	14.05	16.87
13.23	18.62	14.09	15.18	14.33
16.79	18.01	13.95	16.04	14.51
16.85	17.73	15.32	14.06	16.21
20.19	13.99	19.27	16.02	16.55
16.82	17.90	14.53	15.46	15.98
16.04	16.23	18.20	16.72	17.25
12.60	17.57	17.58	18.13	16.31
19.31	14.35	16.34	16.33	14.57
19.65	14.78	15.94	14.14	16.44
14.37	16.26	17.09	14.85	15.81
14.33	15.71	15.10	15.29	14.94
14.77	17.35	16.92	17.41	16.75
12.64	13.52	15.43	16.78	14.46
17.92	14.04	15.49	15.54	16.53
18.64	16.54	14.89	15.41	16.80
15.80	15.96	12.50	17.01	15.56
18.75	18.00	16.38	14.85	16.67
17.24	16.35	15.26	16.42	15.74
14.45	16.22	16.80	18.24	14.52
19.15	18.14	16.86	13.07	17.75
13.22	14.81	14.14	15.99	16.33
16.78	14.56	17.78	16.25	17.56
17.86	17.30	17.82	15.48	17.50
14.44	16.32	20.00	13.66	15.98
14.81	17.62	16.77	13.61	16.06
15.71	12.84	15.04	14.89	17.33
16.39	17.83	20.06	17.55	15.44
17.37	17.23	18.47	16.24	14.75
16.42	17.44	16.75	16.97	16.66
16.04	17.23	13.72	13.68	13.31
15.89	18.28	16.46	15.45	16.76
15.08	16.64	13.26	13.72	15.26
16.75	18.41	16.05	16.99	15.77
19.02	17.38	18.42	14.08	15.00
16.11	16.91	15.29	17.34	13.97
16.15	14.97	17.66	14.97	14.62
17.00	18.44	14.42	14.85	15.95

16.83	*15.44*	*16.30*	*14.20*	*14.45*
12.96	*17.00*	*17.78*	*15.06*	*16.49*
16.80	*15.56*	*17.62*	*15.05*	*17.21*
17.16	*18.14*	*19.16*	*16.98*	*16.30*
17.51	*16.63*	*16.99*	*15.22*	*15.39*
20.51	*18.01*	*17.30*	*17.61*	*16.74*
17.12	*17.31*	*13.93*	*14.85*	*17.68*
16.89	*15.26*	*17.27*	*12.92*	*14.91*
17.64	*18.35*	*18.83*	*14.40*	*16.03*
13.35	*16.12*	*15.73*	*15.52*	*16.12*
17.60	*19.44*	*15.48*	*16.27*	*17.23*
19.42	*16.99*	*13.33*	*16.92*	*14.53*
14.53	*13.02*	*18.33*	*16.01*	*14.04*
18.14	*15.07*	*15.97*	*15.33*	*15.17*
15.68	*14.82*	*19.01*	*15.87*	*17.80*
18.03	*17.09*	*15.96*	*17.38*	*15.23*
16.62	*16.18*	*14.49*	*14.96*	*13.87*
17.16	*15.93*	*15.90*	*15.39*	*18.69*
18.77	*15.00*	*18.40*	*17.13*	*14.05*
17.56	*13.81*	*15.09*	*14.01*	*16.86*
18.28	*13.89*	*18.81*	*14.47*	*15.02*
16.53	*13.85*	*17.42*	*16.60*	*14.15*
14.93	*15.25*	*14.39*	*15.54*	*16.43*
17.36	*17.82*	*16.32*	*15.78*	*15.83*
15.76	*17.87*	*19.14*	*15.34*	*15.71*
13.78	*15.56*	*13.41*	*15.57*	*15.04*
17.60	*16.02*	*15.20*	*13.95*	*15.96*
16.23	*16.58*	*19.20*	*13.80*	*16.17*
16.79	*17.17*	*16.99*	*15.08*	*17.00*
16.96	*13.94*	*15.52*	*14.33*	*15.72*
18.58	*16.48*	*17.18*	*16.10*	*15.72*
19.64	*14.45*	*16.05*	*16.73*	*14.68*
14.28	*13.11*	*14.54*	*15.50*	*15.62*
17.91	*13.06*	*12.92*	*12.88*	*14.99*
13.16	*18.33*	*15.81*	*12.79*	*17.90*
17.10	*14.91*	*16.54*	*16.12*	*17.39*
20.59	*13.27*	*18.41*	*13.74*	*15.68*
14.07	*17.53*	*16.87*	*16.20*	*16.16*
15.38	*14.65*	*14.26*	*17.62*	*15.79*
16.71	*16.39*	*14.04*	*18.37*	*13.93*
16.88	*13.68*	*15.46*	*17.96*	*15.61*

19.41	14.78	17.14	16.35	17.25
17.77	16.60	17.72	17.61	14.74
14.00	14.54	13.67	13.68	15.25
19.62	15.79	15.58	15.22	18.31
18.76	17.38	16.18	15.61	15.70
13.17	14.16	16.62	15.85	15.31
19.56	17.05	18.80	16.20	15.94
19.20	14.40	18.67	17.00	17.36
17.43	15.84	14.84	16.40	15.48
15.88	16.08	12.96	16.14	14.40
14.45	17.10	18.66	18.23	16.09
14.49	17.21	14.03	14.71	17.09
17.15	13.69	14.36	15.82	15.06
16.06	15.13	15.85	15.73	15.62
18.31	16.25	16.36	15.69	15.32
16.31	16.37	17.52	14.21	14.09
16.88	13.91	18.61	15.37	14.71
15.00	17.70	19.04	13.97	15.47
14.59	13.30	16.81	13.10	15.07
17.11	15.16	16.92	15.34	18.43
13.89	14.01	16.16	14.61	15.36
17.21	14.91	15.46	16.03	14.38
17.07	13.09	19.23	14.36	15.08
16.75	14.66	17.23	15.15	13.84
16.91	15.52	15.11	14.36	15.03
18.11	18.52	16.25	14.76	16.72
14.62	18.62	15.10	14.27	12.97
16.44	16.67	16.91	14.02	16.14
20.48	16.20	15.20	12.75	16.93
14.45	14.01	15.83	16.53	16.76
16.23	16.53	14.75	15.16	15.70
17.93	17.74	15.02	12.83	16.14
17.58	17.26	12.63	17.54	18.14
17.37	17.31	17.66	14.35	17.06
19.13	16.41	16.53	16.99	13.98
13.34	13.84	15.08	15.20	14.32
17.54	16.33	17.46	15.66	15.30
16.96	17.19	18.29	16.51	15.07
17.26	15.69	16.87	15.70	17.52
15.17	16.15	15.67	13.26	14.45
16.04	15.51	14.59	17.84	17.28

18.72	13.71	15.71	14.93	15.56
17.49	16.47	18.12	17.35	17.56
14.41	13.43	16.17	15.81	15.60
19.27	18.41	20.31	17.79	14.73
16.68	18.87	19.64	17.84	17.20
16.85	17.09	14.83	14.71	16.74
15.77	15.60	17.79	16.28	15.83
16.66	15.65	16.34	14.98	16.23
13.30	16.42	17.44	16.11	16.83
14.90	13.52	17.73	15.96	14.93
16.44	15.54	14.99	16.52	15.40
19.06	14.04	15.98	15.48	17.26
19.76	15.62	16.50	14.09	16.13
18.14	15.15	17.66	13.91	17.57
16.79	15.87	17.00	14.91	14.52
19.65	15.05	15.35	14.27	16.38
16.64	18.83	16.74	13.43	15.14
20.36	14.28	12.57	14.97	16.19
16.19	18.83	19.96	15.49	16.42
17.53	13.47	16.64	13.76	18.48
19.49	15.29	17.03	16.41	16.60
13.09	17.09	18.80	15.85	15.62
17.33	17.52	14.92	17.17	15.42
20.52	17.46	16.25	17.21	16.20
17.37	15.10	15.85	15.57	15.90
16.99	15.95	14.08	16.19	15.85
19.18	16.95	14.72	14.32	16.66
14.95	15.41	18.35	14.94	15.03
15.36	14.94	15.92	17.88	18.00
17.18	17.15	14.05	14.13	16.47
19.05	16.42	17.29	15.48	15.40
17.50	18.29	13.95	14.50	14.42
17.04	16.54	14.81	13.95	15.95
19.74	16.55	12.99	14.06	14.52
17.49	18.62	14.09	15.90	15.33
16.23	17.88	16.09	15.74	17.48
18.66	15.45	19.51	12.98	16.21
15.77	12.77	17.32	17.06	13.84
15.56	14.87	16.88	14.42	16.49
17.47	13.10	15.23	15.23	13.29
12.51	17.00	19.68	12.86	13.14

19.71	*15.95*	*13.54*	*14.22*	*17.81*
18.45	*16.03*	*16.50*	*14.94*	*15.19*
15.28	*16.73*	*14.69*	*15.56*	*14.70*
19.67	*18.32*	*14.57*	*13.73*	*17.30*
16.40	*15.46*	*18.82*	*17.82*	*16.47*
16.14	*16.46*	*12.16*	*15.69*	*17.44*
14.44	*15.60*	*19.37*	*12.90*	*16.42*
19.02	*18.57*	*16.43*	*17.56*	*14.97*
18.55	*16.95*	*15.11*	*17.64*	*15.67*
12.92	*17.67*	*17.63*	*14.56*	*14.00*
14.02	*16.24*	*18.58*	*14.09*	*16.09*
17.19	*16.34*	*14.11*	*15.48*	*16.02*
15.18	*16.02*	*19.55*	*15.34*	*14.55*
19.07	*16.97*	*14.60*	*17.24*	*15.24*
12.24	*15.75*	*15.13*	*17.07*	*13.60*
18.06	*13.86*	*19.78*	*15.52*	*16.40*
17.01	*17.74*	*17.67*	*15.43*	*16.95*
17.22	*16.11*	*17.96*	*15.29*	*13.76*
15.78	*17.62*	*12.16*	*15.05*	*13.22*
15.93	*17.14*	*17.91*	*16.60*	*16.03*
15.75	*16.72*	*18.51*	*17.84*	*13.99*
17.67	*15.12*	*12.81*	*13.91*	*17.02*
16.80	*16.44*	*16.85*	*17.13*	*18.08*
16.16	*17.08*	*16.22*	*16.18*	*16.04*
16.14	*18.23*	*17.54*	*16.94*	*18.22*
14.84	*15.74*	*18.62*	*17.02*	*16.49*
13.07	*15.25*	*14.75*	*18.32*	*15.31*
19.59	*18.95*	*18.02*	*15.18*	*14.14*
15.90	*16.03*	*17.22*	*16.04*	*15.95*
18.06	*14.85*	*14.27*	*15.17*	*16.26*
17.36	*15.12*	*13.93*	*14.46*	*14.48*
16.29	*18.34*	*13.07*	*18.18*	*17.47*
15.59	*15.68*	*14.55*	*15.27*	*16.89*
15.24	*15.64*	*16.94*	*15.59*	*13.58*
16.32	*18.35*	*13.22*	*15.80*	*14.72*
19.52	*14.93*	*13.63*	*14.82*	*14.86*
20.20	*15.09*	*16.19*	*14.49*	*13.62*
18.10	*14.69*	*19.75*	*16.98*	*17.55*
12.92	*18.53*	*18.22*	*15.59*	*16.98*
20.14	*15.27*	*14.89*	*17.25*	*15.10*
16.08	*16.52*	*16.85*	*15.07*	*14.66*

17.85	*14.89*	*16.42*	*13.30*	*14.86*
14.92	*17.77*	*17.46*	*16.52*	*17.65*
13.31	*18.44*	*19.26*	*15.16*	*13.30*
13.56	*15.76*	*17.87*	*15.99*	*13.27*
16.64	*13.95*	*16.40*	*16.75*	*14.87*
17.32	*12.76*	*14.70*	*13.36*	*17.17*
16.04	*16.79*	*13.57*	*13.47*	*15.25*
16.85	*16.89*	*19.14*	*15.91*	*16.59*
14.80	*14.88*	*13.62*	*15.92*	*16.80*
13.39	*15.55*	*18.06*	*17.17*	*14.85*
20.47	*17.61*	*19.57*	*15.04*	*16.50*
17.35	*17.07*	*17.43*	*16.89*	*16.17*
14.88	*16.73*	*17.19*	*17.60*	*16.02*
16.07	*17.88*	*18.62*	*13.82*	*15.82*
16.05	*16.04*	*14.43*	*17.76*	*17.16*
15.48	*12.97*	*18.64*	*13.34*	*14.65*
15.48	*14.75*	*15.53*	*16.96*	*17.26*
16.96	*16.97*	*17.32*	*15.05*	*16.46*
18.57	*18.94*	*13.96*	*13.25*	*15.94*
16.83	*16.35*	*14.36*	*13.70*	*15.48*
14.87	*16.06*	*17.38*	*15.10*	*17.18*
16.71	*16.78*	*12.85*	*15.63*	*15.58*
17.29	*17.74*	*17.17*	*16.03*	*15.23*
20.90	*15.38*	*18.23*	*13.58*	*18.19*
17.63	*14.55*	*16.36*	*15.24*	*16.37*
16.22	*15.61*	*14.11*	*15.20*	*15.18*
17.87	*17.92*	*17.94*	*16.14*	*18.37*
18.39	*16.13*	*19.14*	*18.93*	*15.36*
19.32	*16.87*	*14.27*	*18.37*	*13.69*
20.75	*15.32*	*16.17*	*16.41*	*15.95*
15.10	*17.09*	*13.66*	*13.89*	*16.52*
13.05	*19.12*	*15.14*	*16.52*	*15.67*
14.53	*16.27*	*16.81*	*14.58*	*16.47*
18.13	*13.51*	*20.07*	*16.09*	*15.91*
16.66	*15.69*	*18.24*	*16.43*	*13.91*
12.81	*13.23*	*16.43*	*15.11*	*16.40*
14.16	*18.30*	*15.84*	*17.54*	*13.97*
12.59	*17.43*	*17.22*	*18.65*	*18.04*
18.55	*14.96*	*14.53*	*15.73*	*14.72*
16.04	*13.89*	*18.65*	*14.80*	*15.10*
19.82	*15.39*	*17.94*	*14.48*	*13.30*

18.65	*18.12*	*15.59*	*13.44*	*16.46*
12.21	*16.02*	*18.47*	*13.82*	*15.28*
15.21	*14.41*	*17.25*	*14.27*	*16.44*
20.51	*15.63*	*20.22*	*16.28*	*16.49*
15.41	*14.84*	*15.10*	*15.63*	*16.53*
19.64	*14.40*	*14.72*	*13.96*	*16.58*
18.29	*14.22*	*14.39*	*17.45*	*14.92*
14.28	*15.93*	*16.92*	*14.86*	*18.03*
15.94	*15.63*	*13.52*	*14.60*	*17.96*
15.17	*15.76*	*17.33*	*16.04*	*15.16*
17.03	*15.43*	*13.73*	*15.67*	*16.76*
17.28	*16.69*	*17.94*	*15.01*	*16.71*
18.82	*15.15*	*17.56*	*15.14*	*15.99*
14.28	*19.36*	*17.82*	*17.98*	*16.04*
16.85	*17.27*	*17.17*	*16.49*	*15.28*
19.19	*14.43*	*20.31*	*15.82*	*15.76*
16.81	*15.96*	*16.58*	*17.02*	*14.34*
16.48	*13.38*	*16.82*	*14.13*	*16.24*
16.59	*16.77*	*15.03*	*15.82*	*14.20*
13.98	*16.72*	*17.14*	*16.42*	*17.16*
15.24	*16.67*	*17.57*	*13.84*	*16.76*
18.55	*16.82*	*15.56*	*14.52*	*17.24*
16.56	*16.71*	*14.67*	*17.58*	*14.76*
16.20	*17.11*	*18.70*	*14.70*	*13.91*
13.92	*15.73*	*16.90*	*14.95*	*13.84*
19.13	*16.19*	*13.51*	*16.03*	*14.89*
15.33	*16.11*	*15.11*	*16.59*	*14.82*
19.28	*17.08*	*16.07*	*13.78*	*15.20*
18.36	*17.00*	*15.65*	*14.81*	*14.36*
18.74	*16.00*	*15.50*	*15.12*	*16.55*
15.99	*17.27*	*15.74*	*16.13*	*16.77*
18.75	*13.08*	*15.80*	*13.44*	*17.27*
15.69	*16.54*	*17.28*	*13.03*	*16.19*
20.70	*15.67*	*16.02*	*16.31*	*15.18*
17.64	*15.25*	*17.90*	*18.56*	*15.06*
16.08	*13.49*	*15.35*	*14.47*	*14.80*
16.32	*14.69*	*17.16*	*17.98*	*17.30*
16.66	*14.24*	*16.76*	*13.09*	*15.44*
19.11	*15.48*	*15.79*	*14.55*	*18.32*
14.95	*13.06*	*15.54*	*16.37*	*14.41*
16.50	*13.42*	*16.90*	*13.84*	*12.97*

13.86	18.96	15.78	15.15	15.44
18.41	17.09	14.34	17.06	15.66
14.36	18.57	17.52	14.14	14.11
18.94	17.51	15.90	14.95	15.59
15.91	18.30	16.53	12.88	13.91
16.00	17.05	16.70	13.76	16.73
16.13	16.44	16.61	17.96	16.90
16.81	17.21	14.52	16.09	16.07
14.71	14.71	16.50	16.93	17.28
15.38	15.26	14.50	15.99	15.05
17.53	16.71	15.11	16.30	16.40
14.71	15.90	15.73	14.94	18.46
14.04	14.45	13.30	13.86	13.54
16.91	15.70	17.79	15.06	16.07
14.36	16.65	17.57	16.77	14.93
14.65	15.68	17.39	14.12	17.00
13.86	16.31	19.14	16.98	13.95
18.05	15.39	18.30	14.78	16.25
14.08	15.66	18.15	16.14	15.77
12.93	14.39	15.97	16.78	15.21
18.99	16.23	17.88	13.69	14.41
13.41	18.27	16.16	15.37	15.87
18.27	17.15	14.78	15.64	17.63
16.91	14.89	14.80	13.36	15.10
15.19	16.33	16.19	16.64	15.76
18.02	17.56	13.42	14.93	14.84
12.98	18.96	18.82	17.12	17.71
16.93	17.30	18.31	16.28	13.44
18.76	17.95	15.70	16.89	17.10
15.99	14.59	15.17	16.57	17.57
18.36	18.50	15.72	15.57	13.93
15.78	13.72	12.21	15.97	15.52
15.23	17.83	13.95	14.62	15.80
18.51	17.72	15.63	15.96	15.41
18.32	15.66	16.39	13.15	15.66
16.00	14.68	17.02	18.02	14.09
17.04	16.30	15.31	15.27	15.63
13.99	16.56	15.73	16.73	16.19
16.63	17.29	14.77	14.85	16.91
12.37	17.30	13.84	14.97	18.73
16.82	17.67	17.01	15.16	14.25

16.27	*15.86*	*15.57*	*13.86*	*16.56*
14.51	*15.86*	*13.18*	*15.64*	*17.01*
17.71	*16.37*	*17.13*	*17.09*	*15.49*
15.06	*16.02*	*16.61*	*13.31*	*17.29*
13.26	*14.61*	*14.56*	*14.55*	*15.64*
17.20	*14.00*	*15.23*	*18.04*	*16.06*
18.06	*18.27*	*18.59*	*14.91*	*18.48*
17.49	*15.15*	*15.08*	*13.79*	*15.73*
13.75	*17.08*	*17.11*	*15.54*	*14.04*
16.39	*14.11*	*14.99*	*18.45*	*16.93*
13.75	*15.17*	*16.79*	*15.68*	*13.97*
15.28	*15.05*	*13.75*	*16.23*	*14.09*
13.54	*14.45*	*13.66*	*12.75*	*13.73*
18.33	*16.91*	*15.44*	*17.15*	*16.61*
19.80	*14.85*	*16.14*	*15.82*	*16.93*
15.72	*16.23*	*17.11*	*14.19*	*18.17*
16.68	*17.86*	*15.30*	*14.23*	*15.84*
16.58	*15.38*	*15.44*	*14.65*	*16.75*
16.24	*14.67*	*16.63*	*13.02*	*15.55*
19.45	*16.71*	*17.08*	*15.39*	*15.14*
18.11	*17.47*	*15.77*	*14.68*	*17.18*
18.82	*17.67*	*20.18*	*16.64*	*16.78*
17.87	*16.54*	*18.95*	*16.37*	*16.15*
14.96	*17.93*	*18.79*	*15.56*	*16.09*
16.56	*15.62*	*13.17*	*13.92*	*15.18*
18.11	*16.80*	*16.05*	*14.38*	*17.33*
17.59	*18.01*	*14.50*	*17.35*	*14.81*
17.80	*16.07*	*12.42*	*14.92*	*16.29*
17.48	*15.43*	*16.53*	*15.54*	*13.35*
18.49	*15.16*	*18.22*	*15.25*	*14.71*
13.60	*17.21*	*14.07*	*17.63*	*17.01*
16.14	*17.25*	*15.07*	*18.49*	*13.98*
14.94	*15.73*	*17.86*	*17.54*	*13.96*
18.79	*15.88*	*12.79*	*15.52*	*17.31*
17.85	*17.88*	*16.61*	*17.51*	*17.53*
14.59	*17.74*	*16.44*	*13.83*	*15.83*
16.63	*17.70*	*20.06*	*13.11*	*17.03*
19.68	*17.28*	*15.02*	*13.72*	*17.06*
20.12	*14.93*	*12.72*	*14.66*	*15.65*
15.41	*16.33*	*16.93*	*15.30*	*14.57*
16.09	*15.05*	*15.42*	*15.76*	*15.79*

14.97	*14.72*	*14.77*	*13.17*	*16.38*
16.94	*14.97*	*14.28*	*15.50*	*16.14*
16.01	*15.79*	*17.69*	*13.85*	*14.39*
14.07	*14.70*	*19.11*	*16.30*	*17.51*
16.64	*17.77*	*15.21*	*15.43*	*16.32*
17.19	*14.87*	*13.42*	*17.87*	*14.12*
15.26	*16.22*	*15.91*	*15.69*	*16.23*
18.00	*16.35*	*14.81*	*15.27*	*15.00*
17.90	*13.95*	*16.38*	*16.26*	*13.75*
18.84	*17.49*	*16.40*	*14.86*	*13.90*
14.94	*15.42*	*16.83*	*16.22*	*18.10*
15.97	*18.37*	*17.43*	*15.12*	*13.65*
15.86	*14.63*	*14.68*	*15.20*	*15.33*
18.79	*12.81*	*14.65*	*15.49*	*15.52*
16.88	*19.07*	*16.27*	*15.32*	*14.57*
16.22	*15.48*	*16.70*	*15.27*	*16.86*
18.48	*17.05*	*17.54*	*17.33*	*17.48*
19.47	*18.41*	*17.42*	*15.83*	*14.94*
18.59	*17.78*	*18.06*	*15.16*	*17.59*
16.92	*18.17*	*13.61*	*15.02*	*14.74*
18.79	*16.57*	*20.32*	*17.86*	*15.95*
15.11	*17.82*	*14.23*	*15.57*	*16.07*
13.11	*15.52*	*15.13*	*15.97*	*14.87*
17.32	*15.95*	*15.38*	*15.60*	*15.61*
19.60	*15.29*	*16.78*	*14.66*	*16.07*
17.74	*14.57*	*13.49*	*15.66*	*16.24*
16.74	*15.12*	*14.70*	*14.58*	*17.65*
15.02	*17.08*	*17.87*	*15.03*	*16.45*
13.82	*17.44*	*14.54*	*13.36*	*14.81*
16.58	*16.46*	*14.52*	*14.30*	*15.09*
14.15	*16.51*	*16.52*	*18.12*	*15.04*
16.92	*13.08*	*17.47*	*15.10*	*17.04*
13.57	*17.43*	*16.73*	*17.69*	*13.63*
18.11	*14.46*	*12.15*	*16.37*	*13.23*
19.41	*16.85*	*19.10*	*17.24*	*15.33*
14.53	*14.26*	*16.55*	*13.55*	*13.95*
14.34	*19.56*	*18.53*	*14.71*	*15.90*
19.54	*17.15*	*14.91*	*12.54*	*15.43*
14.90	*19.76*	*15.81*	*15.71*	*16.25*
15.56	*14.82*	*15.01*	*12.94*	*15.73*
15.80	*16.46*	*16.13*	*14.26*	*15.42*

16.35	*16.83*	*17.13*	*15.98*	*14.28*
16.33	*16.06*	*17.08*	*14.87*	*16.50*
13.62	*18.35*	*15.30*	*15.23*	*14.25*
13.21	*18.44*	*12.09*	*15.01*	*17.08*
19.42	*15.24*	*15.67*	*14.63*	*13.66*
19.68	*18.07*	*16.49*	*15.94*	*16.72*
16.88	*16.34*	*17.27*	*17.74*	*13.87*
15.38	*13.86*	*16.78*	*17.34*	*17.71*
17.80	*15.55*	*13.31*	*17.36*	*16.05*
16.05	*18.40*	*18.05*	*17.48*	*15.62*
16.20	*16.45*	*13.63*	*15.01*	*15.70*
14.56	*15.35*	*15.82*	*15.84*	*14.63*
16.90	*18.74*	*12.75*	*15.82*	*14.40*
16.70	*14.96*	*15.65*	*15.03*	*17.22*
19.95	*15.48*	*14.01*	*15.27*	*14.19*
16.97	*14.98*	*16.20*	*16.37*	*16.43*
12.90	*13.85*	*16.92*	*14.42*	*15.31*
20.17	*16.06*	*15.42*	*15.46*	*17.60*
19.90	*16.95*	*19.99*	*16.34*	*15.48*
18.11	*15.47*	*16.14*	*16.56*	*13.64*
14.51	*16.42*	*16.04*	*13.53*	*15.75*
13.75	*16.02*	*16.97*	*14.65*	*17.36*
19.38	*17.84*	*17.14*	*17.83*	*14.53*
16.54	*15.48*	*17.99*	*14.65*	*14.57*
13.24	*18.42*	*18.36*	*15.35*	*17.48*
15.40	*15.56*	*15.86*	*13.64*	*15.35*
15.16	*17.45*	*17.35*	*16.21*	*15.95*
16.41	*16.75*	*16.59*	*16.59*	*15.02*
16.67	*17.85*	*13.10*	*15.97*	*18.49*
14.14	*13.36*	*13.12*	*15.69*	*17.50*
16.30	*16.29*	*14.54*	*15.84*	*18.77*
15.11	*17.10*	*19.48*	*14.23*	*14.70*
17.80	*13.85*	*16.57*	*17.78*	*16.35*
14.35	*14.47*	*19.68*	*15.22*	*16.60*
18.59	*17.46*	*12.96*	*13.05*	*16.42*
14.83	*18.11*	*14.81*	*15.39*	*16.92*
15.18	*15.39*	*18.19*	*14.28*	*17.60*
17.67	*16.60*	*13.82*	*16.21*	*15.17*
17.87	*16.96*	*15.74*	*15.77*	*16.03*
16.30	*15.34*	*13.85*	*18.86*	*17.34*
19.89	*13.75*	*16.85*	*17.14*	*13.90*

17.35	*16.18*	*14.37*	*17.86*	*17.08*
15.82	*16.19*	*16.25*	*15.11*	*17.95*
16.15	*15.05*	*15.66*	*13.23*	*17.88*
16.72	*13.69*	*15.22*	*14.05*	*18.24*
14.45	*15.84*	*16.11*	*15.39*	*14.91*
19.01	*17.48*	*14.82*	*15.90*	*17.14*
14.70	*17.07*	*19.59*	*13.96*	*15.08*
14.84	*16.00*	*14.30*	*17.25*	*17.97*
15.07	*14.88*	*19.69*	*15.97*	*14.45*
14.78	*18.76*	*13.43*	*13.45*	*15.41*
19.16	*17.47*	*16.17*	*17.32*	*17.71*
15.08	*13.77*	*17.20*	*16.35*	*17.82*
16.86	*15.29*	*18.41*	*15.72*	*16.92*
17.60	*15.24*	*14.89*	*16.59*	*16.81*
13.53	*18.36*	*15.89*	*14.30*	*16.82*
19.45	*15.97*	*18.04*	*14.92*	*13.79*
19.50	*17.16*	*14.39*	*14.63*	*17.80*
16.05	*15.10*	*13.63*	*14.37*	*13.78*
14.27	*17.48*	*16.01*	*17.81*	*15.61*
19.45	*15.60*	*15.88*	*17.09*	*15.77*
19.13	*17.15*	*15.30*	*14.76*	*15.20*
20.34	*15.72*	*15.13*	*13.96*	*12.95*
18.12	*15.11*	*15.49*	*16.13*	*13.25*
18.45	*14.40*	*16.77*	*15.99*	*15.59*
16.28	*14.84*	*12.64*	*16.36*	*16.35*
15.37	*16.13*	*16.16*	*16.69*	*17.19*
16.92	*13.66*	*19.40*	*17.34*	*14.56*
14.90	*15.94*	*18.41*	*18.21*	*17.99*
20.57	*19.76*	*19.33*	*14.36*	*15.14*
18.82	*16.03*	*17.67*	*17.71*	*16.21*
18.21	*17.41*	*17.71*	*15.29*	*13.60*
17.58	*17.08*	*16.68*	*16.09*	*13.61*
16.58	*18.58*	*16.25*	*14.72*	*15.74*
17.76	*15.36*	*16.06*	*15.50*	*17.08*
15.98	*15.25*	*16.89*	*16.18*	*15.63*
16.29	*15.14*	*18.04*	*15.25*	*16.91*
18.31	*17.22*	*16.46*	*14.29*	*13.88*
18.20	*15.31*	*16.35*	*17.12*	*15.84*
16.54	*18.05*	*14.65*	*17.80*	*15.82*
13.46	*16.26*	*17.11*	*16.56*	*16.13*
16.87	*13.43*	*14.96*	*13.89*	*14.91*

16.61	*14.58*	*13.58*	*13.29*	*16.25*
16.22	*18.32*	*14.12*	*17.30*	*14.96*
17.95	*15.83*	*15.24*	*14.48*	*16.46*
16.21	*17.63*	*16.70*	*13.25*	*15.36*
16.60	*14.07*	*17.19*	*14.40*	*15.46*
19.19	*16.61*	*13.18*	*17.21*	*14.93*
18.05	*16.19*	*15.90*	*18.07*	*16.12*
17.18	*14.94*	*16.16*	*14.56*	*13.95*
16.97	*17.28*	*15.38*	*16.27*	*16.70*
17.30	*15.05*	*15.99*	*13.75*	*14.57*
17.88	*16.02*	*14.71*	*16.65*	*16.74*
16.11	*16.16*	*18.41*	*16.15*	*16.62*
18.33	*17.99*	*15.07*	*16.04*	*15.86*
15.16	*13.12*	*15.43*	*16.11*	*13.88*
14.79	*15.59*	*15.46*	*18.15*	*16.88*
17.90	*17.51*	*19.59*	*15.41*	*16.72*
17.39	*14.76*	*19.32*	*16.31*	*15.92*
15.54	*15.37*	*16.93*	*14.45*	*14.66*
14.14	*15.65*	*17.84*	*15.61*	*15.09*
17.67	*16.17*	*17.09*	*14.42*	*15.90*

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APPENDIX F. PRODUCTIVITY HYPOTHESES DATA

As-Is	*AM*	*CIB*	*ML*	*AM + CIB + ML*
1.21	1.19	1.29	1.45	1.41
1.25	1.26	1.44	1.10	1.40
1.12	1.24	1.24	1.62	1.42
1.29	1.24	1.33	1.42	1.43
1.38	1.18	1.17	1.28	1.47
1.19	1.35	1.23	1.48	1.51
1.27	1.33	1.35	0.97	1.61
1.33	1.37	1.10	1.35	1.35
1.21	1.43	1.35	1.29	1.31
1.30	1.32	1.29	1.21	1.26
1.27	1.21	1.25	1.42	1.29
1.18	1.40	1.12	1.60	1.33
1.29	1.16	1.15	1.19	1.06
1.22	1.30	1.23	1.65	1.50
1.33	1.23	1.13	1.16	1.30
1.39	1.27	1.37	1.57	1.10
1.26	1.25	1.10	1.33	1.27
1.24	1.26	1.04	1.39	1.48
1.34	1.34	1.12	1.00	1.51
1.20	1.37	1.29	1.24	1.10
1.17	1.27	1.29	1.28	1.37
1.22	1.17	1.17	1.22	1.31
1.31	1.21	1.16	1.49	1.62
1.22	1.42	1.34	1.50	1.43
1.38	1.30	1.35	1.15	0.95
1.12	1.20	1.11	1.24	1.17
1.15	1.39	1.29	1.48	1.62
1.17	1.36	1.35	1.53	1.02
1.22	1.22	1.36	1.16	1.06
1.30	1.32	1.20	1.01	1.37
1.21	1.23	1.33	1.38	1.15
1.28	1.33	1.23	1.27	1.36
1.19	1.43	1.40	1.05	1.26
1.33	1.33	1.23	1.50	1.50
1.26	1.25	1.36	1.47	1.28
1.31	1.35	1.30	1.07	1.25
1.24	1.38	1.09	1.43	1.56

1.35	1.25	1.40	1.40	1.29
1.25	1.30	1.25	1.28	1.51
1.23	1.26	1.35	1.48	1.20
1.40	1.25	1.26	1.14	1.07
1.38	1.29	1.38	1.19	1.31
1.32	1.21	1.20	0.96	1.12
1.22	1.40	1.16	1.09	1.34
1.26	1.36	1.34	1.31	1.31
1.38	1.40	1.25	1.54	1.02
1.24	1.19	1.35	1.48	1.27
1.14	1.29	1.41	1.39	0.93
1.24	1.29	1.34	1.18	1.39
1.21	1.25	1.24	1.20	1.38
1.24	1.21	1.32	1.26	1.44
1.18	1.32	1.43	1.43	1.13
1.10	1.19	1.41	1.15	0.98
1.30	1.29	1.27	1.40	1.06
1.32	1.17	1.30	1.09	1.09
1.13	1.21	1.29	1.48	1.14
1.29	1.31	1.15	1.25	1.42
1.20	1.30	1.25	1.08	1.17
1.24	1.31	1.17	1.33	0.90
1.21	1.31	1.29	1.16	1.55
1.32	1.37	1.35	1.13	1.48
1.22	1.32	1.30	1.19	1.43
1.40	1.22	1.14	1.36	1.35
1.24	1.43	1.32	1.33	1.47
1.18	1.20	1.24	1.31	1.42
1.19	1.38	1.09	1.08	1.49
1.25	1.33	1.23	1.51	1.29
1.32	1.39	1.47	1.34	1.27
1.28	1.14	1.16	1.29	1.19
1.20	1.28	1.33	1.58	1.39
1.21	1.12	1.03	1.28	1.46
1.29	1.30	1.20	1.32	1.40
1.25	1.31	1.27	1.27	1.19
1.22	1.38	1.20	1.14	1.45
1.25	1.44	1.12	1.11	1.18
1.17	1.42	1.43	1.18	1.32
1.31	1.24	1.12	1.33	1.38
1.25	1.33	1.42	1.09	1.45

1.20	*1.33*	*1.30*	*1.50*	*1.55*
1.40	*1.31*	*1.37*	*1.15*	*1.55*
1.22	*1.23*	*1.29*	*1.18*	*1.12*
1.21	*1.39*	*1.41*	*1.15*	*1.41*
1.29	*1.31*	*1.08*	*1.63*	*1.52*
1.18	*1.29*	*1.43*	*1.45*	*1.46*
1.28	*1.42*	*1.16*	*1.29*	*1.36*
1.32	*1.28*	*1.20*	*1.16*	*1.20*
1.26	*1.22*	*1.37*	*1.21*	*1.13*
1.26	*1.35*	*1.40*	*1.26*	*1.24*
1.27	*1.35*	*1.36*	*1.31*	*1.07*
1.28	*1.32*	*1.31*	*1.58*	*1.46*
1.25	*1.32*	*1.06*	*1.28*	*1.26*
1.23	*1.18*	*1.11*	*1.41*	*1.27*
1.33	*1.33*	*1.36*	*1.54*	*1.12*
1.25	*1.36*	*1.37*	*1.49*	*1.28*
1.23	*1.32*	*1.32*	*1.32*	*1.20*
1.33	*1.23*	*1.35*	*1.24*	*1.56*
1.17	*1.39*	*1.21*	*1.28*	*1.46*
1.34	*1.21*	*1.27*	*1.53*	*1.48*
1.25	*1.33*	*1.19*	*1.58*	*1.34*
1.34	*1.17*	*1.39*	*1.23*	*1.40*
1.31	*1.37*	*1.35*	*1.37*	*1.31*
1.33	*1.18*	*1.32*	*1.12*	*1.36*
1.16	*1.27*	*1.37*	*1.43*	*1.20*
1.35	*1.28*	*1.25*	*1.12*	*1.24*
1.22	*1.28*	*1.40*	*0.97*	*1.57*
1.29	*1.28*	*1.33*	*1.57*	*1.30*
1.31	*1.27*	*1.28*	*1.41*	*1.17*
1.20	*1.23*	*1.34*	*1.56*	*1.58*
1.31	*1.31*	*1.22*	*1.28*	*1.44*
1.14	*1.40*	*1.29*	*1.43*	*1.40*
1.24	*1.33*	*1.35*	*1.58*	*1.26*
1.22	*1.13*	*1.35*	*1.39*	*1.47*
1.24	*1.28*	*1.33*	*1.42*	*1.47*
1.30	*1.40*	*1.13*	*1.34*	*0.94*
1.29	*1.34*	*1.26*	*1.14*	*1.37*
1.30	*1.21*	*1.30*	*1.23*	*1.53*
1.30	*1.39*	*1.42*	*1.25*	*0.94*
1.11	*1.32*	*1.29*	*1.25*	*1.52*
1.20	*1.30*	*1.11*	*1.13*	*1.38*

1.22	*1.42*	*1.32*	*1.37*	*0.97*
1.16	*1.36*	*1.47*	*1.42*	*1.58*
1.29	*1.26*	*1.31*	*1.29*	*1.41*
1.18	*1.29*	*1.27*	*1.42*	*1.09*
1.25	*1.30*	*1.23*	*1.42*	*1.46*
1.12	*1.29*	*1.37*	*1.39*	*1.46*
1.16	*1.33*	*1.21*	*1.37*	*1.20*
1.30	*1.31*	*1.42*	*1.21*	*1.47*
1.34	*1.40*	*1.20*	*1.27*	*1.27*
1.30	*1.19*	*1.12*	*1.41*	*1.45*
1.30	*1.20*	*1.25*	*0.99*	*1.10*
1.32	*1.32*	*1.40*	*1.46*	*0.87*
1.29	*1.17*	*1.26*	*1.53*	*1.50*
1.38	*1.17*	*1.50*	*1.13*	*1.55*
1.27	*1.31*	*1.16*	*1.52*	*1.22*
1.26	*1.25*	*1.44*	*1.25*	*1.07*
1.37	*1.27*	*1.14*	*1.50*	*1.06*
1.39	*1.25*	*1.20*	*1.31*	*1.32*
1.12	*1.33*	*1.15*	*1.21*	*1.14*
1.32	*1.31*	*1.24*	*1.33*	*1.30*
1.28	*1.19*	*1.44*	*1.43*	*1.15*
1.17	*1.43*	*1.29*	*1.44*	*1.39*
1.26	*1.34*	*1.31*	*1.42*	*1.06*
1.21	*1.41*	*1.30*	*1.48*	*1.52*
1.28	*1.36*	*1.31*	*1.41*	*1.53*
1.34	*1.28*	*1.41*	*1.43*	*1.35*
1.37	*1.41*	*1.28*	*1.53*	*1.33*
1.33	*1.28*	*1.26*	*1.41*	*1.57*
1.40	*1.36*	*1.30*	*1.48*	*1.57*
1.22	*1.21*	*1.28*	*1.16*	*1.53*
1.33	*1.17*	*1.29*	*1.37*	*1.47*
1.32	*1.30*	*1.22*	*1.47*	*1.26*
1.29	*1.18*	*1.37*	*1.19*	*1.42*
1.27	*1.24*	*1.33*	*1.18*	*1.22*
1.33	*1.31*	*1.39*	*1.50*	*1.54*
1.32	*1.26*	*1.36*	*1.42*	*1.39*
1.29	*1.13*	*1.36*	*1.46*	*1.44*
1.35	*1.29*	*1.40*	*1.10*	*1.42*
1.21	*1.21*	*1.32*	*1.26*	*1.24*
1.35	*1.18*	*1.22*	*1.12*	*1.31*
1.12	*1.30*	*1.20*	*1.52*	*1.08*

1.20	*1.23*	*1.33*	*1.40*	*0.95*
1.25	*1.35*	*1.32*	*1.17*	*1.42*
1.29	*1.26*	*1.45*	*1.33*	*1.48*
1.14	*1.27*	*1.31*	*1.35*	*0.96*
1.29	*1.13*	*1.29*	*1.36*	*1.00*
1.30	*1.16*	*1.33*	*1.22*	*1.38*
1.17	*1.35*	*1.39*	*1.41*	*1.35*
1.28	*1.36*	*1.20*	*1.08*	*1.19*
1.25	*1.31*	*1.26*	*1.40*	*1.41*
1.26	*1.19*	*1.37*	*1.24*	*1.28*
1.28	*1.44*	*1.35*	*1.51*	*1.32*
1.19	*1.34*	*1.12*	*1.39*	*1.24*
1.24	*1.22*	*1.23*	*1.38*	*1.36*
1.35	*1.30*	*1.23*	*1.60*	*1.17*
1.20	*1.21*	*1.28*	*1.23*	*1.37*
1.15	*1.32*	*1.39*	*1.52*	*1.36*
1.28	*1.24*	*1.23*	*1.52*	*1.57*
1.17	*1.17*	*1.45*	*1.20*	*1.24*
1.35	*1.34*	*1.33*	*1.45*	*1.48*
1.21	*1.24*	*1.37*	*1.11*	*1.47*
1.40	*1.36*	*1.38*	*1.10*	*1.14*
1.25	*1.30*	*1.28*	*1.24*	*1.28*
1.27	*1.39*	*1.18*	*1.08*	*1.44*
1.18	*1.37*	*1.27*	*1.39*	*1.29*
1.33	*1.31*	*1.10*	*1.40*	*1.25*
1.25	*1.31*	*1.34*	*1.32*	*1.23*
1.32	*1.36*	*1.35*	*1.09*	*1.37*
1.32	*1.28*	*1.19*	*1.43*	*1.35*
1.28	*1.32*	*1.34*	*1.49*	*1.45*
1.39	*1.30*	*1.30*	*1.03*	*1.42*
1.24	*1.37*	*1.17*	*1.43*	*1.63*
1.24	*1.34*	*1.17*	*1.45*	*1.43*
1.35	*1.37*	*1.47*	*0.92*	*1.38*
1.30	*1.22*	*1.13*	*1.35*	*1.55*
1.30	*1.33*	*1.35*	*1.10*	*1.48*
1.18	*1.39*	*1.20*	*1.52*	*1.28*
1.36	*1.16*	*1.33*	*1.45*	*1.54*
1.38	*1.33*	*1.03*	*1.09*	*1.12*
1.12	*1.24*	*1.27*	*0.97*	*1.40*
1.30	*1.32*	*1.34*	*1.21*	*1.00*
1.31	*1.28*	*1.01*	*1.09*	*1.59*

1.30	*1.21*	*1.10*	*1.52*	*1.48*
1.26	*1.30*	*1.22*	*1.29*	*1.47*
1.34	*1.23*	*1.20*	*1.07*	*1.41*
1.13	*1.22*	*1.03*	*1.28*	*1.54*
1.25	*1.24*	*1.35*	*1.32*	*1.08*
1.26	*1.24*	*1.45*	*1.50*	*1.39*
1.25	*1.16*	*1.31*	*1.45*	*1.19*
1.32	*1.31*	*1.14*	*1.22*	*1.41*
1.26	*1.12*	*1.08*	*1.19*	*1.47*
1.26	*1.28*	*1.32*	*1.38*	*0.91*
1.27	*1.28*	*1.33*	*1.15*	*1.37*
1.25	*1.29*	*1.32*	*1.46*	*1.25*
1.20	*1.31*	*1.27*	*1.45*	*1.26*
1.32	*1.33*	*1.28*	*1.49*	*1.51*
1.24	*1.18*	*1.36*	*1.43*	*1.32*
1.25	*1.23*	*1.29*	*1.40*	*1.40*
1.16	*1.32*	*1.25*	*1.49*	*1.03*
1.42	*1.28*	*1.26*	*1.19*	*1.46*
1.22	*1.15*	*1.24*	*1.55*	*1.30*
1.36	*1.31*	*1.21*	*1.50*	*0.96*
1.32	*1.42*	*1.36*	*1.43*	*1.38*
1.26	*1.33*	*1.42*	*1.42*	*1.11*
1.20	*1.11*	*1.43*	*1.15*	*1.19*
1.27	*1.22*	*1.32*	*1.43*	*1.27*
1.23	*1.25*	*1.20*	*1.05*	*1.37*
1.24	*1.34*	*1.38*	*1.23*	*1.36*
1.34	*1.40*	*1.33*	*1.39*	*1.49*
1.16	*1.40*	*1.34*	*1.21*	*1.38*
1.22	*1.29*	*1.34*	*1.08*	*1.37*
1.22	*1.18*	*1.16*	*1.42*	*1.50*
1.30	*1.14*	*1.31*	*1.34*	*1.41*
1.26	*1.34*	*1.34*	*1.14*	*1.17*
1.30	*1.38*	*1.33*	*1.15*	*1.23*
1.21	*1.27*	*1.23*	*1.26*	*1.10*
1.28	*1.30*	*1.24*	*1.12*	*1.05*
1.35	*1.32*	*1.16*	*1.34*	*1.21*
1.22	*1.31*	*1.14*	*1.30*	*1.49*
1.33	*1.27*	*1.15*	*1.61*	*1.27*
1.23	*1.24*	*1.30*	*1.02*	*1.51*
1.24	*1.37*	*1.30*	*1.45*	*1.23*
1.37	*1.35*	*1.38*	*1.37*	*1.21*

1.17	*1.33*	*1.27*	*1.30*	*1.46*
1.34	*1.31*	*1.18*	*1.51*	*1.54*
1.15	*1.35*	*1.19*	*1.25*	*1.33*
1.34	*1.24*	*1.23*	*1.58*	*1.45*
1.23	*1.17*	*1.22*	*1.21*	*1.42*
1.40	*1.20*	*1.26*	*1.18*	*1.26*
1.26	*1.35*	*1.31*	*1.14*	*1.44*
1.17	*1.43*	*1.35*	*1.17*	*1.36*
1.32	*1.17*	*1.33*	*1.10*	*1.47*
1.28	*1.32*	*1.18*	*1.23*	*1.31*
1.29	*1.29*	*1.40*	*1.47*	*1.53*
1.15	*1.27*	*1.18*	*1.43*	*1.47*
1.30	*1.23*	*1.47*	*1.35*	*1.31*
1.22	*1.24*	*1.10*	*1.38*	*1.27*
1.35	*1.30*	*1.15*	*1.31*	*1.61*
1.21	*1.28*	*1.18*	*1.31*	*1.06*
1.22	*1.40*	*1.13*	*1.45*	*1.43*
1.10	*1.40*	*1.35*	*1.20*	*1.41*
1.30	*1.35*	*1.46*	*1.28*	*1.48*
1.27	*1.18*	*1.14*	*1.40*	*1.35*
1.23	*1.31*	*1.32*	*1.54*	*1.37*
1.16	*1.26*	*1.27*	*1.48*	*1.40*
1.29	*1.23*	*1.36*	*1.40*	*1.34*
1.31	*1.20*	*1.20*	*1.47*	*1.31*
1.23	*1.30*	*1.39*	*1.56*	*1.41*
1.14	*1.31*	*1.36*	*1.38*	*1.31*
1.19	*1.26*	*1.30*	*1.55*	*1.44*
1.30	*1.26*	*1.17*	*1.17*	*1.39*
1.29	*1.29*	*1.41*	*1.38*	*0.96*
1.25	*1.17*	*1.24*	*1.51*	*1.05*
1.24	*1.37*	*1.23*	*1.19*	*1.14*
1.33	*1.35*	*1.34*	*1.21*	*1.35*
1.26	*1.31*	*1.39*	*1.28*	*1.32*
1.22	*1.33*	*1.38*	*1.52*	*1.47*
1.24	*1.40*	*1.09*	*1.18*	*1.46*
1.34	*1.32*	*1.20*	*1.54*	*1.16*
1.41	*1.23*	*1.40*	*1.34*	*0.97*
1.23	*1.15*	*1.23*	*1.45*	*1.54*
1.36	*1.33*	*1.43*	*1.41*	*1.07*
1.12	*1.32*	*1.30*	*1.13*	*1.44*
1.31	*1.24*	*1.28*	*1.07*	*1.41*

1.25	*1.35*	*1.12*	*1.31*	*1.25*
1.18	*1.30*	*1.36*	*1.03*	*1.35*
1.21	*1.34*	*1.24*	*1.27*	*1.10*
1.21	*1.28*	*1.09*	*1.59*	*1.52*
1.31	*1.14*	*1.26*	*1.10*	*1.45*
1.18	*1.20*	*1.13*	*1.18*	*1.32*
1.31	*1.35*	*1.37*	*1.49*	*1.37*
1.26	*1.40*	*1.40*	*1.31*	*1.45*
1.23	*1.40*	*1.41*	*1.14*	*1.48*
1.21	*1.26*	*1.17*	*0.98*	*1.32*
1.23	*1.23*	*1.29*	*1.16*	*1.54*
1.25	*1.28*	*1.46*	*1.41*	*1.14*
1.12	*1.28*	*1.31*	*1.38*	*1.47*
1.26	*1.43*	*1.29*	*1.46*	*1.38*
1.22	*1.30*	*1.33*	*1.18*	*1.36*
1.32	*1.20*	*1.20*	*1.23*	*1.34*
1.33	*1.42*	*1.11*	*1.44*	*1.10*
1.26	*1.25*	*1.32*	*1.53*	*1.10*
1.16	*1.41*	*1.18*	*1.21*	*1.44*
1.36	*1.27*	*1.23*	*1.26*	*1.26*
1.21	*1.37*	*1.25*	*1.30*	*1.12*
1.32	*1.31*	*1.22*	*1.40*	*1.12*
1.22	*1.22*	*1.35*	*1.15*	*1.26*
1.14	*1.27*	*1.38*	*1.32*	*1.23*
1.19	*1.27*	*1.32*	*1.40*	*1.34*
1.23	*1.26*	*1.25*	*1.32*	*1.41*
1.24	*1.37*	*1.41*	*1.56*	*1.19*
1.39	*1.31*	*1.34*	*1.38*	*1.27*
1.37	*1.15*	*1.45*	*1.45*	*1.48*
1.35	*1.24*	*1.08*	*1.53*	*1.42*
1.26	*1.31*	*1.39*	*1.03*	*1.14*
1.35	*1.24*	*1.35*	*1.54*	*1.47*
1.24	*1.23*	*1.39*	*1.61*	*1.45*
1.25	*1.25*	*1.37*	*1.54*	*1.28*
1.25	*1.34*	*1.18*	*1.10*	*1.28*
1.18	*1.28*	*1.38*	*1.48*	*1.39*
1.15	*1.26*	*1.29*	*1.45*	*1.13*
1.32	*1.15*	*1.39*	*1.45*	*1.27*
1.30	*1.38*	*1.36*	*1.47*	*1.57*
1.30	*1.22*	*1.46*	*0.97*	*1.29*
1.27	*1.29*	*1.14*	*1.34*	*1.19*

1.32	*1.27*	*1.36*	*1.41*	*0.98*
1.25	*1.29*	*1.41*	*1.24*	*1.44*
1.14	*1.34*	*1.10*	*1.48*	*1.58*
1.24	*1.29*	*1.48*	*1.36*	*1.43*
1.27	*1.44*	*1.26*	*1.13*	*1.42*
1.38	*1.28*	*1.38*	*1.30*	*1.01*
1.27	*1.23*	*1.44*	*1.35*	*1.28*
1.23	*1.25*	*1.18*	*1.44*	*1.53*
1.19	*1.13*	*1.28*	*1.06*	*1.52*
1.38	*1.20*	*1.16*	*1.02*	*1.61*
1.16	*1.30*	*1.31*	*1.47*	*1.43*
1.32	*1.14*	*1.32*	*1.61*	*1.06*
1.41	*1.33*	*1.28*	*1.21*	*1.15*
1.34	*1.35*	*1.30*	*1.31*	*1.39*
1.16	*1.25*	*1.21*	*1.40*	*1.34*
1.27	*1.30*	*1.24*	*1.20*	*1.45*
1.33	*1.25*	*1.37*	*1.31*	*1.55*
1.12	*1.32*	*1.16*	*1.48*	*1.39*
1.23	*1.33*	*1.18*	*1.40*	*1.54*
1.26	*1.30*	*1.18*	*1.52*	*1.02*
1.17	*1.31*	*1.35*	*1.30*	*1.51*
1.33	*1.24*	*1.42*	*1.24*	*1.13*
1.20	*1.33*	*1.25*	*1.20*	*1.23*
1.30	*1.39*	*1.08*	*1.24*	*1.13*
1.19	*1.32*	*1.35*	*1.48*	*1.22*
1.24	*1.19*	*1.33*	*1.42*	*1.60*
1.41	*1.26*	*1.28*	*1.16*	*1.39*
1.19	*1.31*	*1.24*	*1.35*	*1.12*
1.31	*1.34*	*1.39*	*1.41*	*1.29*
1.29	*1.26*	*1.44*	*1.27*	*1.20*
1.28	*1.29*	*1.41*	*1.43*	*1.50*
1.26	*1.39*	*1.41*	*1.13*	*1.34*
1.30	*1.32*	*1.19*	*1.24*	*1.14*
1.34	*1.24*	*1.18*	*1.39*	*1.09*
1.15	*1.31*	*1.30*	*1.14*	*1.29*
1.25	*1.35*	*1.07*	*1.30*	*1.40*
1.13	*1.21*	*1.21*	*1.32*	*1.29*
1.25	*1.29*	*1.35*	*1.24*	*1.11*
1.21	*1.33*	*1.19*	*1.02*	*1.32*
1.16	*1.30*	*1.31*	*1.34*	*1.36*
1.24	*1.21*	*1.24*	*1.21*	*1.15*

1.10	*1.14*	*1.36*	*1.25*	*1.31*
1.29	*1.37*	*1.29*	*1.34*	*1.32*
1.27	*1.27*	*1.37*	*1.53*	*1.43*
1.24	*1.30*	*1.41*	*1.34*	*1.49*
1.23	*1.27*	*1.28*	*1.42*	*1.24*
1.36	*1.24*	*1.31*	*1.50*	*1.21*
1.34	*1.36*	*1.03*	*1.22*	*1.29*
1.25	*1.33*	*1.26*	*1.50*	*1.32*
1.24	*1.23*	*1.35*	*1.37*	*1.53*
1.30	*1.34*	*1.33*	*1.46*	*1.13*
1.33	*1.25*	*1.39*	*1.29*	*1.48*
1.28	*1.30*	*1.09*	*0.97*	*1.35*
1.24	*1.26*	*1.33*	*1.20*	*1.39*
1.30	*1.27*	*1.29*	*1.34*	*1.20*
1.29	*1.21*	*1.05*	*1.00*	*1.32*
1.16	*1.33*	*1.41*	*1.46*	*1.40*
1.17	*1.31*	*1.36*	*1.42*	*1.32*
1.27	*1.12*	*1.32*	*1.31*	*1.46*
1.36	*1.33*	*1.25*	*1.26*	*1.02*
1.13	*1.32*	*1.29*	*1.58*	*1.17*
1.21	*1.24*	*1.15*	*1.35*	*1.34*
1.29	*1.24*	*1.38*	*1.56*	*1.44*
1.37	*1.32*	*1.21*	*1.28*	*1.29*
1.32	*1.31*	*1.42*	*1.45*	*1.00*
1.30	*1.35*	*1.10*	*1.43*	*1.26*
1.40	*1.35*	*1.35*	*1.59*	*1.30*
1.25	*1.23*	*1.43*	*1.37*	*1.27*
1.34	*1.29*	*1.19*	*1.17*	*1.47*
1.22	*1.22*	*1.34*	*1.42*	*1.49*
1.20	*1.28*	*1.47*	*1.55*	*1.21*
1.25	*1.33*	*1.35*	*1.54*	*1.34*
1.25	*1.23*	*1.26*	*1.16*	*1.35*
1.34	*1.31*	*1.39*	*1.34*	*1.20*
1.30	*1.34*	*1.35*	*0.96*	*1.36*
1.22	*1.27*	*1.36*	*1.58*	*1.45*
1.26	*1.20*	*1.25*	*1.51*	*1.10*
1.27	*1.35*	*1.36*	*1.42*	*1.63*
1.31	*1.29*	*1.03*	*1.06*	*1.53*
1.29	*1.19*	*1.07*	*1.41*	*1.58*
1.30	*1.26*	*1.16*	*1.32*	*1.12*
1.26	*1.34*	*1.46*	*1.29*	*1.57*

1.13	*1.45*	*1.36*	*1.15*	*0.92*
1.22	*1.37*	*1.30*	*1.05*	*1.57*
1.12	*1.36*	*1.15*	*1.34*	*1.34*
1.19	*1.34*	*1.33*	*1.09*	*1.52*
1.19	*1.26*	*1.09*	*1.61*	*1.02*
1.17	*1.43*	*1.41*	*1.44*	*1.40*
1.33	*1.36*	*1.25*	*1.44*	*1.56*
1.31	*1.34*	*1.39*	*1.05*	*1.39*
1.32	*1.31*	*1.46*	*1.42*	*1.56*
1.34	*1.23*	*1.34*	*1.56*	*1.55*
1.31	*1.19*	*1.41*	*1.33*	*1.46*
1.30	*1.40*	*1.37*	*1.11*	*1.50*
1.22	*1.42*	*1.37*	*1.30*	*1.12*
1.19	*1.29*	*1.26*	*1.36*	*1.45*
1.25	*1.38*	*1.32*	*1.33*	*1.11*
1.28	*1.27*	*1.25*	*1.00*	*1.16*
1.35	*1.26*	*1.44*	*1.46*	*1.51*
1.31	*1.40*	*1.40*	*1.59*	*1.22*
1.33	*1.13*	*1.36*	*1.16*	*1.23*
1.32	*1.35*	*1.31*	*1.36*	*1.45*
1.24	*1.37*	*1.13*	*1.17*	*1.35*
1.34	*1.30*	*1.26*	*1.27*	*1.13*
1.22	*1.31*	*1.36*	*1.53*	*1.61*
1.39	*1.14*	*1.48*	*1.36*	*1.30*
1.21	*1.31*	*1.27*	*1.22*	*1.56*
1.24	*1.21*	*1.26*	*1.17*	*1.26*
1.33	*1.36*	*1.38*	*1.22*	*1.48*
1.11	*1.24*	*1.37*	*1.22*	*0.96*
1.19	*1.30*	*1.30*	*1.47*	*1.60*
1.20	*1.24*	*1.38*	*1.17*	*1.25*
1.32	*1.35*	*1.02*	*1.12*	*1.35*
1.32	*1.28*	*1.39*	*1.20*	*1.09*
1.30	*1.20*	*1.19*	*0.92*	*1.26*
1.25	*1.35*	*1.29*	*1.08*	*1.58*
1.30	*1.24*	*1.36*	*1.35*	*1.20*
1.30	*1.18*	*1.32*	*1.23*	*1.45*
1.17	*1.26*	*1.19*	*1.50*	*1.38*
1.10	*1.36*	*1.34*	*1.44*	*1.01*
1.27	*1.28*	*1.30*	*1.13*	*1.25*
1.13	*1.26*	*1.30*	*1.32*	*1.36*
1.24	*1.35*	*1.36*	*1.18*	*1.40*

1.26	1.17	1.29	1.51	1.48
1.30	1.37	1.31	1.33	1.59
1.23	1.39	1.25	1.30	1.26
1.28	1.20	1.36	1.02	1.30
1.21	1.34	1.32	1.17	1.17
1.23	1.30	1.15	1.44	1.26
1.23	1.31	1.49	1.20	1.06
1.38	1.26	1.37	1.53	1.27
1.30	1.37	1.07	1.15	0.92
1.16	1.43	1.13	1.12	1.53
1.21	1.17	1.35	1.46	1.27
1.31	1.29	1.23	1.41	1.32
1.17	1.33	1.38	1.14	1.40
1.30	1.39	1.14	1.26	1.29
1.21	1.26	1.39	1.41	1.43
1.24	1.33	1.28	1.16	1.07
1.23	1.29	1.04	1.48	1.05
1.21	1.39	1.19	1.51	1.25
1.26	1.17	1.14	1.31	1.20
1.41	1.17	1.41	1.35	1.23
1.18	1.37	1.37	1.43	1.41
1.37	1.23	1.06	1.08	1.58
1.13	1.15	1.14	1.37	1.07
1.29	1.33	1.47	1.06	1.27
1.32	1.34	1.20	1.66	1.54
1.19	1.23	1.26	1.30	1.44
1.22	1.36	1.43	1.51	1.54
1.26	1.33	1.22	1.15	1.13
1.14	1.39	1.14	1.52	1.22
1.25	1.40	1.30	1.27	1.39
1.21	1.18	1.38	1.14	1.36
1.25	1.32	1.37	1.47	1.32
1.30	1.36	1.32	1.28	1.41
1.20	1.19	1.20	1.40	1.39
1.38	1.28	1.39	1.53	1.24
1.34	1.31	1.24	1.43	1.33
1.21	1.33	1.07	1.47	1.31
1.20	1.12	1.37	1.26	1.34
1.34	1.39	1.29	1.42	1.33
1.19	1.25	1.36	1.20	1.03
1.23	1.33	1.41	1.44	1.41

1.34	1.24	1.42	1.48	1.42
1.33	1.25	1.10	1.25	1.17
1.39	1.36	1.38	1.54	1.31
1.20	1.26	1.41	1.14	1.46
1.13	1.40	1.15	1.30	1.09
1.27	1.37	1.14	1.40	1.12
1.27	1.36	1.23	1.14	1.38
1.40	1.18	1.43	1.40	1.42
1.27	1.37	1.17	1.34	1.35
1.24	1.30	1.39	1.46	1.49
1.10	1.35	1.36	1.59	1.40
1.36	1.20	1.29	1.43	1.13
1.38	1.22	1.27	1.15	1.41
1.17	1.30	1.34	1.25	1.32
1.17	1.27	1.21	1.32	1.19
1.19	1.34	1.33	1.53	1.44
1.11	1.16	1.23	1.47	1.11
1.31	1.18	1.24	1.35	1.42
1.34	1.31	1.20	1.33	1.45
1.23	1.28	1.04	1.49	1.28
1.34	1.37	1.30	1.26	1.44
1.28	1.30	1.22	1.44	1.31
1.18	1.30	1.32	1.60	1.12
1.36	1.38	1.32	0.99	1.54
1.13	1.22	1.15	1.40	1.40
1.27	1.21	1.37	1.42	1.52
1.31	1.34	1.37	1.34	1.51
1.17	1.30	1.46	1.08	1.35
1.19	1.35	1.32	1.07	1.36
1.22	1.12	1.21	1.26	1.50
1.25	1.36	1.47	1.54	1.27
1.29	1.34	1.40	1.42	1.16
1.25	1.35	1.32	1.49	1.44
1.24	1.34	1.12	1.08	0.94
1.23	1.38	1.30	1.34	1.44
1.20	1.31	1.09	1.09	1.24
1.26	1.39	1.27	1.49	1.32
1.35	1.34	1.40	1.14	1.20
1.24	1.33	1.22	1.52	1.04
1.24	1.23	1.36	1.27	1.14
1.27	1.39	1.17	1.25	1.35

1.27	*1.26*	*1.29*	*1.16*	*1.11*
1.12	*1.33*	*1.37*	*1.29*	*1.42*
1.27	*1.26*	*1.36*	*1.28*	*1.49*
1.28	*1.38*	*1.43*	*1.49*	*1.40*
1.29	*1.31*	*1.33*	*1.31*	*1.26*
1.41	*1.37*	*1.35*	*1.54*	*1.44*
1.28	*1.34*	*1.13*	*1.26*	*1.53*
1.27	*1.25*	*1.35*	*0.97*	*1.18*
1.30	*1.39*	*1.41*	*1.19*	*1.36*
1.13	*1.29*	*1.25*	*1.35*	*1.37*
1.30	*1.43*	*1.24*	*1.42*	*1.49*
1.37	*1.33*	*1.09*	*1.48*	*1.12*
1.18	*1.13*	*1.39*	*1.40*	*1.05*
1.32	*1.24*	*1.27*	*1.32*	*1.22*
1.22	*1.22*	*1.42*	*1.39*	*1.54*
1.31	*1.33*	*1.27*	*1.52*	*1.23*
1.26	*1.29*	*1.17*	*1.27*	*1.02*
1.28	*1.28*	*1.26*	*1.33*	*1.62*
1.34	*1.23*	*1.40*	*1.50*	*1.05*
1.30	*1.17*	*1.21*	*1.13*	*1.45*
1.32	*1.18*	*1.41*	*1.20*	*1.20*
1.26	*1.17*	*1.35*	*1.45*	*1.06*
1.19	*1.25*	*1.16*	*1.35*	*1.41*
1.29	*1.36*	*1.29*	*1.38*	*1.33*
1.23	*1.37*	*1.43*	*1.33*	*1.31*
1.15	*1.26*	*1.10*	*1.35*	*1.20*
1.30	*1.28*	*1.22*	*1.12*	*1.35*
1.24	*1.31*	*1.43*	*1.10*	*1.38*
1.27	*1.34*	*1.33*	*1.29*	*1.47*
1.27	*1.18*	*1.24*	*1.18*	*1.31*
1.34	*1.31*	*1.34*	*1.41*	*1.31*
1.38	*1.20*	*1.27*	*1.46*	*1.15*
1.17	*1.14*	*1.17*	*1.34*	*1.29*
1.31	*1.13*	*1.07*	*0.97*	*1.20*
1.13	*1.38*	*1.26*	*0.95*	*1.55*
1.28	*1.23*	*1.31*	*1.41*	*1.50*
1.41	*1.14*	*1.40*	*1.09*	*1.30*
1.16	*1.35*	*1.33*	*1.42*	*1.38*
1.21	*1.22*	*1.16*	*1.54*	*1.32*
1.26	*1.30*	*1.14*	*1.61*	*1.03*
1.27	*1.17*	*1.24*	*1.58*	*1.29*

1.37	1.22	1.34	1.43	1.49
1.30	1.31	1.37	1.54	1.16
1.16	1.21	1.12	1.08	1.24
1.38	1.27	1.24	1.31	1.59
1.34	1.34	1.28	1.36	1.31
1.13	1.19	1.31	1.38	1.25
1.37	1.33	1.41	1.42	1.34
1.36	1.20	1.41	1.49	1.50
1.29	1.28	1.19	1.43	1.27
1.23	1.29	1.07	1.41	1.10
1.18	1.33	1.41	1.60	1.37
1.18	1.34	1.14	1.23	1.47
1.28	1.17	1.16	1.38	1.21
1.24	1.24	1.26	1.37	1.29
1.32	1.30	1.29	1.37	1.25
1.25	1.30	1.36	1.16	1.06
1.27	1.18	1.40	1.33	1.15
1.20	1.36	1.42	1.13	1.27
1.18	1.15	1.32	1.00	1.21
1.28	1.24	1.33	1.33	1.60
1.15	1.18	1.28	1.22	1.25
1.28	1.23	1.24	1.40	1.10
1.28	1.14	1.43	1.18	1.21
1.26	1.22	1.34	1.30	1.02
1.27	1.26	1.21	1.18	1.20
1.32	1.39	1.29	1.24	1.44
1.18	1.40	1.21	1.17	0.88
1.25	1.32	1.33	1.13	1.37
1.41	1.29	1.22	0.95	1.46
1.18	1.18	1.26	1.45	1.45
1.24	1.31	1.19	1.30	1.31
1.31	1.36	1.21	0.96	1.37
1.30	1.34	1.05	1.54	1.57
1.29	1.34	1.36	1.18	1.47
1.36	1.30	1.31	1.49	1.04
1.13	1.17	1.21	1.31	1.09
1.29	1.30	1.35	1.36	1.24
1.27	1.34	1.39	1.44	1.21
1.28	1.27	1.33	1.37	1.51
1.20	1.29	1.25	1.02	1.11
1.24	1.26	1.18	1.56	1.49

1.34	1.17	1.25	1.27	1.28
1.29	1.31	1.38	1.52	1.52
1.17	1.15	1.28	1.38	1.29
1.36	1.39	1.48	1.56	1.16
1.26	1.41	1.45	1.57	1.48
1.27	1.33	1.19	1.23	1.44
1.23	1.26	1.37	1.42	1.33
1.26	1.27	1.29	1.27	1.39
1.13	1.30	1.35	1.41	1.45
1.19	1.16	1.37	1.39	1.19
1.25	1.26	1.20	1.45	1.26
1.35	1.18	1.27	1.34	1.49
1.38	1.26	1.30	1.14	1.37
1.32	1.24	1.36	1.12	1.52
1.27	1.28	1.33	1.26	1.12
1.38	1.24	1.23	1.17	1.40
1.26	1.41	1.32	1.05	1.22
1.40	1.20	1.04	1.27	1.38
1.24	1.41	1.46	1.34	1.41
1.29	1.15	1.31	1.09	1.60
1.37	1.25	1.33	1.43	1.43
1.12	1.33	1.41	1.38	1.29
1.29	1.35	1.20	1.50	1.26
1.41	1.35	1.29	1.51	1.38
1.29	1.24	1.26	1.35	1.34
1.27	1.28	1.14	1.41	1.33
1.36	1.33	1.19	1.18	1.44
1.19	1.25	1.39	1.27	1.20
1.21	1.23	1.27	1.57	1.56
1.28	1.34	1.14	1.15	1.41
1.35	1.30	1.35	1.34	1.26
1.29	1.38	1.14	1.20	1.11
1.28	1.31	1.19	1.12	1.35
1.38	1.31	1.07	1.14	1.12
1.29	1.40	1.14	1.39	1.25
1.24	1.37	1.28	1.37	1.51
1.34	1.26	1.44	0.98	1.38
1.23	1.12	1.35	1.49	1.02
1.22	1.23	1.33	1.19	1.42
1.29	1.14	1.22	1.31	0.93
1.10	1.33	1.45	0.96	0.91

1.38	*1.28*	*1.11*	*1.16*	*1.54*
1.33	*1.29*	*1.30*	*1.27*	*1.23*
1.21	*1.32*	*1.18*	*1.35*	*1.15*
1.38	*1.38*	*1.18*	*1.09*	*1.49*
1.25	*1.26*	*1.41*	*1.56*	*1.41*
1.24	*1.31*	*1.02*	*1.37*	*1.51*
1.17	*1.26*	*1.44*	*0.97*	*1.41*
1.35	*1.39*	*1.30*	*1.54*	*1.19*
1.33	*1.33*	*1.21*	*1.55*	*1.30*
1.12	*1.36*	*1.36*	*1.21*	*1.04*
1.16	*1.30*	*1.40*	*1.14*	*1.37*
1.28	*1.30*	*1.15*	*1.34*	*1.36*
1.20	*1.29*	*1.45*	*1.33*	*1.13*
1.35	*1.33*	*1.18*	*1.51*	*1.23*
1.09	*1.27*	*1.21*	*1.50*	*0.98*
1.31	*1.17*	*1.46*	*1.35*	*1.41*
1.27	*1.36*	*1.36*	*1.34*	*1.46*
1.28	*1.29*	*1.38*	*1.32*	*1.01*
1.23	*1.35*	*1.02*	*1.28*	*0.92*
1.23	*1.33*	*1.37*	*1.45*	*1.36*
1.23	*1.32*	*1.40*	*1.57*	*1.04*
1.30	*1.24*	*1.06*	*1.12*	*1.47*
1.27	*1.31*	*1.32*	*1.50*	*1.57*
1.24	*1.33*	*1.29*	*1.41*	*1.36*
1.24	*1.38*	*1.36*	*1.48*	*1.58*
1.19	*1.27*	*1.40*	*1.49*	*1.42*
1.12	*1.25*	*1.19*	*1.61*	*1.25*
1.37	*1.41*	*1.38*	*1.30*	*1.06*
1.23	*1.29*	*1.34*	*1.40*	*1.35*
1.31	*1.23*	*1.16*	*1.30*	*1.39*
1.29	*1.24*	*1.13*	*1.20*	*1.12*
1.25	*1.38*	*1.08*	*1.60*	*1.51*
1.22	*1.27*	*1.18*	*1.32*	*1.46*
1.21	*1.27*	*1.33*	*1.36*	*0.98*
1.25	*1.39*	*1.09*	*1.38*	*1.15*
1.37	*1.23*	*1.11*	*1.25*	*1.18*
1.40	*1.24*	*1.28*	*1.20*	*0.98*
1.32	*1.22*	*1.45*	*1.49*	*1.52*
1.12	*1.39*	*1.39*	*1.36*	*1.46*
1.40	*1.25*	*1.20*	*1.51*	*1.21*
1.24	*1.31*	*1.32*	*1.29*	*1.14*

1.31	*1.23*	*1.30*	*1.03*	*1.18*
1.19	*1.36*	*1.35*	*1.44*	*1.53*
1.13	*1.39*	*1.43*	*1.30*	*0.93*
1.14	*1.27*	*1.37*	*1.40*	*0.93*
1.26	*1.18*	*1.30*	*1.47*	*1.18*
1.29	*1.12*	*1.19*	*1.04*	*1.48*
1.24	*1.32*	*1.11*	*1.05*	*1.24*
1.27	*1.32*	*1.43*	*1.39*	*1.43*
1.19	*1.23*	*1.11*	*1.39*	*1.45*
1.13	*1.26*	*1.38*	*1.50*	*1.17*
1.41	*1.35*	*1.45*	*1.28*	*1.42*
1.29	*1.33*	*1.35*	*1.48*	*1.38*
1.19	*1.32*	*1.34*	*1.54*	*1.36*
1.24	*1.37*	*1.40*	*1.10*	*1.32*
1.24	*1.29*	*1.17*	*1.56*	*1.48*
1.22	*1.13*	*1.41*	*1.03*	*1.14*
1.21	*1.22*	*1.24*	*1.48*	*1.49*
1.27	*1.33*	*1.35*	*1.28*	*1.41*
1.33	*1.41*	*1.14*	*1.02*	*1.34*
1.27	*1.30*	*1.16*	*1.09*	*1.27*
1.19	*1.29*	*1.35*	*1.29*	*1.48*
1.26	*1.32*	*1.06*	*1.36*	*1.29*
1.29	*1.36*	*1.34*	*1.40*	*1.23*
1.42	*1.25*	*1.39*	*1.07*	*1.57*
1.30	*1.21*	*1.29*	*1.31*	*1.40*
1.24	*1.26*	*1.15*	*1.31*	*1.23*
1.31	*1.37*	*1.37*	*1.41*	*1.59*
1.33	*1.29*	*1.43*	*1.66*	*1.25*
1.36	*1.32*	*1.16*	*1.61*	*0.99*
1.42	*1.25*	*1.28*	*1.43*	*1.35*
1.20	*1.33*	*1.12*	*1.11*	*1.42*
1.12	*1.42*	*1.21*	*1.45*	*1.30*
1.18	*1.30*	*1.32*	*1.22*	*1.42*
1.32	*1.16*	*1.47*	*1.41*	*1.34*
1.26	*1.27*	*1.39*	*1.44*	*1.03*
1.11	*1.14*	*1.30*	*1.29*	*1.41*
1.16	*1.38*	*1.26*	*1.54*	*1.04*
1.10	*1.35*	*1.34*	*1.64*	*1.56*
1.33	*1.23*	*1.17*	*1.37*	*1.15*
1.24	*1.18*	*1.41*	*1.25*	*1.21*
1.38	*1.25*	*1.37*	*1.20*	*0.93*

1.34	*1.38*	*1.24*	*1.05*	*1.41*
1.09	*1.29*	*1.40*	*1.10*	*1.24*
1.20	*1.20*	*1.34*	*1.17*	*1.41*
1.41	*1.27*	*1.47*	*1.42*	*1.42*
1.21	*1.22*	*1.21*	*1.36*	*1.42*
1.38	*1.20*	*1.19*	*1.12*	*1.43*
1.32	*1.19*	*1.16*	*1.53*	*1.19*
1.17	*1.28*	*1.33*	*1.26*	*1.56*
1.23	*1.27*	*1.11*	*1.22*	*1.55*
1.20	*1.27*	*1.35*	*1.40*	*1.22*
1.28	*1.25*	*1.12*	*1.36*	*1.44*
1.28	*1.32*	*1.37*	*1.28*	*1.44*
1.34	*1.24*	*1.36*	*1.30*	*1.35*
1.17	*1.43*	*1.37*	*1.58*	*1.36*
1.27	*1.34*	*1.34*	*1.44*	*1.24*
1.36	*1.20*	*1.48*	*1.38*	*1.32*
1.27	*1.28*	*1.31*	*1.49*	*1.10*
1.25	*1.15*	*1.32*	*1.15*	*1.39*
1.26	*1.32*	*1.21*	*1.38*	*1.07*
1.16	*1.32*	*1.34*	*1.44*	*1.48*
1.21	*1.32*	*1.36*	*1.11*	*1.44*
1.33	*1.32*	*1.24*	*1.21*	*1.49*
1.26	*1.32*	*1.18*	*1.54*	*1.16*
1.24	*1.33*	*1.41*	*1.23*	*1.03*
1.15	*1.27*	*1.33*	*1.27*	*1.02*
1.36	*1.29*	*1.11*	*1.40*	*1.18*
1.21	*1.29*	*1.21*	*1.45*	*1.17*
1.36	*1.33*	*1.28*	*1.10*	*1.23*
1.33	*1.33*	*1.25*	*1.25*	*1.10*
1.34	*1.28*	*1.24*	*1.29*	*1.42*
1.23	*1.34*	*1.25*	*1.41*	*1.45*
1.34	*1.13*	*1.26*	*1.05*	*1.49*
1.22	*1.31*	*1.35*	*0.99*	*1.38*
1.42	*1.27*	*1.27*	*1.43*	*1.23*
1.30	*1.25*	*1.37*	*1.63*	*1.21*
1.24	*1.16*	*1.23*	*1.20*	*1.17*
1.25	*1.22*	*1.34*	*1.58*	*1.49*
1.26	*1.19*	*1.32*	*1.00*	*1.27*
1.36	*1.26*	*1.26*	*1.21*	*1.59*
1.19	*1.13*	*1.24*	*1.43*	*1.11*
1.25	*1.15*	*1.33*	*1.11*	*0.88*

1.15	1.41	1.26	1.30	1.27
1.33	1.33	1.16	1.49	1.30
1.17	1.39	1.36	1.15	1.06
1.35	1.35	1.26	1.27	1.29
1.23	1.38	1.31	0.97	1.03
1.24	1.33	1.32	1.10	1.44
1.24	1.31	1.31	1.58	1.46
1.27	1.34	1.17	1.41	1.36
1.19	1.22	1.30	1.48	1.49
1.21	1.25	1.17	1.40	1.21
1.29	1.32	1.21	1.42	1.41
1.19	1.28	1.25	1.27	1.60
1.16	1.20	1.09	1.11	0.97
1.27	1.27	1.37	1.29	1.36
1.17	1.31	1.36	1.47	1.19
1.18	1.27	1.35	1.15	1.47
1.15	1.30	1.43	1.49	1.03
1.31	1.25	1.39	1.24	1.39
1.16	1.27	1.38	1.41	1.32
1.12	1.20	1.27	1.47	1.23
1.35	1.30	1.37	1.08	1.11
1.13	1.38	1.28	1.33	1.33
1.32	1.34	1.19	1.36	1.52
1.27	1.23	1.19	1.04	1.21
1.20	1.30	1.28	1.46	1.32
1.31	1.35	1.10	1.27	1.17
1.12	1.41	1.41	1.50	1.53
1.27	1.34	1.39	1.42	0.95
1.34	1.37	1.25	1.48	1.48
1.23	1.21	1.22	1.45	1.52
1.33	1.39	1.25	1.35	1.03
1.23	1.17	1.02	1.39	1.28
1.21	1.36	1.14	1.22	1.32
1.33	1.36	1.25	1.39	1.26
1.32	1.27	1.30	1.01	1.30
1.24	1.22	1.33	1.58	1.06
1.28	1.30	1.23	1.32	1.30
1.16	1.31	1.25	1.46	1.38
1.26	1.34	1.19	1.25	1.46
1.09	1.34	1.13	1.27	1.62
1.27	1.36	1.33	1.30	1.08

1.25	1.28	1.24	1.11	1.42
1.18	1.28	1.08	1.36	1.47
1.30	1.30	1.34	1.50	1.27
1.20	1.29	1.31	1.03	1.49
1.13	1.21	1.18	1.21	1.30
1.28	1.18	1.22	1.58	1.36
1.31	1.38	1.40	1.26	1.60
1.29	1.24	1.21	1.10	1.31
1.15	1.33	1.34	1.35	1.05
1.25	1.19	1.20	1.62	1.46
1.15	1.24	1.32	1.37	1.04
1.21	1.24	1.12	1.42	1.06
1.14	1.20	1.12	0.95	1.00
1.33	1.33	1.23	1.50	1.43
1.38	1.23	1.28	1.38	1.46
1.22	1.30	1.34	1.16	1.57
1.26	1.36	1.22	1.16	1.33
1.26	1.25	1.23	1.22	1.44
1.24	1.22	1.31	0.99	1.28
1.37	1.32	1.34	1.33	1.22
1.32	1.35	1.26	1.23	1.48
1.34	1.36	1.47	1.46	1.45
1.31	1.31	1.42	1.43	1.37
1.20	1.37	1.41	1.35	1.37
1.26	1.26	1.08	1.12	1.23
1.32	1.32	1.27	1.19	1.50
1.30	1.37	1.17	1.52	1.17
1.30	1.29	1.03	1.27	1.39
1.29	1.25	1.31	1.35	0.94
1.33	1.24	1.39	1.31	1.15
1.14	1.34	1.14	1.55	1.47
1.24	1.34	1.21	1.62	1.04
1.19	1.27	1.37	1.54	1.04
1.34	1.28	1.06	1.35	1.50
1.31	1.37	1.31	1.53	1.52
1.18	1.36	1.30	1.10	1.33
1.26	1.36	1.47	1.00	1.47
1.38	1.34	1.21	1.09	1.47
1.39	1.23	1.05	1.23	1.30
1.21	1.30	1.33	1.32	1.13
1.24	1.24	1.23	1.37	1.32

1.20	*1.22*	*1.19*	*1.01*	*1.40*
1.27	*1.23*	*1.16*	*1.35*	*1.37*
1.24	*1.27*	*1.36*	*1.11*	*1.10*
1.16	*1.22*	*1.43*	*1.42*	*1.51*
1.26	*1.36*	*1.22*	*1.34*	*1.40*
1.28	*1.23*	*1.10*	*1.57*	*1.06*
1.21	*1.30*	*1.27*	*1.37*	*1.39*
1.31	*1.30*	*1.19*	*1.32*	*1.20*
1.31	*1.18*	*1.30*	*1.42*	*1.00*
1.35	*1.35*	*1.30*	*1.26*	*1.03*
1.19	*1.25*	*1.32*	*1.42*	*1.57*
1.23	*1.39*	*1.35*	*1.29*	*0.99*
1.23	*1.21*	*1.18*	*1.31*	*1.25*
1.34	*1.12*	*1.18*	*1.34*	*1.28*
1.27	*1.42*	*1.29*	*1.32*	*1.13*
1.24	*1.26*	*1.32*	*1.32*	*1.45*
1.33	*1.33*	*1.36*	*1.52*	*1.51*
1.37	*1.39*	*1.35*	*1.38*	*1.19*
1.34	*1.36*	*1.38*	*1.30*	*1.52*
1.27	*1.38*	*1.11*	*1.28*	*1.16*
1.34	*1.31*	*1.48*	*1.57*	*1.35*
1.20	*1.36*	*1.15*	*1.35*	*1.36*
1.12	*1.26*	*1.21*	*1.40*	*1.18*
1.29	*1.28*	*1.23*	*1.36*	*1.29*
1.37	*1.25*	*1.32*	*1.23*	*1.36*
1.30	*1.21*	*1.11*	*1.36*	*1.39*
1.26	*1.24*	*1.19*	*1.22*	*1.53*
1.20	*1.33*	*1.37*	*1.28*	*1.41*
1.15	*1.35*	*1.17*	*1.04*	*1.17*
1.26	*1.31*	*1.17*	*1.17*	*1.21*
1.16	*1.31*	*1.31*	*1.59*	*1.20*
1.27	*1.14*	*1.35*	*1.29*	*1.47*
1.14	*1.35*	*1.32*	*1.55*	*0.98*
1.32	*1.21*	*1.02*	*1.43*	*0.92*
1.37	*1.32*	*1.43*	*1.51*	*1.25*
1.18	*1.20*	*1.31*	*1.06*	*1.03*
1.17	*1.44*	*1.40*	*1.23*	*1.34*
1.37	*1.34*	*1.20*	*0.92*	*1.26*
1.19	*1.44*	*1.26*	*1.37*	*1.39*
1.22	*1.22*	*1.21*	*0.98*	*1.31*
1.23	*1.31*	*1.28*	*1.17*	*1.26*

1.25	*1.32*	*1.34*	*1.40*	*1.09*
1.25	*1.29*	*1.34*	*1.26*	*1.42*
1.14	*1.39*	*1.22*	*1.31*	*1.08*
1.13	*1.39*	*1.01*	*1.28*	*1.47*
1.37	*1.25*	*1.25*	*1.22*	*0.99*
1.38	*1.37*	*1.30*	*1.39*	*1.44*
1.27	*1.30*	*1.35*	*1.56*	*1.02*
1.21	*1.17*	*1.32*	*1.52*	*1.53*
1.30	*1.26*	*1.09*	*1.52*	*1.36*
1.24	*1.39*	*1.38*	*1.53*	*1.29*
1.24	*1.31*	*1.11*	*1.28*	*1.31*
1.18	*1.25*	*1.26*	*1.38*	*1.14*
1.27	*1.40*	*1.06*	*1.38*	*1.10*
1.26	*1.23*	*1.25*	*1.28*	*1.49*
1.39	*1.26*	*1.14*	*1.32*	*1.07*
1.27	*1.23*	*1.28*	*1.43*	*1.41*
1.12	*1.17*	*1.33*	*1.19*	*1.25*
1.40	*1.29*	*1.23*	*1.34*	*1.52*
1.39	*1.33*	*1.46*	*1.43*	*1.27*
1.32	*1.26*	*1.28*	*1.45*	*0.99*
1.18	*1.30*	*1.27*	*1.06*	*1.32*
1.15	*1.29*	*1.33*	*1.22*	*1.50*
1.37	*1.36*	*1.34*	*1.56*	*1.12*
1.26	*1.26*	*1.38*	*1.23*	*1.13*
1.13	*1.39*	*1.39*	*1.33*	*1.51*
1.21	*1.26*	*1.26*	*1.08*	*1.25*
1.20	*1.35*	*1.35*	*1.42*	*1.35*
1.25	*1.32*	*1.31*	*1.45*	*1.20*
1.26	*1.36*	*1.08*	*1.39*	*1.60*
1.16	*1.15*	*1.08*	*1.37*	*1.51*
1.25	*1.30*	*1.17*	*1.38*	*1.63*
1.20	*1.33*	*1.44*	*1.16*	*1.15*
1.30	*1.17*	*1.31*	*1.56*	*1.40*
1.17	*1.21*	*1.45*	*1.31*	*1.43*
1.34	*1.35*	*1.07*	*0.99*	*1.41*
1.19	*1.38*	*1.19*	*1.33*	*1.46*
1.20	*1.25*	*1.39*	*1.17*	*1.52*
1.30	*1.31*	*1.13*	*1.42*	*1.22*
1.31	*1.33*	*1.25*	*1.38*	*1.36*
1.25	*1.25*	*1.13*	*1.66*	*1.50*
1.39	*1.17*	*1.32*	*1.50*	*1.03*

1.29	*1.29*	*1.16*	*1.57*	*1.47*
1.23	*1.29*	*1.29*	*1.29*	*1.55*
1.24	*1.24*	*1.25*	*1.02*	*1.55*
1.26	*1.17*	*1.22*	*1.14*	*1.58*
1.18	*1.28*	*1.28*	*1.33*	*1.18*
1.35	*1.35*	*1.19*	*1.39*	*1.48*
1.18	*1.33*	*1.45*	*1.12*	*1.21*
1.19	*1.28*	*1.16*	*1.51*	*1.56*
1.20	*1.23*	*1.45*	*1.39*	*1.11*
1.19	*1.40*	*1.10*	*1.05*	*1.26*
1.36	*1.35*	*1.28*	*1.52*	*1.53*
1.20	*1.17*	*1.34*	*1.43*	*1.54*
1.27	*1.25*	*1.40*	*1.37*	*1.46*
1.30	*1.25*	*1.20*	*1.45*	*1.45*
1.14	*1.39*	*1.26*	*1.17*	*1.45*
1.37	*1.28*	*1.38*	*1.26*	*1.01*
1.37	*1.34*	*1.16*	*1.22*	*1.54*
1.24	*1.24*	*1.11*	*1.18*	*1.01*
1.17	*1.35*	*1.27*	*1.56*	*1.29*
1.37	*1.26*	*1.26*	*1.50*	*1.32*
1.36	*1.34*	*1.22*	*1.24*	*1.23*
1.40	*1.27*	*1.21*	*1.12*	*0.88*
1.32	*1.24*	*1.24*	*1.41*	*0.93*
1.33	*1.20*	*1.32*	*1.40*	*1.29*
1.25	*1.22*	*1.05*	*1.43*	*1.40*
1.21	*1.29*	*1.28*	*1.46*	*1.48*
1.27	*1.16*	*1.44*	*1.52*	*1.13*
1.19	*1.28*	*1.40*	*1.60*	*1.56*
1.41	*1.44*	*1.44*	*1.18*	*1.22*
1.34	*1.29*	*1.36*	*1.55*	*1.38*
1.32	*1.35*	*1.36*	*1.32*	*0.98*
1.30	*1.33*	*1.31*	*1.41*	*0.98*
1.26	*1.40*	*1.29*	*1.24*	*1.31*
1.30	*1.25*	*1.27*	*1.35*	*1.47*
1.23	*1.25*	*1.33*	*1.41*	*1.30*
1.25	*1.24*	*1.38*	*1.31*	*1.46*
1.32	*1.34*	*1.30*	*1.17*	*1.02*
1.32	*1.25*	*1.29*	*1.50*	*1.33*
1.26	*1.37*	*1.18*	*1.56*	*1.32*
1.14	*1.30*	*1.34*	*1.45*	*1.37*
1.27	*1.15*	*1.20*	*1.11*	*1.18*

1.26	*1.21*	*1.11*	*1.03*	*1.39*
1.24	*1.38*	*1.15*	*1.52*	*1.19*
1.31	*1.28*	*1.22*	*1.20*	*1.41*
1.24	*1.36*	*1.32*	*1.02*	*1.25*
1.26	*1.19*	*1.34*	*1.19*	*1.27*
1.36	*1.31*	*1.08*	*1.51*	*1.19*
1.31	*1.29*	*1.26*	*1.59*	*1.37*
1.28	*1.23*	*1.28*	*1.21*	*1.03*
1.27	*1.34*	*1.23*	*1.42*	*1.44*
1.29	*1.24*	*1.27*	*1.09*	*1.13*
1.31	*1.29*	*1.19*	*1.46*	*1.44*
1.24	*1.29*	*1.40*	*1.41*	*1.43*
1.33	*1.37*	*1.21*	*1.40*	*1.33*
1.20	*1.14*	*1.23*	*1.41*	*1.02*
1.19	*1.26*	*1.24*	*1.59*	*1.46*
1.31	*1.35*	*1.45*	*1.33*	*1.44*
1.29	*1.22*	*1.44*	*1.43*	*1.34*
1.22	*1.25*	*1.33*	*1.20*	*1.14*
1.16	*1.27*	*1.37*	*1.36*	*1.21*
1.30	*1.29*	*1.34*	*1.19*	*1.34*

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APPENDIX G. DISTRO FITTING

Cycle Time (As-Is)

Distributional Fitting: Continuous (Kolmogorov-Smirnov)

Rank	P-Value	Distribution
1	0.9330	Normal
2	0.7599	Triangular
3	0.6570	PERT
4	0.5418	Logistic
5	0.5090	Cosine
6	0.4763	Erlang
7	0.4626	Gamma
8	0.4362	Beta 4
9	0.4067	Lognormal (Arithmetic)
10	0.4023	Lognormal (Log)

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