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ARCHITECTURE FOR A CBM+ AND PHM CENTRIC DIGITAL TWIN FOR WARFARE SYSTEMS

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SYSTEMS ENGINEERING CAPSTONE REPORT

ARCHITECTURE FOR A CBM+ AND PHM CENTRIC DIGITAL TWIN FOR WARFARE SYSTEMS

by

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December 2021

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The Department of the Navy’s continued progression from time-based maintenance into condition-based maintenance plus (CBM+) shows the importance of increasing operational availability (Ao) across fleet weapon systems. This capstone uses the concept of digital efficiency from a digital twin (DT) combined with a three-dimensional (3D) direct metal laser melting printer as the physical host on board a surface vessel. The DT provides an agnostic conduit for combining model-based systems engineering with a digital analysis for real-time prognostic health monitoring while improving predictive maintenance. With the DT at the forefront of prioritized research and development, the 3D printer combines the value of additive manufacturing with complex systems in dynamic shipboard environments. To demonstrate that the DT possesses parallel abilities for improving both the physical host’s Ao and end-goal mission, this capstone develops a DT architecture and a high-level model. The model focuses on specific printer components (deionized [DI] water level, DI water conductivity, air filters, and laser motor drive system) to demonstrate the DT’s inherent effectiveness towards CBM+. To embody the system of systems analysis for printer suitability and performance, more components should be evaluated and combined with the ship’s environment data. Additionally, this capstone recommends the use of DTs as a nexus into more complex weapon systems while using a deeper level of design of experiment.

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ABSTRACT

The Department of the Navy's continued progression from time-based maintenance into condition-based maintenance plus (CBM+) shows the importance of increasing operational availability (Ao) across fleet weapon systems. This capstone uses the concept of digital efficiency from a digital twin (DT) combined with a three-dimensional (3D) direct metal laser melting printer as the physical host on board a surface vessel. The DT provides an agnostic conduit for combining model-based systems engineering with a digital analysis for real-time prognostic health monitoring while improving predictive maintenance. With the DT at the forefront of prioritized research and development, the 3D printer combines the value of additive manufacturing with complex systems in dynamic shipboard environments. To demonstrate that the DT possesses parallel abilities for improving both the physical host's Ao and end-goal mission, this capstone develops a DT architecture and a high-level model. The model focuses on specific printer components (deionized [DI] water level, DI water conductivity, air filters, and laser motor drive system) to demonstrate the DT's inherent effectiveness towards CBM+. To embody the system of systems analysis for printer suitability and performance, more components should be evaluated and combined with the ship's environment data. Additionally, this capstone recommends the use of DTs as a nexus into more complex weapon systems while using a deeper level of design of experiment.

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LIST OF ACRONYMS AND ABBREVIATIONS

3D	three-dimensional
ADT	administrative delay time
Ao	operational availability
AM	additive manufacturing
AML	additive manufacturing laboratory
ANOVA	analysis of variance
API	application programming interfaces
ASTM	American Society for Testing and Materials
AWS	Amazon Web Services
BDD	block definition diagram
CAD	computer aided design
CBM	condition based maintenance
CBM+	condition based maintenance plus
CD	condition directed
CEA	Cameo Enterprise Architecture
CNC	computer numerical controlled
CNO	Chief of Naval Operations
COMOPTEVFOR	Commander Operational Test and Evaluation Force
CONOPS	concept of operations
CUI	controlled unclassified information
DCP	data collection plan
DI	deionized
DMLM	direct metal laser melting
DMLS	direct metal laser sintering
DOD	Department of Defense
DOE	design of experiments
DON	Department of the Navy
DOT&E	developmental operational test and evaluation

DT	digital twin
DT&E	developmental test and evaluation
E2E	end-to-end
FMEA	failure modes and affects analysis
FOC	full operating capability
FOD	foreign object debris
fpt	preventive maintenance rate
GE	General Electric
GUI	graphical user interface
HPDA	high-performance data analytics
IBD	internal block diagram
I-Level	intermediate level
I/O	input/output
IOC	initial operational capability
IOT	internet of things
ISEA	in-service engineering agent
IT	information technology
LDT	logistical delay time
LRIP	low-rate initial production
M&S	modeling and simulation
M_bar	mean active maintenance time
MBSE	model based system engineering
Mct_bar	mean active corrective maintenance time
MDT	maintenance downtime
MIL-STD	military standard
ML	machine learning
MLH/cycle	maintenance labor hours per cycle
MOE	measure of effectiveness
MOP	measure of performance
MOS	measure of suitability

Mpt_bar	mean active preventive maintenance time
MSSE	Master of Science in Systems Engineering
MTBMs	mean time between maintenance scheduled
MTBMu	mean time between maintenance unscheduled
MTBR	mean time between replacement
MTTF	mean time to failure
NAVSEA	Naval Sea Systems Command
NAVSUP	Naval Supply Systems Command
NPS	Naval Postgraduate School
NSWC PHD	Naval Surface Warfare Center Port Hueneme Division
O&M	operations and maintenance
O&S	operations and sustainment
O-Level	operations level
OT&E	operational test and evaluation
OV	operational view
PEO	Program Executive Officer
PHASED	prognostics and health analysis to support engineering design
PHM	prognostics and health management
PM	program manager
RAID	redundant array of independent disks
RCM	reliability centered maintenance
RDT&E	research, development test and evaluation
RF	radio frequency
RMC	regional maintenance center
ROI	return on investment
RRM	refine requirement matrix
RUL	remaining useful life
SATCOM	satellite communications
SE	systems engineering
SME	subject matter expert

SOS	system of systems
SUT	system under test
SV	surface vessel
SysML	Systems Modeling Language
TBM	time based maintenance
TD	time directed
TPM	technical performance measure
USN	United States Navy

EXECUTIVE SUMMARY

The current maintenance philosophy the United States Navy employs either continual or responsive maintenance strategies to sustain operational availability (Ao) of complex defense systems. Particularly, these maintenance strategies are performed through what is known as time-based maintenance (TBM) and corrective maintenance. Time-based maintenance requires periodic inspection and/or repair of a component to ensure that failure does not occur prior to the designed useful life, which affects Ao because of system downtime. In addition, corrective maintenance is a reaction to a failure of a component or system, which affects availability due to administrative and logistical delay time, as well as system downtime. The primary goal of this capstone project was to develop an architecture and rudimentary model for a digital twin (DT) to explore a transition in maintenance strategy from TBM to condition-based maintenance plus (CBM+) while leveraging existing prognostic health management technology.

To explore the concept of utilizing a DT onboard a naval surface vessel, a team of students from Naval Postgraduate School (NPS) examined DT capabilities currently available or under development and systems that may benefit from the use of a DT. The project scope was constrained with a classification level not to exceed Controlled Unclassified Information (CUI), which excluded emphasis on weapon, combat, and radar systems. In addition, actual performance data for naval systems below a classification level of CUI were not available, so the concept of operation for the DT was developed based on research of openly available information. To address the classification constraint and a topic of great interest to the Navy, additive manufacturing (AM), the team explored the application of a DT system for a three-dimensional (3D) printer onboard a surface vessel. Additionally, creating a DT architecture for a 3D printer provides invaluable insights regarding sensitive, high-precision systems in dynamic environments unique to naval operations. The team determined the DT for a 3D printer's effectiveness benefited through the creation of an architecture and rudimentary model.

An operational view, or OV-1 diagram, which is a high-level operational concept diagram, was created to illustrate the operational concept for this capstone project (see

Figure 1). The diagram depicts interactions among system of systems, which include a 3D printer onboard the manned surface vessel, ship personnel, hybrid cloud, satellite communications (SATCOM), and shore support to include the supply chain system. The DT receives sensor inputs from the 3D printer as well as shipboard environmental data to predict necessary maintenance in addition to the quality of printed parts. The hybrid cloud that encompasses the DT stores raw and processed data to maintain historical artifacts and provide alerts to ship personnel and shore support through either SATCOM or wired connection when the surface vessel is in-port. The alerts assist in providing necessary information to ship personnel about upcoming maintenance or providing parts that need to be prepared by the shore support activity resulting in a reduction in administrative and logistical lead time.

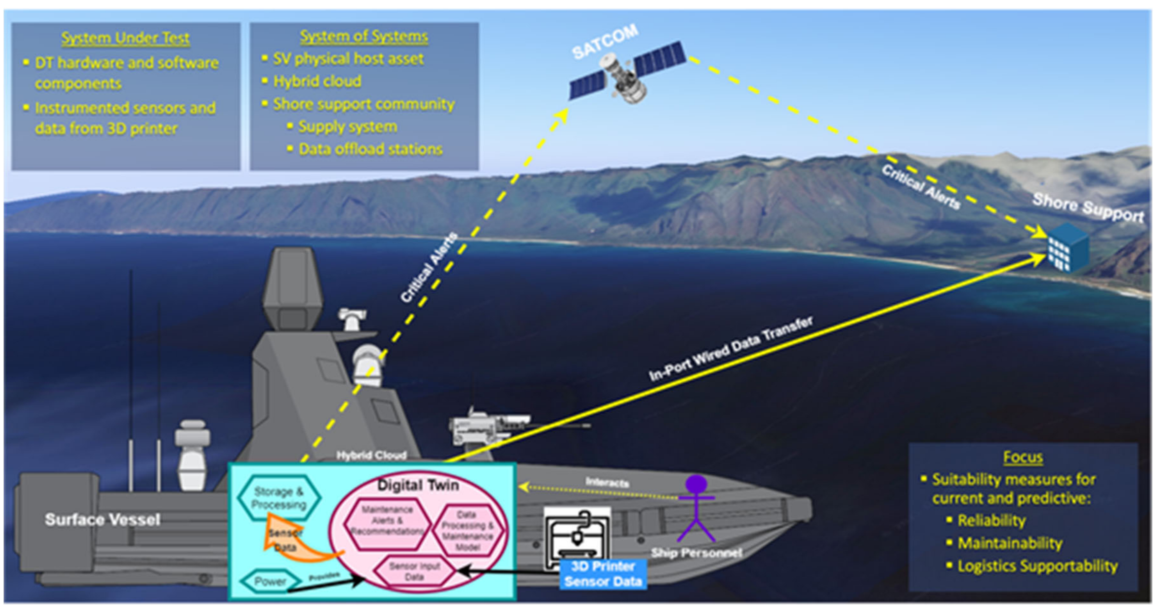

Figure 1. OV-1: High-level Operational Concept Diagram

This capstone project narrowed the focus to a specific 3D printer model to determine the type of sensors and data that was important for the DT architecture. The team selected a printer model that is currently in use by a few laboratories within the DOD, the General Electric M2 cusing series 5. This printer uses direct metal laser melting (DMLM) to fabricate prints. The DMLM fabrication process consists of melting metal powder particles to create ultra-thin pools that solidify as they cool (GE Additive 2021). This process produces parts that have reduced weight while retaining strength, durability, and precision required to meet the Navy's AM requirements for parts. The DMLM 3D printer major components, shown in Figure 2, consist of a laser, focal lens, collimator, mirror, recoater blade, and three powder chambers consisting of powder supply, build powder bed, and used powder collection. The collimator and focal lens work together to focus the laser. The recoater blade is used to distribute, smooth, and flatten the metal powder in-between layers. In addition to these components, the printer must have quality air flow and maintain an inert gas environment during the printing process; the GE M2 cusing uses nitrogen gas. The team focused on employing a DT system to leverage the 3D printer's embedded sensors in addition to sensors placed within the printer and ship's compartments to determine factors that affect system availability and quality of the printed part.

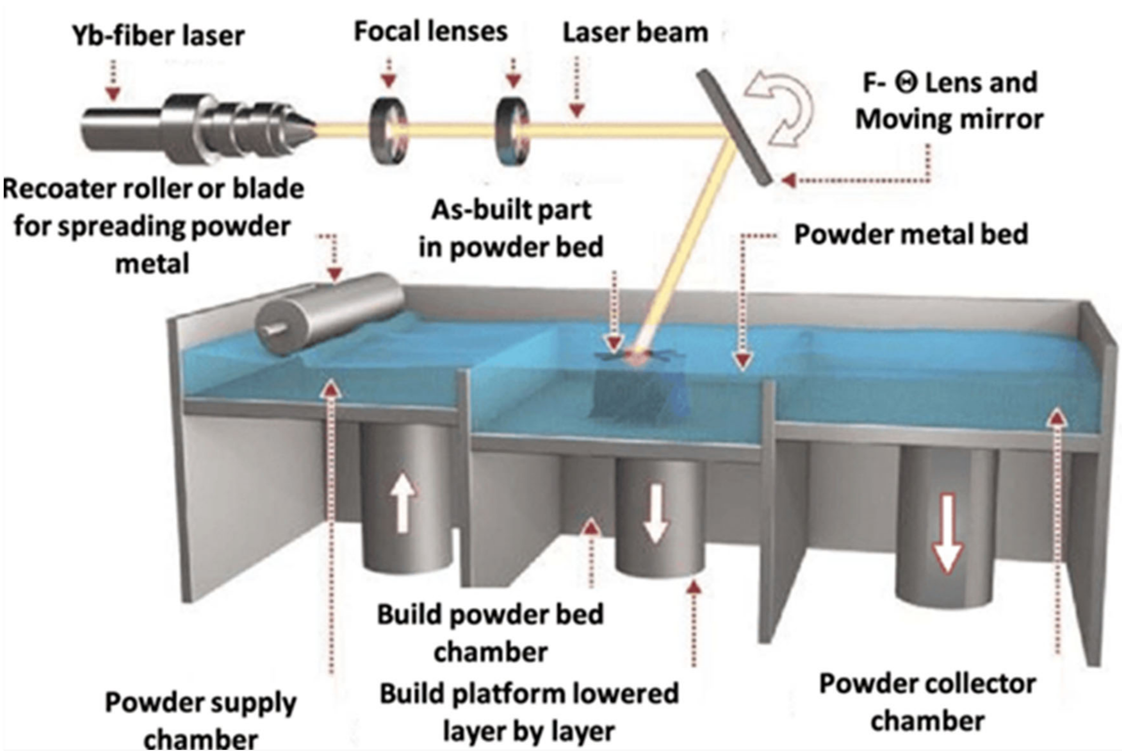

Figure 2. Typical Laser Power Bed Fusion Printer. Source: Özel et al. (2020).

For this capstone project, the team decided it was best to follow a modified systems engineering (SE) approach, shown in Figure 3, that consisted of a plan-driven software process as the foundation with an integrated agile method. This hybrid process allowed the team to increase the flexibility and adaptability throughout the design and development phases by using the iterative and collaborative environment established with the agile method, as well as providing feedback, which was used to generate and refine the requirements. To align this capstone's focus with the digital transformation strategy established by the Department of the Navy (DON), the team utilized a model-based systems engineering (MBSE) approach to decompose stakeholder requirements, formulate a conceptual design, and assess system performance in a simulated operational environment. The use of MBSE aligns with the DON digital transformation strategy by creating interconnected models through use of standard language to improve traceability and manage complexity of the system.

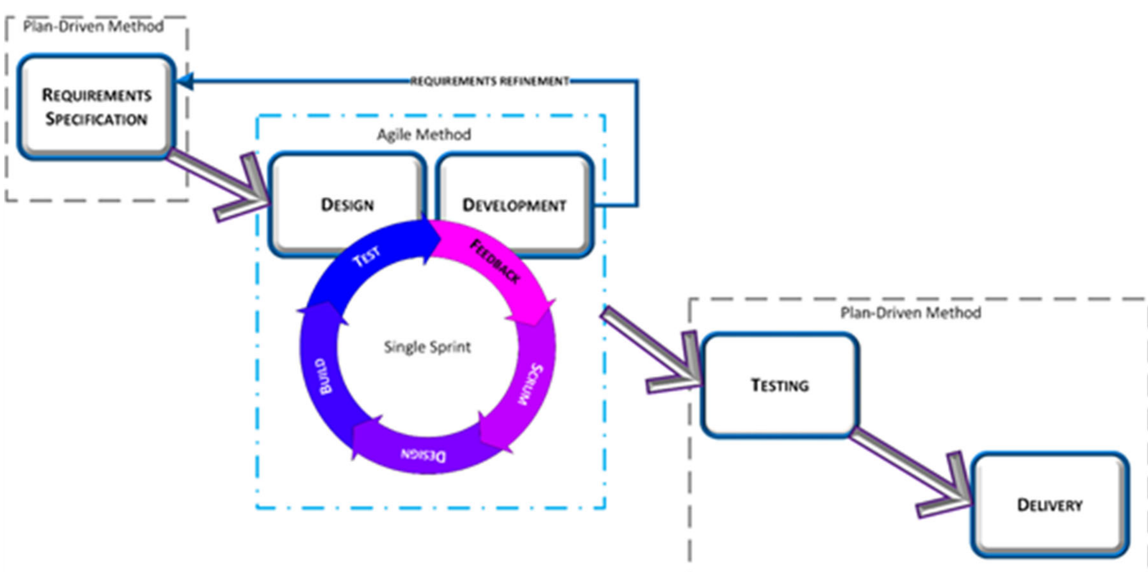

Figure 3. Hybrid SE Process, Plan-driven with Agile Method

The MagicGrid method was the primary process for the development of the DT architecture. This approach outlines the modeling process using Cameo and Systems Modeling Language (SysML) to define the problem and solution domain. This capstone focused on the problem domain which includes the decomposition into two phases, black-box and white-box perspectives, as shown in Figure 4. Each of these phases examines the problem through different perspectives resulting in the creation of various scenarios, tables, and diagrams to outline the DT system structure, behavior, and function. The black-box perspective focuses on operational analysis of the DT through creation of use cases and system context diagrams without specifying the DT system's internal structure or behavior. The white-box perspective determines how the system shall operate by identifying necessary behaviors and logical subsystems for the DT. In addition, the white-box perspective establishes the activity, state machine, block definition, and internal block diagrams.

<table>
<tr><th colspan="6">PILLAR</th></tr>
<tr><th colspan="2"></th><th>Requirements</th><th>Behavior</th><th>Structure</th><th>Parameters</th></tr>
<tr><th rowspan="2">Problem</th><th>Black Box</th><td rowspan="2">B1-W1 Stakeholder Needs</td><td>B2 Use Cases</td><td>B3 System Context</td><td>B4 Measurements of Effectiveness</td></tr>
<tr><th>White Box</th><td>W2 Functional Analysis</td><td>W3 Logical Subsystems Communication</td><td>W4 MoEs for Subsystems</td></tr>
</table>

Figure 4. MagicGrid Problem Domain Matrix. Adapted from Aleksandraviciene and Morkevicius (2018).

The team initially performed a stakeholder analysis which considered stakeholders that would benefit from the use of a DT for naval systems. These stakeholders' needs were based on guidance from both the primary sponsor, from the Naval Surface Warfare Center Port Hueneme Code 00T, and NPS advisors. Using the stakeholders' needs, a requirements analysis was performed. Based on desired functionality of the DT system, this analysis determined the functional/non-functional requirements, as well as external interfaces. The team narrowed the DT system's functional needs into seven high level requirements which are presented in Table 1.

Table 1. High-Level Functional Requirements Table

SN-6	Functional Requirements	The DT shall…
FR-6.1	Receive 3D Printer Data	Receive raw data from embedded sensors.
FR-6.2	Manage Ship Space Environmental Sensors	Maintain sensors able to record environmental data external to the physical host.
FR-6.3	Collect Ship Sensor Data	Receive data from ship sensors external to the 3D printer physical asset.
FR-6.4	Record Data	Record data from embedded and external sensors.
FR-6.5	Manage Ship Space Instrument Faults	Manage faults from environmental instrument sensors.
FR-6.6	Process Data	Process data for current and predictive system effectiveness and suitability.
FR-6.7	Communicate Data	Transmit data through the ship communication system

Next, the functional description of the system was illustrated through the development of a context diagram, use cases, and scenarios. The system context diagram illustrated users and external systems that interact with the DT. The use cases characterized the functions necessary for the DT to achieve stakeholders' goals. The primary use case the team focused on for the development of the DT architecture was the Perform DT Functions. This use case covers the DT receiving sensor data from the environment and the 3D printer, processing that data, sending raw and processed data for storage, and providing predictions as well as alerts. In addition, several measures of effectiveness were defined that benefit the DON. These included improving maintainability of the 3D printer, improving logistical supportability of a printed part, and improving probability of success for a printed part.

Upon determining the resources necessary for the system to accomplish its mission, behavior and structure diagrams for the DT system's function were created. Using SysML diagrams, dynamic behavior of the system was captured as part of the functional analysis and allocation. The functional analysis consisted of a top-down process of translating system level requirements to define the DT architecture which ensured all required system functions were accounted for. First, this was detailed in an activity diagram that described control flow and data processes. Next, various system states, transitions, and events of the DT system were defined using a state machine diagram. The determination of system actions and states helped to identify logical subsystems communications through the identification of generic components that are essential for the system to perform the necessary functions. A block definition diagram was created to establish inputs and outputs for the DT system, which included sensor data, control signals, and energy sources.

Following the development of the DT architecture, the team conducted research to determine which components would benefit from the application of a DT system. Through interaction with stakeholders and review of the 3D printer maintenance manual, the focus for the analysis was determined to be for the following components/factors: deionized (DI) water level, DI water conductivity, air filters, and laser motor drive system. The team then created an Excel model as a base to demonstrate proof of the concept for the model. The model design methodology was based on the degradation of the selected components as the 3D printer is used to print parts, comparing the use of scheduled maintenance (TBM) against CBM. Based on the Excel model, the results showed that applying a DT system to a 3D printer increased the Ao from 90.56% for TBM, to 96.15% for CBM. This increase in availability was due to a decrease in the amount of preventive maintenance performed over a two-year period.

An ExtendSim model was created based on the Excel model to allow examination of Ao while allowing parameters, such as time between prints and mean time to repair, to be modified. Comparing the results between TBM and CBM indicated that for TBM, Ao was significantly affected for shorter times between each print due to components of the 3D printer failing more frequently while still having to perform scheduled maintenance. As time between each print increased for TBM, the effect of component failures appeared to taper off since scheduled maintenance was performed consistently while failure of each component was reduced. In contrast, the Ao for CBM was approximately 5% higher for a shorter time between each print due to maintenance only being performed when a component failed. In addition, as the time between each print increased, the Ao using CBM increased at a steady rate due to not having to perform preventive maintenance.

The effect of implementing a DT system on a 3D printer demonstrated that transitioning to a CBM approach improved the current maintenance methodology utilized by the Navy through a reduction in system downtime. The transition from using TBM to CBM, using a DT system, essentially changed the maintenance philosophy from proactive to reactive through enhanced knowledge of system conditions and performance. A cost analysis was performed to complement the model and to determine the cost savings that could be achieved by implementing a DT system. Using the maintenance manual as a guide, it was determined that over a two-year span, the cost savings associated with replacing just the air filters was an approximate reduction of 78 hours of labor and $4500 in maintenance costs.

The modeling and simulation efforts, in conjunction with cost analysis, determined that implementing a DT system on a 3D printer demonstrated an improvement in system availability while reducing costs associated with maintenance. The scope of this capstone focused on how to improve Ao using CBM+; therefore, various topics and sensors were not explored but were identified by the team as areas of future work that the DT development would benefit from. Further analysis warrants connecting data collection plans that involve more internal and external sensors. To fully understand how environmental factors and the 3D printer affect performance metrics, future work should include an analysis of variance (ANOVA). The combined efforts of data analysis and historical data fed into standard design of experiment methodologies bring forth response variables and key factors able to inform this ANOVA for 3D printers onboard surface vessels. Additionally, the DMLM process would benefit from additional sensor and environmental data feeding into the DT. The DT benefits from a historical section of data collection, leveraging historical performance, real-time assessments, and predictive maintenance. These additional sensors, when combined with machine learning, would help to better predict required maintenance, individual print quality, and aid mission planning/performance. Additional topics explored for future work included hybrid cloud integration into the fleet and securing data transfer.

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I. INTRODUCTION

Throughout the Department of Defense (DOD), systems need to have the ability to provide accurate, real-time, system health performance feedback during their entire life cycle. Defense systems require analytical data extraction methods that support early conceptual design, inform fleet operational performance, assist with maintenance decisions, and retain operational availability (Ao). Once a system reaches the fleet, opportunities for operational performance assessment are few and sparse; leadership lacks the necessary real-time data or post-mission analysis to truly measure mission effectiveness and improve Ao. Real-time data enables flexible decision-making during a live combat engagement, and normal operations can improve maintenance decisions, or provide feedback for follow-on system development.

A. PROBLEM DEFINITION

Currently, stakeholders do not get a full picture of their system's health due to latent or low-quality system health information. This lack of high-fidelity system health information regarding a system's degradation or need for maintenance can cause greater programmatic costs. These problems manifest themselves during three periods during the life cycle: early conceptual development, low-rate initial production (LRIP) to initial operational capability (IOC), and the operations and sustainment (O&S) phase.

1. Early Conceptual Development

As systems mature and are integrated with newer systems, the historical data collected from the legacy design becomes unreliable or inaccurate. Additionally, as new systems develop, outdated and inefficient maintenance information recycles back into the iterative design process.

2. Low-Rate Initial Production to Initial Operational Capability

As the system integrates with the fleet, decision makers lack the adaptive capability for forecasting the true operational system effectiveness while deployed. Many

DOD systems suffer from long logistics delays and increased system downtime, which ultimately decreases up time, or Ao.

3. Operations and Sustainment Phase

Continued incorporation of time-based maintenance (TBM) requires system down time, even if the system does not need corrective action. Conversely, system components suffer under-maintenance, due to this rigid scheduling construct. This inefficiency exhausts the operational level (O-Level) and intermediate level (I-Level) maintainers. From a logistical supportability lens, poor maintenance health management leads to logistics delays, due to replacement parts and spares needed outside of TBM requirements.

These problems appear across all warfighting enterprises regardless of the technological discipline attached to the system. The major impact, however, typically affects weapons systems of greater complexity and/or value. Inefficient analysis of system life cycle performance continues to increase program cost, affect mission performance, and create inefficient system implementation affecting system maintenance. In 2020 the Department of the Navy (DON) established a digital transformation strategy titled "Digital Systems Engineering Transformation Strategy," which aligns with the DOD Digital Engineering Strategy from June 2018 to combat these issues (United States Navy and Marine Corps 2020). This strategy aims "to transform systems engineering capabilities by using common, composable, interactive, model-based systems to store and exchange data, models, and information within and across programs" (United States Navy and Marine Corps 2020, 6). The DON Digital System Engineering Transformation Strategy has five specific objectives:

- Formalize the development, integration and use of models.
- Provide an enduring authoritative knowledge source.
- Incorporate technological innovation to improve the engineering practice.
- Establish the supporting infrastructure and environments for the Digital Engineering practice.
- Transform the culture and workforce to adopt and support Digital Engineering across the life cycle. (United States Navy and Marine Corps 2020, 6–7)

B. OBJECTIVES

The objective of this project was to develop an architecture for a digital twin (DT) which employs the strategies of condition-based maintenance plus (CBM+) and prognostics health management (PHM) for warfare systems. In addition, this capstone's research team, Team Gemini, created a working rudimentary model for the DT capable of integrating existing PHM technology to inform CBM+ centric information for defense systems. More information on the team is found in Appendix A. For clarity, the team's preferred definition for a DT comes from NASA which defines a DT as an: "integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc." (Glassegen and Stargel 2012, 7).

The deliverables for this capstone project align with the objectives of the Navy's digital transformation strategy. The information gathered by the DT facilitates forecasted defense system maintenance, as well as replacement part necessity. From the categories presented in the problem definition, the team focused on the operations and maintenance (O&M) phases of system maintainability. However, with unique physical host pairing, the project discussed minor areas of system performance and logistical supportability, including additive manufacturing (AM). This project's insights benefit logistic activities, such as Naval Supply Systems Command (NAVSUP), and maintenance facilities by providing more accurate predictions for parts and labor required to bring defense systems back to operational condition. The model and architecture broaden the horizon of possibilities for the use of DTs within the DOD. These possibilities include expanding the use of this DT model and architecture for mission engineering forecasts, predicting operational effectiveness. Ultimately, future endeavors involving complex weapon systems could benefit from DT modeling and application.

C. BACKGROUND AND KEY TERMINOLOGY

The DOD is concerned with the maintenance of complex systems that require high levels of sustainability and availability. Many of these complex systems are critical to the broader mission success; therefore, they do not allow much latitude with system Ao. In addition, the DOD develops maintenance plans that span the entirety of a defense system's life cycle to extend operational longevity through effective cost management.

Maintenance aims to restore or preserve reliability of a system for a minimum cost (RCM Handbook 2007). Traditionally, the DOD developed maintenance to achieve inherent performance, safety, and reliability levels for the system to meet the readiness and sustainability objectives to accomplish the mission (CBM+ Guidebook 2008). The tenet of traditional maintenance focused on restoring safety and reliability levels of a system after a fault or failure occurrence, which is also known as reactive or corrective maintenance (CBM+ Guidebook 2008). Without real-time feedback, this type of maintenance promoted unscheduled corrective labor due to the inherent nature of component failures being unpredictable.

Various DOD organizations have striven to decrease the amount of corrective, or unscheduled, maintenance required on a system. At first, the DOD utilized TBM, which is also known as preventive or scheduled maintenance, to reduce the need for unscheduled maintenance. The goal of the TBM process leveraged periodic inspection and/or repair of a system to avoid failures. TBM encompassed those tasks that are time-directed (TD). Tasks that do not consider the material condition when determining when an item needs to be restored or replaced are TD tasks (RCM Handbook 2007). Historically, TBM used the originally designed useful life of the component as the established periodicity for maintenance (CBM+ Guidebook 2008). This metric potentially increased in frequency based on failure data of the component in an operational environment. The TBM process for complex and critical systems followed an extremely conservative outlook on component failure rates. This view manifested from a fear of potential catastrophic loss that further complicated the system's mission availability. Due to these implications of a failure, unnecessary downtime was compounded due to excessive maintenance.

Blanchard and Fabrycky (2011) provide an overview of Ao in objectively comparing system uptime versus downtime factors. Uptime represents a system's time cycle containing all standby, ready, and operational conditions. Downtime aggregates all active maintenance, logistics delays, and administrative delay times. Figure 1 illustrates an operating cycle for a given system. The various downtime segments represent the failure rate of the system due to corrective maintenance and the number of failures contribute to the overall system downtime affecting the availability of a system (Blanchard and Fabrycky 2011). To decrease the amount of unnecessary maintenance and to increase Ao of a system, the DOD developed the reliability-centered maintenance (RCM) process. RCM's objective was to preserve the inherent reliability of the system. The RCM Handbook (2007) states the RCM process focuses on the periodic evaluation of operational and maintenance feedback to continuously improve both the scope and periodicity of the prescribed maintenance tasks. The process considers an abundance of system aspects when determining maintenance tasks, which include the system functions, failures, consequences of those failures, risks, and cost of prevention. When determining which maintenance tasks to select, the RCM process ensures safety of personnel, environment, equipment, and a reasonable assurance of accomplishing the ship's mission at a lower cost than correcting failures (RCM Handbook 2007). The analysis provides a tailored approach that leads to the implementation of cost-effective maintenance plans and redesign recommendations (Blanchard and Fabrycky 2011).

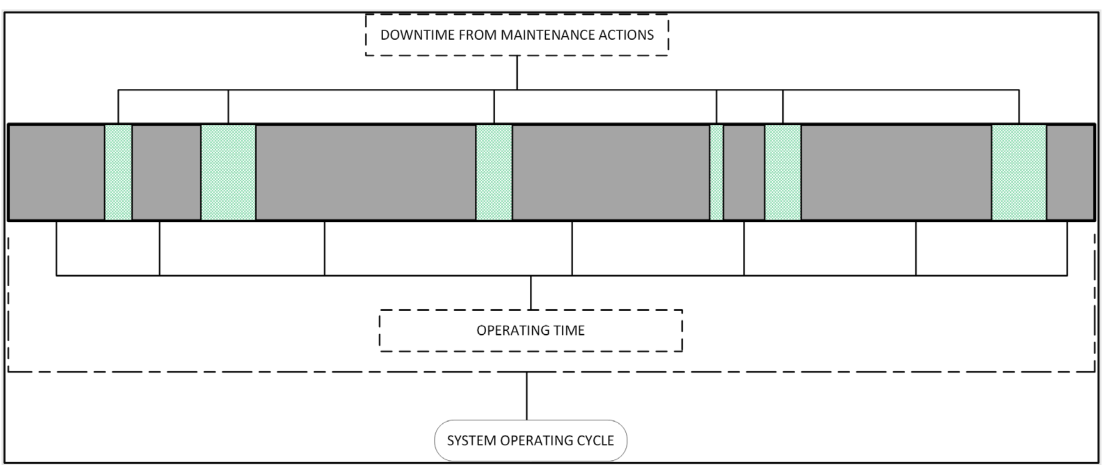

Figure 1. A System Operational Cycle. Adapted from Blanchard and Fabrycky (2011).

As mentioned in the RCM Handbook, preventive maintenance tasks are condition directed (CD), which consist of periodic diagnostic testing or inspection. They compare existing system conditions or performance of an item to determine what action to take.

RCM methods for developing planned maintenance focus on the effectiveness and performance areas of a system. Those who take part in the development, review, modification, planning, and verification of maintenance tasks for Navy ships, systems, subsystems, components, and associated equipment can apply the principles of RCM to both new and established planned maintenance requirements (RCM Handbook 2007).

Following the establishment of the RCM process, the Chief of Naval Operations (CNO) realized the importance of continuous maintenance, which consists of the practically uninterrupted process of analyzing the system, planning, and accomplishing maintenance (RCM Handbook 2007). The policy for establishing these maintenance programs is called condition-based maintenance (CBM). The core of CBM requires objective evidence of need, derived from an RCM analysis and/or other enabling technologies, to support the selection of the appropriate levels of maintenance (CBM+ Guidebook 2008). CBM implements a more proactive approach to maintenance with conditional scheduling. The maintenance and logistical organizations strive for necessary corrective and preventative actions for maximized efficiency. Figure 2 illustrates the relationship between the number of failure events and the maintenance cost. The goal of shifting towards CBM is to select an optimum maintenance schedule that balances total cost while increasing the Ao of a system. Also demonstrated in Figure 2, frequent preventive maintenance reduces failure rate at the expense of higher maintenance costs, while frequent corrective maintenance, due to a higher failure rate, decreases the availability of a system and increases operating costs.

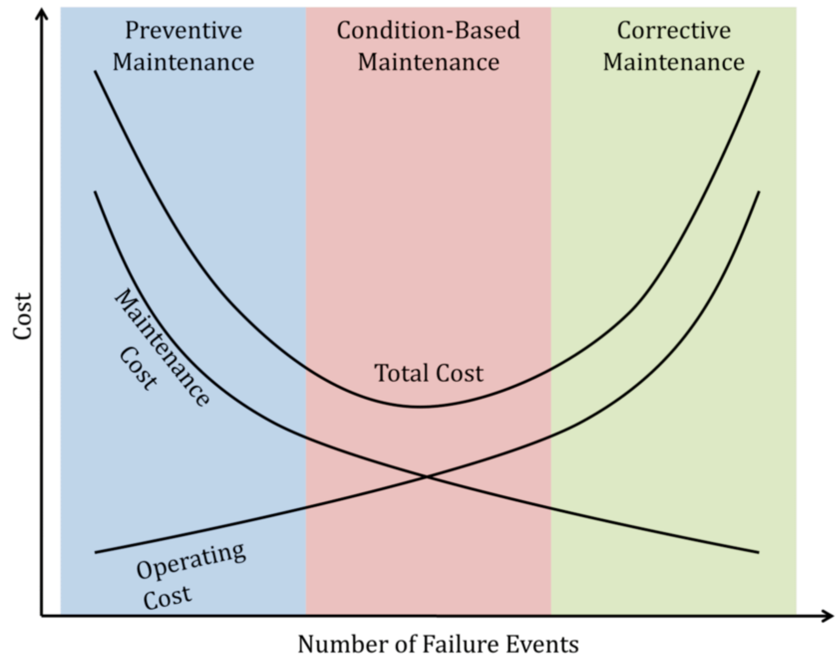

Figure 2. Cost Versus Number of Failure Events. Source: Coble (2010).

CBM later evolved into condition-based maintenance plus (CBM+), which now involves CBM principles with the addition of advanced technologies to support an end-to-end (E2E), closed-loop process supporting the infrastructure, data transmission, analysis, and reporting (RCM Handbook 2007). CBM+ applies the same traditional processes of CBM with the inclusion of complementary "… technologies and knowledge-based capabilities to achieve the target availability, reliability, and operation and support costs of DOD systems…" (RCM Handbook 2007, 1–5). The E2E closed-loop process profits from advanced technologies that support the infrastructure, data transmission, analysis, and reporting (RCM Handbook 2007). The CBM+ Guidebook states, "CBM+ uses a systems engineering (SE) approach to collect data, enable analysis, and support the decision-making process for systems acquisition, modernization, sustainment, and operations" (CBM+ Guidebook 2008, 6). Throughout the system's life cycle, SE processes are used to ensure the CBM+ strategy progresses a system from a required capability to an operationally effective and suitable system (CBM+ Guidebook 2008). This method relies on the RCM failure modes and effects analysis (FMEA) to identify where the system should use sensors for optimum effectiveness (RCM Handbook 2007).

In addition to CBM+, the DOD takes interest in prognostics and health management (PHM) to predict failures and reduce downtime. PHM incorporates a studied approach to assess system performance and introduces CBM to a system (Bickford et al. 2020). PHM consists of the process for predicting system faults given the current degree of degradation, the anticipated future operational and environmental conditions. PHM involves “the process of decision-making and implementation of actions based on the estimate of the state of health derived from health monitoring and expected future use of the system” (IEEE 2017). PHM analyzes historical data such as past failures to develop ways to evaluate system performance based on current monitoring data (L’Her, Van Bossuyt, and O’Halloran 2020).

A DT concept provides the versatile nexus between systems engineering and model-based system engineering (MBSE). A DT implements both CBM+ and PHM concepts through data monitoring and analysis. On a basic level, a DT encompasses any digital replica of a system or component. DTs virtually represent physical systems that can be updated with performance, health status, and maintenance information (Madni, Madni, and Lucero 2019). In addition to the aforementioned NASA definition, the term DT is also described by the development and fielding of a virtual representation of a physical system (Bickford et al. 2020).

The creation of a DT requires data for analytical consumption from a physical system, encompassing all or a focused period of its life cycle. DTs connect in parallel to the physical asset and collect sensor data (Bickford et al. 2020). DTs receive information from connected sensors that model and predict system performance, predict changes in the physical system over time, and optimize maintenance cycles. Contributions from DTs regarding maintenance help an organization transition from TBM to CBM+, reducing system maintenance costs and improving system availability. DT integration and simulation pose integral benefits towards MBSE methodology (Madni, Madni, and Lucero 2019). Additionally, DTs’ fielding aligns with the objectives of PHM and provides an infrastructure to analyze data for stakeholders to make informed decisions about maintenance (Bickford et al. 2020).

As a way forward, the fleet stands to benefit from current developments in DTs using embedded, distributed sensors. Combined with wireless communications and improved computing systems, a recorded digital footprint of a DT could revolutionize the Navy's approach to decision-making across the life cycle. DT data analysis software provides looped feedback for early design phases, efficient predictive maintenance, and tactical performance aids. This efficient predictive maintenance done by DTs will allow the Navy to effectively apply CBM+ to reach the optimal compromise where maintenance costs and operating costs converge, as shown in Figure 2. Therefore, this data-driven analysis provides a system-agnostic approach to proactively arm the fleet support community with predictive performance, supporting real-time daily analysis and projecting long term actions.

D. SYSTEMS ENGINEERING PROCESS

This capstone project used systems engineering processes, combined with MBSE tools and methodology, to develop an architecture for a CBM+ and PHM centric DT for both current and future systems employed on United States Navy (USN) platforms. The team used a phased approach, starting with concept exploration and preliminary design, followed by detailed design. This detailed design included a working model and architecture for a generic DT paired to physical host. Due to equipment variation onboard USN platforms, Team Gemini examined suitable combinations of systems engineering processes along with MBSE methodology and tools to develop a DT architecture that satisfied stakeholder needs.

1. Hybrid Process

Several SE processes such as the "Vee," plan-driven software process, and the agile process were examined to determine the most suitable for designing a product. After stakeholder engagement and further review, Team Gemini decided to use a hybrid SE process which consisted of the plan-driven software process as the foundation with an integrated agile method. The "Vee" process catered to more traditional defense systems and proved unsuitable for the scope of this project due to the structure of the right half of the "Vee." The right side consists of developmental test and evaluation (DT&E),

operational test and evaluation (OT&E), and initial operational capability/full operating capability (IOC/FOC) and requires the development of a prototype and field testing by future users, while the capstone deliverable is a DT architecture and model that is software application based.

The team selected a plan-driven software waterfall method as the best fit for the foundation of its SE process since the project required the team to lay out a plan and schedule ahead of time, prior to starting the development process. The plan-driven software process, depicted in Figure 3, illustrates a basic waterfall model for software development. This process includes five steps, beginning with requirements definition and ending with operation and maintenance. Step two involves the design of the system and step three is where the development of the system and integration occurs. This project concluded with testing and delivery of the DT architecture which is step four "integration and system testing." However, the plan-driven software process is not fault proof. The downside to the process is that it consists of linear transitions, where the next phase starts only when the current phase is completed. This limited the team's ability to go back and make modifications to requirements and use cases as a result of new ideas or limitations discovered while conducting research.

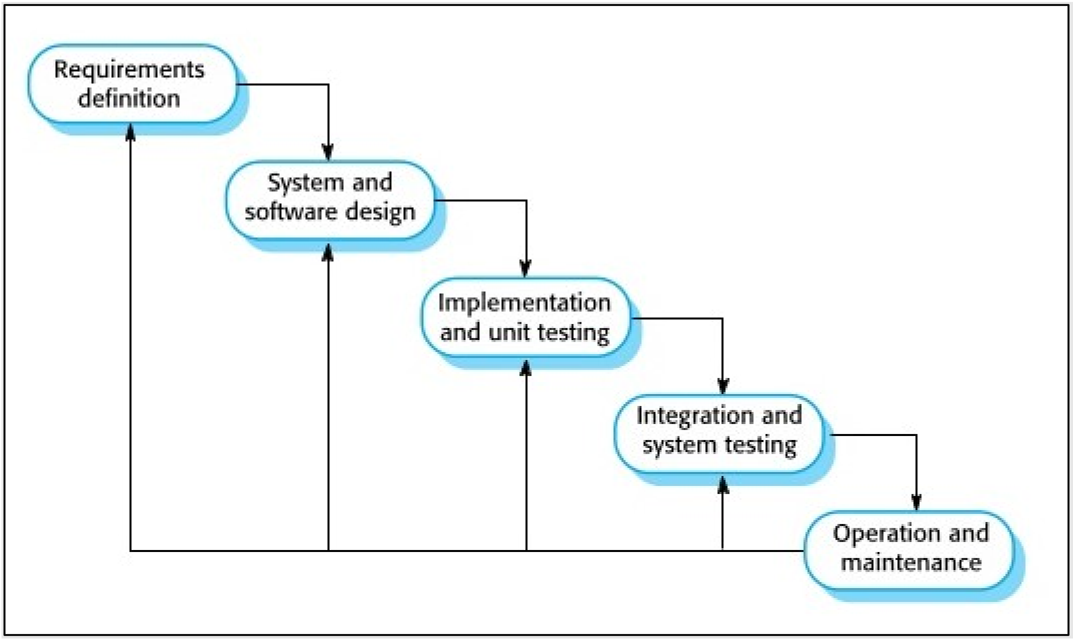

Figure 3. Waterfall Model. Source: Sommerville (2016).

To mitigate this downside, Team Gemini incorporated an agile process during the design and development phases to create a hybrid SE process. The hybrid process illustrated in Figure 4 shows the agile sprint cycles embedded into the design and development phases of the project. The two-week long sprint cycles consisted of scrums (or recurrent standup meetings), design, build, test, and feedback. The feedback portion assisted with generating and refining requirements through taking lessons learned and outcomes, feeding them back into the requirements generation phase, and then repeating the design and development phases. The team then adjusted the requirements and repeated the two-week sprint cycle of the design and development phase to accommodate requirements refinement as the project progressed and more research was conducted into the development of a DT architecture. An agile SE process increased flexibility and adaptability throughout the design and development phases through creating a more iterative and collaborative environment. Some of the agile practices implemented included planning, priority identification, commitment, and scrums, to ensure the establishment of a collaborative environment. The collaborative environment amongst the team established that information and knowledge sharing occurred as the project progressed to ensure obstacles were not preventing the project from moving forward as planned. Although each team member had defined roles for the project, the collaborative environment created by the agile method also leveraged the unique work experiences of everyone on the team. In contrast, the traditional SE process requires a lot of the requirements and documentation to be created upfront, which proposed less time to develop the final deliverable for stakeholders. The incorporation of an agile process allowed the team to be open to experimentation and adapt to potential changes in stakeholder needs.

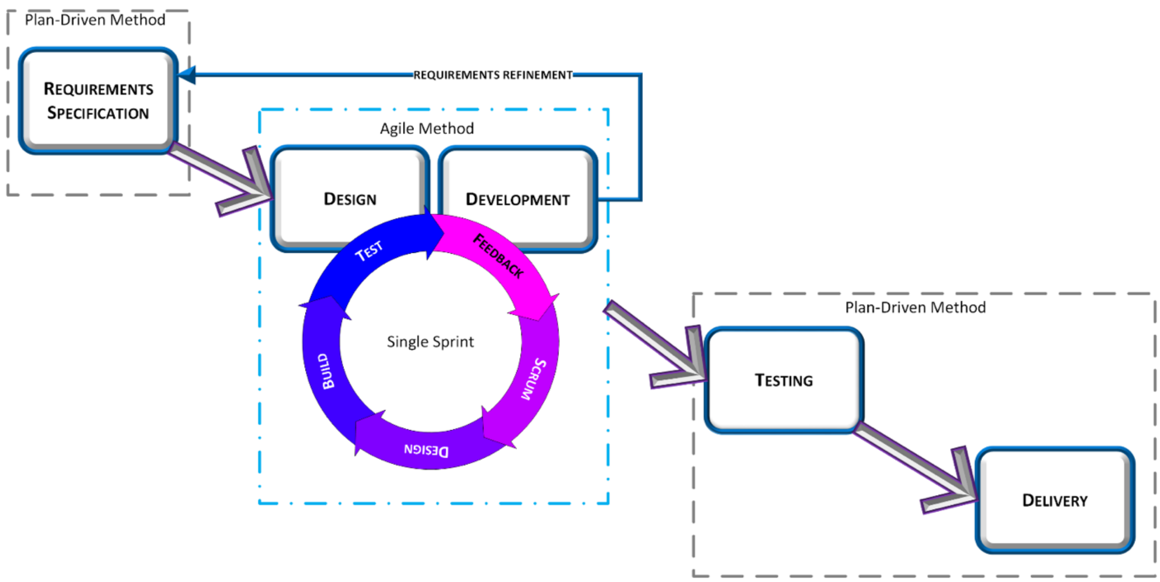

Figure 4. Hybrid SE Process, Plan-driven with Agile Method

The requirements specification phase addressed the stakeholders' need relating to system features, performance, and constraints. Team Gemini obtained this information through stakeholder meetings and literature reviews with continuous modification throughout the process. Specifically, for the literature reviews, Team Gemini elicited heuristic data from existing programs to drive early conceptual design through reviewing technical journal entries and other academic literature. Collecting these requirements proved essential to designing and verifying the product.

Following the requirements analysis, the next phase focused on design and development of the system. This combined phase explained system functionality specifications and included information that related to operational and performance requirements identified by the stakeholders. It consisted of designing architectural features and interfaces that information passes through to establish adequate architectural specifications which ensured proper implementation of defined models and system requirements. With DTs being a relatively new technology, the research focus proved vital in gaining the necessary knowledge of system functionality for reaching the capstone's end goal.

The final phases of the hybrid SE process are testing and delivery. Testing determines whether the module, system, or sub-system satisfies the criteria established during the requirements specification. Team Gemini's verification testing consisted of testing the model and acceptance testing. While each type of testing varies, the following attributes were tested to establish acceptance of the system: correct functionality, integrity of the function or data, usability, performability, confidentiality, availability, and scalability. Once the DT model satisfied testing, it was ready to be delivered to the sponsor.

2. Model-Based Systems Engineering

In addition to the hybrid process, the team utilized MBSE to alleviate any potential hurdles, help with requirement decomposition and conceptual design, and assess performance throughout the life cycle. MBSE is defined as "the formalized application of modeling to support system requirements, design, analysis, verification and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycle phases" (INCOSE 2007, 15). The use of MBSE resulted in improved quality and productivity while reducing risk as the system developed. MBSE enabled automation through data-centric specifications, which allowed the architecture team to focus on value-added tasks. Some important MBSE characteristics included a set of interconnected models, standard language, and a shared system information base. These characteristics improved the ability to manage traceability and complexity of the system.

However, this methodology alone lacked the value from an in-depth, integrated data collection architecture. The environment remained model-based and required a more "operational instance of those various models developed in the early stages of the program" (Bickford et al. 2020, 7). To ensure success, warfare systems require data extraction and performance analysis that support early conceptual design, inform fleet operational performance, and retain Ao throughout the life cycle. While MBSE looked to support the system feedback loop, early collection of physical data further refined requirements, integrated the system components, and decreased performance costs.

3. Architecture Method, Language, and Tool

To facilitate the MBSE process, the team utilized the MagicGrid method as the primary technique to guide DT architecture development. The MagicGrid approach outlines the modeling process, which defines the problem, solution, and implementation domains for the system model (Aleksandraviciene and Morkevicius 2018). Using MagicGrid leveraged Systems Modeling Language (SysML) as the modeling language and Cameo Enterprise Architecture (CEA) as the base modeling tool.

The MagicGrid method matrix, shown in Figure 5, consists of four pillars and the three aforementioned domains. The pillar categories—requirements, behavior, structure, and parameters—guide and structure the system model through the domains. The problem domain is further decomposed into two phases, black-box and white-box perspectives. The black-box perspective consists of steps to identify and specify the problem that the system solves without being specific about the DT system's internal structure and behavior (Aleksandraviciene and Morkevicius 2018). The black-box implements use cases and system context diagrams to accomplish the operational analysis of the problem the DT solves. The white-box perspective details how the system shall operate through identifying necessary behaviors and logical subsystems for the DT system. The white-box uses activity, block definition, and internal block diagrams to accomplish the functional analysis and logical subsystems.

It should be noted that for this capstone project, only the problem domain is explored, so the solution and implementation domains are not discussed in this report. The MagicGrid method facilitated SE modeling which is adaptable to both civilian and military audiences. More importantly, the CEA software provided uniformity and convenience across complex integration and decomposition of the DT system.

<table>
<tr><th></th><th colspan="7">PILLAR</th></tr>
<tr><td rowspan="8">DOMAIN</td><td colspan="2"></td><td>Requirements</td><td>Behavior</td><td>Structure</td><td>Parameters</td><td rowspan="8">Specialty Engineering
Integrated Testing
Analysis</td></tr>
<tr><td rowspan="2">Problem</td><td>Black Box</td><td rowspan="2">B1-W1 Stakeholder Needs</td><td>B2 Use Cases</td><td>B3 System Context</td><td>B4 Measurements of Effectiveness</td></tr>
<tr><td>White Box</td><td>W2 Functional Analysis</td><td>W3 Logical Subsystems Communication</td><td>W4 MoEs for Subsystems</td></tr>
<tr><td colspan="2" rowspan="4">Solution</td><td>S1 System Requirements</td><td>S2 System Behavior</td><td>S3 System Structure</td><td>S4 System Parameters</td></tr>
<tr><td>SS1 Subsystem Requirements</td><td>SS2 Subsystem Behavior</td><td>SS3 Subsystem Structure</td><td>SS4 Subsystem Parameters</td></tr>
<tr><td>...</td><td>...</td><td>...</td><td>...</td></tr>
<tr><td>C1 Component Requirements</td><td>C2 Component Behavior</td><td>C3 Component Structure</td><td>C4 Component Parameters</td></tr>
<tr><td colspan="2">Implementation</td><td>I1 Physical Requirements</td><td colspan="3">Software, Electrical, Mechanical</td></tr>
</table>

Figure 5. MagicGrid Method Matrix. Source: Aleksandraviciene and Morkevicius (2018).

E. SCOPE

The broad application of DTs spans across a system's life cycle and contains the potential to evaluate operational performance, increase suitability efficiencies, and influence mission engineering. These goals prove invaluable to the DOD community and truly resonate in application across almost any physical asset. However, many of these broad applications continue progression from the various complex disciplines across the SE enterprise. Team Gemini refined the scope of the original project topic to a manageable target focusing on a topic of great interest to the DOD, which is based on the team's experience, research, and sponsor-provided information, in addition to the constraints defined below. This study only focused on integrating software modeling algorithms with the hardware data collection system, in a DT environment, in parallel with a three-dimensional (3D) printer onboard a manned surface vessel. With a 3D printer as the surrogate asset, this research project acted as a pivot into further development of unique complex systems and additive manufacturing.

1. Constraints

A group of eight Master of Science in Systems Engineering (MSSE) students from the Naval Postgraduate School (NPS) conducted this research and analysis effort over a nine-month period as part of the NPS Systems Engineering master's degree graduation requirements. These unavoidable constraints mostly stemmed from the NPS SE department's project deliverable timeline. This study was conducted within the following environment and under the following limitations:

- The study had to not exceed a classification level of Controlled Unclassified Information (CUI).
- Actual performance parameters were not available to use within the study as these values were unavailable and have not been measured and recorded for DT Concept of Operation (CONOPS) implementation, therefore they were developed based on research of open sources.

2. Definition of Scope

The DT CONOPS example shown in Figure 6 shows a high-level illustration of the intended interaction between systems. While this is not a traditional operational view (OV) diagram, it represents need-lines between the physical asset, DT, and support network much like an OV-2. The illustration in Figure 6 shows the integration required between multiple systems and allowed Team Gemini to refine the scope of the project. The basic environment includes the host physical system and the DT system using a framework of instrumented sensors monitoring the system's status to achieve host prognosis.

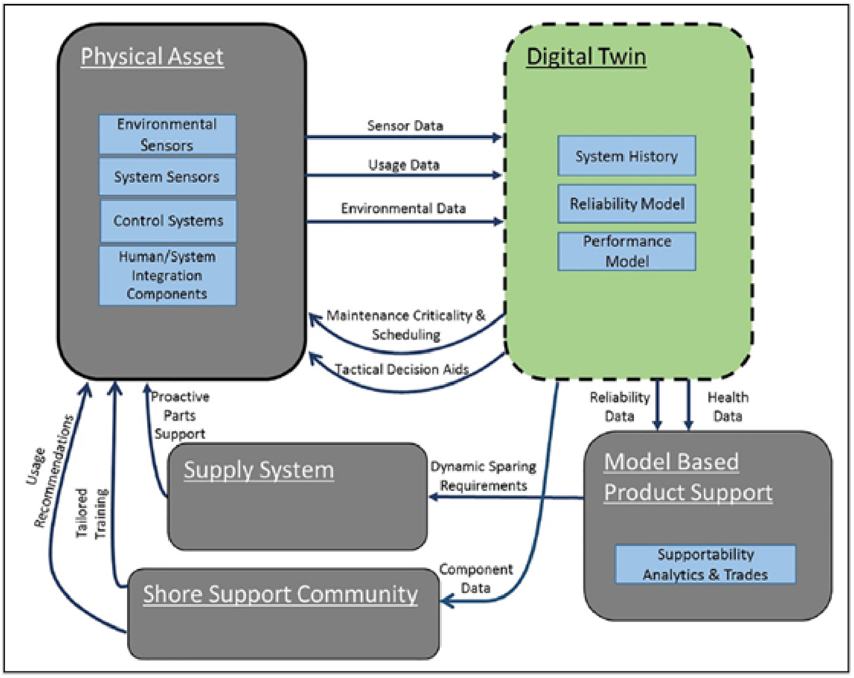

Figure 6. Digital Twin CONOPS. Source: Bickford et al. (2020).

Currently, a variety of systems operating with PHM or CBM+ are included into the Navy's processes. However, the DT frontier continues to remain fairly new and wide open. Team Gemini's scope used the DT in parallel with a 3D printer on a manned surface vessel as the host physical asset. The 3D printer served to fulfill multiple purposes; first it provided a manageable system of complexity to implement onto a DT, while staying within the timeline constraint.

Another purpose of focusing on the use of the DT for a 3D printer aboard a vessel, was to align with the Navy's interests in AM and the National Defense Strategy as defined in the DOD's Digital Engineering Strategy (Joint Defense Manufacturing Council 2021). As defined in the DOD's AM Strategy, AM (also known as 3D printing) consists of the process of joining materials layer by layer to make parts using 3D model data. AM is a manufacturing tool which allows for rapid, on-demand, and customizable solutions to problems as well as being a versatile technology to build a more ready and lethal force. The use of a DT for a 3D printer ensures this critical manufacturing tool maintains high levels of availability to meet the Navy's growing AM mission.

In addition, Team Gemini decided to concentrate focus on sensor data from the 3D printer's systems and basic ship's sensor information to ensure the project does not exceed the CUI classification. Any deviation into combat system performance or mission success rates increased the likelihood of raising the classification level of the project. However, a DT architecture for a 3D printer still provides invaluable insights regarding sensitive, high-precision systems in dynamic environments unique to naval operations.

While operational performance and mission engineering posed interesting areas for discussion, the team scope focused on the suitability measures for the physical asset and the associated DT hardware components. The team only possessed the capacity to address the potential metrics involved with physical host mission success. Scoping to suitability limited the number of variables to consider for the DT, ensuring the timeline constraint for the project was met. Suitability measures included providing current and predictive reliability, maintainability, and logistics supportability assessments. The project scope leveraged existing supply chain constructs for both domestic and forward deployed fleets. All these metrics provided the foundational data for fleet Ao that directly relates to the user's end mission.

3. Operational Concept (OV-1)

The operational concept for this capstone project is illustrated in the OV-1 diagram or high-level operational concept diagram shown in Figure 7. This diagram shows the interactions between the system of systems (SOS) for the DT. The SOS includes the 3D printer onboard the manned surface vessel physical asset, ship personnel, hybrid cloud, satellite communications (SATCOM), and shore support which includes the supply chain system. The DT interacts with the 3D printer by receiving sensor data. In addition, the DT receives sensor data from the ship regarding environmental conditions (vibrations, compartment space temperature, etc.) and sea conditions. The sensor data from the ship allows the DT to make more robust predictions for both the necessary maintenance for the 3D printer and, eventually, for the quality of the produced components. The DT is housed within the hybrid cloud. The hybrid cloud is a high-powered server with a network connection via SATCOM and is responsible for all the DT's storage, processing, and power needs. The DT interacts with the hybrid cloud by sending initially processed data and raw historical sensor data for further advanced analysis and processing. The DT sends critical alerts, via the hybrid cloud, to ship personnel, for mitigation, or direct to shore personnel through SATCOM. Based on the critical alerts the ship personnel perform any necessary maintenance or interact with the shore support community either while in-port or through SATCOM. The DT also interacts through in-port wired connections to shore support personnel for DT diagnostics, updates, and maintenance. This complex SOS environment is illustrated in the OV-1 diagram.

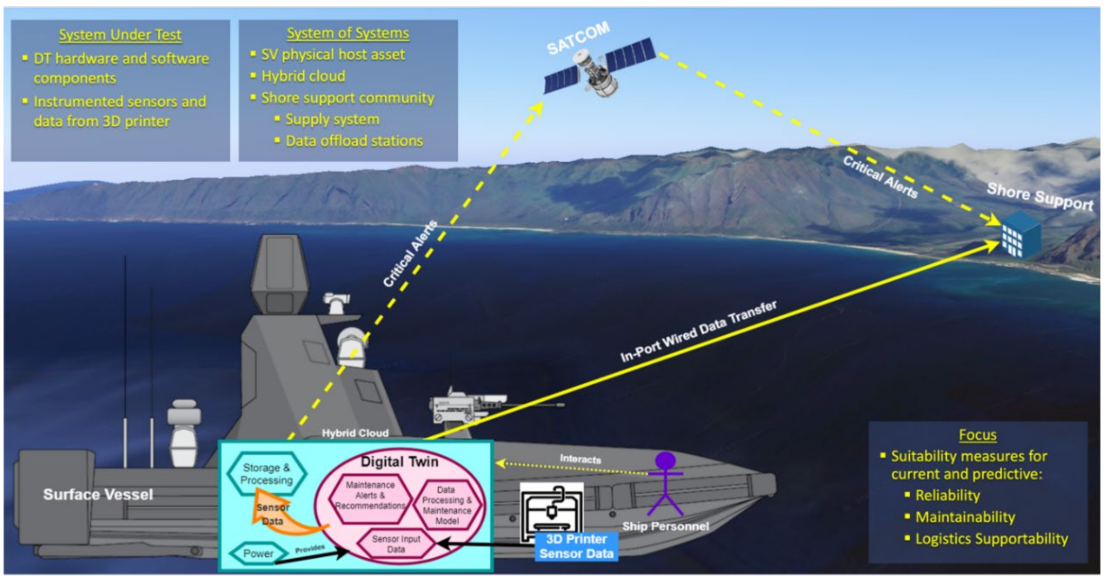

Figure 7. OV-1: High-Level Operational Concept Diagram

The DT high-level hardware/software configuration encompassed the system under test (SUT) as also illustrated in Figure 6. The DT integrates software modeling algorithms with hardware for processing collected sensor data to create maintenance alerts and recommendations. Additional hardware components incorporate existing PHM embedded sensor frameworks to provide CBM+ centric information. Additionally, the DT requires a communication system able to both gather and transmit data for analysis and alerts. The two communication paths required are real-time and bulk storage collection. Timing for those paths include continuous, periodic, and critical.

F. SUMMARY OF CHAPTERS

Chapter II is the literature review for previous work that has been done regarding the problem introduced in Chapter I. The literature review focuses primarily on DTs as well as other relevant topics to provide improved understanding of the technology and applications. Additionally, this chapter investigates current capabilities of DTs both in the DOD and in industry.

Chapter III focuses on the design and development of the DT architecture by building off the foundation established in Chapter I and II. This chapter introduces the stakeholders and transitions the stakeholders' needs into requirements, both functional and nonfunctional. This chapter has the DT's functional description, including use cases. The system decomposition continues through functional analysis and allocation.

Chapter IV consists of the architecture assessment. This chapter starts with an analysis of alternatives, which involves the investigation of trade space and feasibility analysis, as well as a discussion of the modeling of the system. The resulting system model transitions the project into the DT's evaluation assessment. This chapter discusses the limits to the developed architecture and an analysis of the simulation of the model. Additionally, Chapter IV conducts a cost assessment.

Chapter V is the final chapter. This chapter covers recommendations for the DT architecture and model involving suggestions for areas of future work. Additionally, this chapter serves as the conclusion of the report.

II. LITERATURE REVIEW

Chapter II serves to detail the review of previous work regarding the problem introduced in Chapter I. This chapter is composed of a review of journal articles, presentations, a standard, and NPS theses. The review of previous work focused on DTs to improve the understanding of the technology due to its relative newness. The technical research also branched into the review of topics covering MBSE, CBM, PHM, hybrid clouds, AM, and 3D printers to understand broader applications of the system and provide guidance for development of the project deliverables. This chapter ends with an assessment of current capabilities to highlight DTs that exist currently in both the DOD and private industry.

A. DIGITAL TWINS AND MBSE

Bickford et al.'s 2020 article "Operational Digital Twins Through MBSE Methods" played a critical role in this capstone project. The ideas discussed within this article regarding the development of a methodology that systems engineers could use to develop a PHM-centric DT system in parallel to the physical asset being built is the foundation that this project was built on. This article guided the development of the DT architecture and MBSE process for Team Gemini. Additionally, this article discussed the DOD's increased demand for DTs, showing a true need for the deliverables of this capstone. This demand was created because DTs can aid stakeholders' decisions and aim to improve operations of equipment, performance, or readiness.

There were two other articles which provided insight for the development of the team's MBSE process. The first article "MBSE: Motivation, Current Status, and Research Opportunities" explained the fundamentals necessary to apply MBSE tools and methodologies for system design (Madni and Sivers 2018). This article presented the importance of using MBSE methodologies and system models during system development to ensure the system has traceability and consistency, as well as the complexity being managed. The second article, "Leveraging Digital Twin Technology in MBSE," discusses, in general, the concept of DTs and various virtual system models which are created from

MBSE tools and are used to instantiate a DT (Madni, Madni, and Lucero 2019). This article informed Team Gemini of the four levels of a DT, which range from a pre-DT, DT, adaptive DT, and intelligent DT. Furthermore, it mentioned the usefulness and versatility of DTs that incorporate machine learning, or intelligent DTs, which is useful for future capability discussions.

B. DT ARCHITECTURES AND FRAMEWORKS

The article "Digital Twins: Review and Challenges" is a compilation of research that presents basic concepts necessary to understand DT functions (Juarez, Botti, and Giret 2021). Additionally, the article outlines communication methods for DTs and discusses various DT architectures that can be applied. The information within this article proved useful during the conceptual phase of the project as well as supplemented understanding of the concept, operation, and main characteristics of a DT.

Drazen's (2018) presentation "Cyber-Physical Systems: Navy Digital Twin" provided an explanation for the research and development challenges that exist between the current pace of capability delivery of DTs and the United States Navy's goal. Drazen states the basis for a digital fleet is explained as a process that starts with design, model testing, fabrication, and implementation while being built alongside a digital form of the real-world system. The most important takeaway from this presentation for this project is the information on algorithms and frameworks for structural life prognosis, which depicts the data flow and major components of a DT framework.

Another work that investigates a framework for DTs is titled "Digital Twin, Physics-Based Model, and Machine Learning Applied to Damage Detection in Structures," and it develops a simplified framework integrating a physics-based model with machine learning (Ritto and Rochinha 2021). The article gives a representation for a DT framework which includes measurements from the physical asset, a computational model (either physics-based and/or machine learning models), and a stochastic layer to incorporate uncertainties. Additionally, the article discusses how training a machine learning classifier can speed up the evaluation for the physical asset in real-time operations compared to how time consuming the physics-based model is when doing the same evaluation. This article provided the team with invaluable insight into the importance of machine learning in future work with DTs. The key takeaway was what makes up a successful DT framework.

C. DT STANDARDS

Since DTs are relatively new technology and new to the DOD few define DTs. One such standard was recently released, titled *Considerations for Digital Twin Technology and Emerging Standards*, and it provides generic information regarding DT technology and describes differences between static and dynamic DT models (Voas, Mell, and Piroumian 2021). The standard examines cybersecurity and DTs, which is a vital topic applicable to future work. Additionally, the standard discussed challenges relating to topics that Team Gemini needed to consider for the non-functional requirements which included confidentiality, integrity, availability, maintainability, reliability, and safety.

D. CBM/CBM+ IMPLEMENTATION

Two NPS master's theses discussed information regarding CBM/CBM+. The first thesis, titled "Decision Analysis to Support Condition-Based Maintenance Plus" discusses the use of a stochastic modeling tool to select components to be used in the Army Aviation's CBM+ program (Gauthier 2006). This model was created using an Excel-based Monte Carlo simulation to compare CBM+ and non-CBM+ monitored airframes (Gauthier 2006). This thesis provided the team with information regarding sensors used for CBM and how both the sensor's false alarm rates and the reliability/maintainability of the sensor are critical to consider. The second thesis, titled "Machine Learning Techniques for Development of a CBM Program for Naval Propulsion Plants," provided the team with invaluable insights about modeling naval systems (Therrio 2018). Specifically, this thesis focuses on the creation of a support vector machine algorithm which can be taught to make CBM+ maintenance predictions for the degradation of the main engines, propeller, and hull. This information about the machine learning algorithm is important for future work considerations. Therrio's thesis also discusses the General Electric (GE) LM2500 engine type and how there is a MATLAB Simulink developed model which has been tested and verified, which characterizes a combined diesel electric and gas propulsion system. This information helped Team Gemini to develop failure dummy data for the selected modeled components.

E. DIGITAL TWINS AND PHM TECHNIQUES

Some general background information regarding DTs and PHM, as well as insight on considerations for future work, were featured in the article, "Prognostic Systems Representation in a Function-Based Bayesian Model During Engineering Design" (L'Her, Van Bossuyt, and O'Halloran 2020). This article thoroughly examined optimizing the framework for prognostic systems selection and implementation in the early part of the system life cycle. Additionally, it investigated the prognostics and health analysis to support engineering design (PHASED) method, which discussed development of a framework that utilizes a functional failure method throughout the various design stages by exposing system vulnerabilities using a network of sensors. This article provided the team insight on PHM methods providing high fidelity data, which is a consideration for future work for this capstone topic.

Another article detailing DTs and PHM techniques is the article titled, "The Use of DT for Predictive Maintenance in Manufacturing" (Aivaliotis, Georgoulias, and Chryssolouris 2019). The article developed a methodology to calculate remaining useful life (RUL) of equipment using DTs and PHM techniques. This methodology involves using data gathered from the physical asset's controllers and sensors to tune the DT models and simulations allowing equipment to be monitored and use PHM to predict RUL to identify the optimal time for the next maintenance action. This article also defines four phases to address the challenges for using DTs to predict RUL. These four phases consist of advanced physical modeling of machines, simulation tuning of the DT, DT operations, and the RUL calculations. The information about the phases were useful DT design considerations for the team, and RUL calculation considerations were important for capturing part needs to improve supportability.

F. UNIQUE CHALLENGES FOR CBM AND PHM

When combining PHM and CBM, there are unique challenges that need to be addressed which is investigated in the article titled, "A Hybrid Learning Approach to

Prognostics Health Management for Military Ground Vehicles using Time-Series and Maintenance Event Data" (Bond et al. 2020). This article examines the importance of high-performance data analytics (HPDA) on operational time-series datasets and how it is critical for predicting mean time to failure or compiling logistics and life cycle needs. Bond et al. details how they developed a hybrid method for predicting the likelihood of imminent failure using both time-series and relational maintenance data by using an HPDA environment, along with a method for identifying operational data patterns. This article gave the capstone team insights regarding analyzing sensor data to make useful predictions for system reliability, availability, and maintainability, which helped in the creation of the DT.

Another article which covered unique challenges specifically pertaining to PHM concepts for autonomous systems is titled "An Uncertainty Quantification Framework for Autonomous System Tracking and Health Monitoring" (Corbetta et al. 2021). This article focuses on the creation of a framework for sources of uncertainty in autonomous system tracking and health monitoring. Corbetta et al. provides a detailed description of the challenges for effective implementation of health monitoring on autonomous vehicles operating in a time-varying environment. This article provided insight for the team in relation to the unique challenges that should be considered when designing the health monitoring portion of the DT system. The following are some of these unique challenges that were identified by Corbetta et al.: environmental variables affecting the vehicles' dynamics; current position as the only factor determining that the vehicle is operating as planned; and predictions for autonomous system behavior and operations that may require in-time assessment capabilities, such as a weather forecast tool or live communications with shore support to provide this information (2021).

G. HYBRID CLOUD

According to IBM's learning hub website about hybrid clouds, a hybrid cloud is a computing environment that uses a combination of services to deploy workloads in an information technology (IT) environment (Vennam 2021). Hybrid clouds provide greater flexibility, more deployment options, scaling, and cost effectiveness, as well as helping build hybrid architectures with on-premises data storage to address size and connectivity constraints. The services available for hybrid clouds consist of on-premises and either public or private cloud environments. Public clouds are those that share resources with other organizations and private clouds are those used exclusively by one organization. Hybrid clouds allow enterprises and organizations to move data, software, and applications between them to satisfy their computing needs and data deployment options. Hybrid cloud services such as those offered by Amazon Web Services (AWS), create a single environment for organizations to meet the user's needs thanks to the many advantages provided.

According to Amazon's AWS webpage, AWS hybrid cloud services include the AWS Snow Family which includes the AWS Snowcone and AWS Snowball devices (Amazon 2021a). The AWS Snow Family is an edge computing hybrid cloud solution that supports data migrations and storage in both a ruggedized and disconnected device. The Snow Family offers edge processing and storage to support use cases such as machine learning, data processing, and large-scale data transfers in low bandwidth and disconnected environments, such as in military and maritime operations. Organizations needing to process data on premises and later transfer data to the cloud for long term storage can benefit from using an AWS Snow Family device. All these factors make the AWS Snow Family devices good potential candidates for the hybrid cloud needed for Team Gemini's DT.

Amazon has a webpage dedicated to the AWS Snowcone (see Figure 8) which describes this small-form-factor device as ruggedized and secure that is built for users that need to work outside of traditional data centers where space is limited and connectivity unreliable (Amazon 2021c). The Snowcone small-factor design weighs 4.5 pounds, making it portable (users can carry it in a backpack) or use it in confined spaces. Benefits of the Snowcone device include security, portable-edge computing, flexible data transfer, and connectivity with the internet of things (IOT) sensors to act as an IOT hub, application monitor, or analytics engine. Selecting this device to support Team Gemini's DT would provide a lightweight, portable option to collect and process the 3D printer sensor data where space is limited.

Figure 8. AWS Snowcone. Source: AWS Snowcone (2021).

The Amazon webpage dedicate to the AWS Snowball (see Figure 9) describes this device as ruggedized and that it can be configured in disconnected environments for data storage and large-scale data transfers, as well as optimized for use cases such as machine learning, data processing, and IOT sensor stream capture (Amazon 2021b). Machine learning models can be deployed using the Snowball device that is ideal for remote locations where data preprocessing is needed prior to migrating to the cloud for data analysis. Snowball devices are rack-mountable and can be connected in clusters for expansion and scalability that provides secure and flexible tactical edge computing without having to install separate storage racks. The device's ruggedized construction withstands environmental factors such as vibrations and humidity. Selecting this device to support Team Gemini's DT would allow greater local processing power and analysis of 3D printer sensor data using machine learning to gain immediate insight without network connectivity, as well as being used as a data transfer device in remote environments. It would also allow for future development of machine learning algorithms because it can operate in remote locations while testing these algorithms in the cloud for further analysis and development.

Figure 9. AWS Snowball. Source: AWS Snowball (2021).

H. ADDITIVE MANUFACTURING

The DOD Additive Manufacturing Strategy defines basic information regarding AM and the importance of AM technology to the DOD (Joint Defense Manufacturing Council 2021). This strategy states AM can be defined into seven different categories by the American Society for Testing and Materials (ASTM) that are based on the method by which the raw material and energy is combined. The method of interest to Team Gemini, based on stakeholder interviews, is powder bed fusion which consists of thermal energy selectively fusing regions of a print bed covered with powdered metal. One of the DOD mission areas discussed in this strategy important to this capstone is how AM will increase materiel readiness and mission readiness. AM can reduce equipment down time, increase maintenance efficiency, and reduce logistics costs since the part could be manufactured closer to the time and point-of-need. The strategy discusses how AM technology can support legacy systems, improving their readiness, when parts cannot be acquired. This would require reverse engineering of the component. This application of AM informed the team of the importance of the 3D printer DT being able to provide objective quality evidence for the printed component since these legacy components would not have permanent replacement part options.

Additive manufacturing has begun to be deployed aboard naval assets which brings up several implementation questions that are discussed in Banks et al.'s NPS master's thesis, “Navy Additive Manufacturing Afloat Capability Analysis” (2020). This thesis states the importance of monitoring the performance for the parts produced aboard vessels using AM technology due to the harsh operational environment and necessary life span of the component. Monitoring the quality of the parts produced will ensure the readiness of the fleet is not impacted. Additionally, this thesis identifies that sea state, humidity levels, shock, and vibration from the operational environment aboard a vessel have a significant impact on the performance of the 3D printer. This thesis also identifies other challenges that exist for implementing AM technology aboard naval vessels which include the near cleanroom conditions needed for operation and storage requirements for the raw materials (powdered metals) for printing to ensure they maintain quality control in a marine environment. This thesis provided Team Gemini with insights for which environmental factors to monitor with the DT, specific factors to monitor with the DT for the raw materials, as well as facilitating the need of a 3D printer DT aboard a naval vessel.

An example of AM technology currently deployed aboard a vessel is on the USS John C. Stennis (CVN-74) aircraft carrier. The article by Justin Katz (2018) covers the additive manufacturing laboratory (AML) on the CVN-74. This laboratory consists of 3D printers, 3D scanners, laser cutters, and a computer numerical controlled (CNC) milling machine. This AML provides an initial assessment for 3D printers to inform future procurements and training. Even though the 3D printer in the AML is not a metal printer, this printer inhabits the same dynamic operational environment as the 3D printer being focused on by Team Gemini. The master’s thesis by Nicholls, Han, and Davis (2019) evaluates the lessons learned from the AML onboard CVN-74 incorporating a compilation of firsthand accounts from sailors operating the equipment and recommendations for future installations of AMLs in the fleet. Most of the recommendations relate to improving the operations for using the printer and include involving the supply system in the process. However, one key lesson learned from this thesis was that there was a 234 percent return on investment (ROI) for the use of the AML, even in its infancy state, aboard the Stennis. With such a high ROI, there is a need for this equipment to have a high Ao, and a DT can facilitate that. Additionally, the thesis breaks down the AM process onboard the ship into eight steps: receipt, measurement, design, test print, adjustments, final print, quality assurance, and delivery. Using these eight steps allowed Team Gemini to identify where the DT of the 3D printer could improve the ROI of the equipment. The DT monitoring the 3D printer eliminates one of the steps entirely, the test print step, and provides data for the quality assurance step, to reduce inspection time.

Besides AM technology being used aboard naval vessels, the article "U.S. Navy Installs First 3D-Printed Metal Part Aboard a Warship" provides an example of a 3D printed metal part being installed into a Naval vessel (The Maritime Executive 2018). In 2018, a 3D printed metal component for a steam line drain strainer orifice was installed on the USS Harry S. Truman for a one-year test and evaluation period. This part was printed at ship builder Huntington Ingalls Industries – Newport News Shipbuilding, which used a top-end 3D metal printer. This article provided insights to Team Gemini regarding factors, such as shock and vibration, hydrostatic, material, and welding, that are important part acceptance criteria for the DT to consider.

I. 3D PRINTERS

As mentioned in the AM section, the AM technology method of interest is powder bed fusion. Through conversations with the sponsor, this led to the selection of the model of 3D printer the DT would be created for to provide the most value for the Navy AM goals, as well as provide invaluable insights for other DOD systems. The selected model is the GE M2 cusing series 5, which is currently in operation in a few laboratories within the DOD. This printer uses direct metal laser melting (DMLM) to create prints. This method is similar to direct metal laser sintering (DMLS) which is another, more common, 3D printing method. DMLM differs from DMLS because it completely melts the metal powder particles to create ultra-thin pools that solidify as they cool, whereas DMLS only partially melts the metal powder particles to allow them to adhere to one another (GE Additive 2021). According to GE, using the DMLM process yields parts that have reduced weight while still retaining the requisite strength, durability, and precision. These factors helped Team Gemini to ensure they focused on embedding sensors for components within the 3D printer that could affect these factors.

The GE M2 cusing 3D printer has various existing embedded sensors as well as many components that would benefit from having additional sensors added and monitored by a DT. Therefore, knowing about which 3D technology and printer type to focus on determined the type of sensors and data that was important to the DT architecture. The DMLM 3D printer major components (most of which are shown in Figure 10) consist of a laser, focal lens, collimator, mirror, recoater blade, and three powder chambers consisting of powder supply, build powder bed, and used powder collection. The collimator and focal lens work together to focus the laser. The recoater blade is used to distribute, smooth, and flatten the metal powder in-between layers. In addition to these components, the printer must maintain an inert gas environment during the printing process; the GE M2 cusing uses nitrogen gas that is consumed at a rate of less than 1.5 cubic meters per hour and maintains a pressure level of 6 bar(g) (M2 Series 5 Brochure 2021). The GE M2 cusing series 5 brochure lists the component statistics as follows:

- Laser:
    - Dual continuous wave laser with a power output of 400 W, 1070 nm, and a focal length variable range of 70–500 µm
    - Laser radiator uses deionized (DI) water with a desired range of conductance between 2–3 µS/cm
- Build bed:
    - Movement envelope of 20–80 µm
- Overall operating conditions:
    - Power requirements of 400 V, 32 A with a power consumption of 9 kW
    - Operating environment temperature of 18–25 degrees Celsius
    - Compressed air requirement pressure of 6–10 bar(g) (M2 Series 5 Brochure 2021)

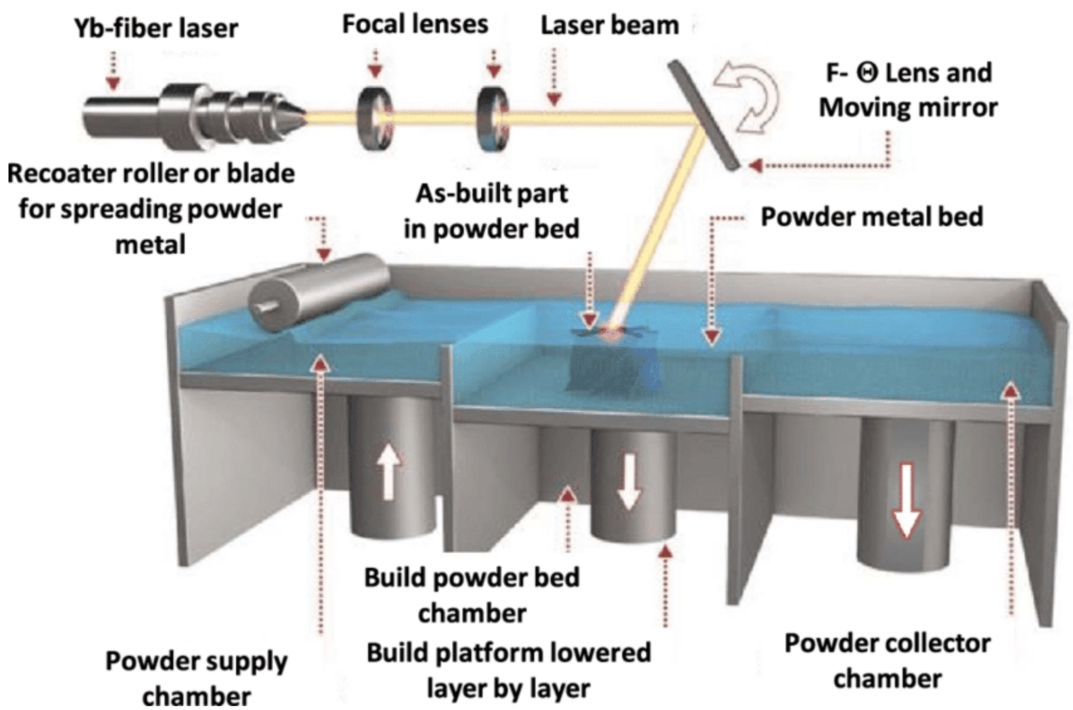

Figure 10. Typical Laser Powder Bed Fusion Printer. Source: Özel et al. (2020).

The M2 cusing 3D printer has several periodic maintenance procedures defined by the manufacturer, that must be performed to keep the system working at peak efficiency. All the current maintenance procedures are TBM. The operating manual for the M2 cusing, section 8.3, lists the maintenance schedule which defines who can perform the task and the periodicity for performing the maintenance (General Electric Additive 2019). The maintenance tasks which stood out as candidates for CBM were related to the laser radiator. The tasks are performed weekly which consist of checking the conductance of the deionized (DI) water, the fill level of the tank, and checking for contamination on the cooling lamellas and radiator air filters. Another task that stood out as a candidate for CBM is the replacement of the glovebox filter, which is an annual task and involves replacing two large filters. Team Gemini considered and drew insights from these TBM procedures provided by the manufacturer when designing the rudimentary CBM prediction algorithm and what components to focus on.

J. ASSESSMENT OF CURRENT DT CAPABILITIES IN DOD

NAVSEA has been pursuing the digital transformation strategy by using DT aboard ships for gas turbine engines. Vice Admiral Bill Galinis stated that the gas turbine engine is the most frequently used DT in the Navy. One example that demonstrated the current capabilities for gas turbine engine DTs was in May of 2021 when the Navy was quickly able to diagnose an engine problem using the DT and shipped the required replacement part to the ship. The DT saved weeks of traditional troubleshooting because the issue did not have to be diagnosed by a technician (Eckstein 2021). The work done at NSWC Philadelphia Division made the creation of this effective DT possible because they compiled data and, using a neural net, were able to predict 24 outputs based upon four inputs (Burmaster et al. 2019). These four inputs allow a comparison which shows the differences enabling the suspect part to be pinpointed (Eckstein 2021). The compiled data used for the neural net consisted of data from over 350 engines from 2012 to 2017, which produced 280,000 healthy sample points for use (Eckstein 2021).

Additionally, DTs were successfully used to test software upgrades and updates before these updates were pushed to the fleet (Eckstein 2021). In a presentation by Dr. Drazen in 2021, he defined a DT as "a model that provides actionable information and integrates data from on and off the platform." He also emphasized that "a DT should be as complex as the application needs it to be" (Drazen 2021). He further stated that the difference between a twin and a model is the fact the twin will be updated throughout its life to be representative of a very specific asset becoming the authoritative source of truth while a model stays static. While DTs and models are useful, the design phase of the asset must be considered for its sustainment and maintenance life cycle to be most useful (Eckstein 2021).

Another way the Navy is using DTs is for creating a digital version of a physical shipyard, showcased in the article "Navy Optimizing Shipyards with Digital Twin Technology" (Tadjdeh 2021). This type of DT does not follow the team's definition of a DT; however, this article does provide an example of how the Navy is currently implementing a form of a DT and the versatility of DTs. The shipyard DT focuses on modeling and simulation to optimize all areas of the shipyard, including the flow within the shops, to provide the most efficient and productive layouts for shipyard operations.

K. ASSESSMENT OF CURRENT DT CAPABILITIES IN INDUSTRY

Team Gemini's research of current DT capabilities utilized by the private sector led to GE's article titled "GE Digital Twin – Analytic Engine for the Digital Power Plant" (General Electric 2016). Based on decades of investments in research and development (R&D) and manufacturing, GE has not only created DTs for existing and newly manufactured products, but a whole suite of tools that are capable of supporting the customer throughout a system's life cycle. These tools seek to maximize profitability through improvement of operations efficiency, reduction of unplanned outages, and management of variation in market conditions. Compared to other private companies, GE has a different take on DTs by defining them as "an organized collection of physics-based methods and advanced analytics that is used to model the present state of every asset in a Digital Power Plant" (General Electric 2016, 3). GE's definition of a DT encompasses characteristics of physics-based model to include thermal, electrical, and mechanical aspects of a model, in addition to an analytical approach that considers factors such as long-term outage planning, prognostics/early fault detection, and management of equipment/site constraints.

In the GE DT article (2016), GE discusses a variety of DT models which Team Gemini was able to gain invaluable insights regarding DTs. The models that are relevant to this capstone project are the Lifing DT and Anomaly DT. Lifing DT assesses each component within the system and predicts how a specific asset will age in relation to its operational environment through reliability modeling of capital equipment. The benefits of employing these types of models include determining trade-offs for dispatching maintenance teams, and planning of long-term outages. Anomaly DT leverages physics and data-based prognostic models for fault detection of a system or component. The benefit to utilizing an Anomaly DT includes failure mode management and reduction in unplanned downtime through improved accuracy of RUL curves, as well as personalized maintenance needs. Creation of aforementioned DTs is only half of the tools necessary to improve operations efficiency.

The GE DT article (2016) continues to discuss Optimizers, that are the other half of the tools needed to improve operations efficiency. These consist of combining a DT with algorithms and artificial intelligence. Optimizers leverage DT models and are designed to receive variable inputs, constraints, and account for the problem that is to be solved by creating connections amongst components that may not be obvious to the customer. An Optimizer that would aid in developing this capstone project is the Asset Life Optimizer. Essentially, the Asset Life Optimizer uses both Lifing and Anomaly DT models to predict remaining time left for an asset before maintenance is required. Generally, every asset has a TBM component which results in a scheduled outage, and this scheduled outage may lead to an unplanned outage due to the discovery of an unexpected anomaly. The Optimizer aims to mitigate this problem by shifting to a maintenance schedule that is condition based, by deliberately and reliably exploiting an equipment's RUL to a planned outage date. The outcome of employing these products should result in optimization of operations leading to maximized profits. Moreover, another benefit would be the ability to extend equipment performance and enhanced planning, so other operational requirements can be met.

L. CHAPTER SUMMARY

DTs are a relatively new concept that have been used successfully in both industry and the DOD. An example of a DT currently being utilized is GE's LM2500 engine on board Navy surface vessels. DTs today are being used to help diagnose encountered problems using the consolidated historical data to determine the root cause of problems without having to touch the physical asset. Compiling the collected data from the DT and using it with neural nets or machine learning opens the possibility for DTs to predict when maintenance tasks are required. This transitions DTs into the realm of CBM and PHM, allowing the maintenance for the system the DT is concerned with to shift away from a TBM approach. The next chapter examines functions and requirements for Team Gemini's DT architecture, which is concerned with predicting required maintenance where the system of focus is a metal powder bed fusion 3D printer.

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III. DESIGN AND DEVELOPMENT

Building on the foundation established in Chapter II, Chapter III focuses on the design and development of the system. This chapter starts with identifying the stakeholders and transforming their needs into functional requirements, both organic and external, through a requirements analysis. Next, the operational concept design is detailed in the functional description to help define the interactions of users and external systems for the DT. The system decomposition continues through to the functional analysis and allocation which defines the behavior diagrams for the system.

A. STAKEHOLDER IDENTIFICATION

The stakeholder collection included any individual, group, or institution with a vested interest in the implementation of CBM+ employing the use of a DT. Stakeholder analysis contributed early to the SE process. The analysis identified the key actors' knowledge, interests, needs, and interdependencies as shown in Table 1. Prioritization of the stakeholders was accomplished through the review of the stakeholders' primitive needs and level of involvement. The primitive needs were established through sight visits, teleconferences, meetings, and emails with the stakeholders that provided insight into the process and revealed restrictions. The prioritization of the stakeholders helped in the determination of critical system parameters.

Table 1. List of Stakeholders

Stakeholders	Prioritization	Level of Involvement	Primitive Need
NSWC PHD, Code 00T	Primary	CBM/DT expert consultant and sponsor for NPS led study.	Interested in providing expert advice for the project team to ensure the development of a quality DT product that is useful.
In-Service Engineering Agent (ISEA)	Primary	Support sailors in operating and maintaining their systems	Interested in increasing the maintainability of systems and lowering the cost of the overall life cycles.
Regional Maintenance Center (RMC)	Primary	Support sailors in operating and maintaining the systems	Interested in increasing the maintainability of systems and lowering the cost of the overall life cycles.
Sailors aboard surface vessels	Primary	Operating and maintaining the systems.	Interested in increasing maintainability and operational availability of systems
Dr. Douglas Van Bossuyt	Secondary	Primary advisor for capstone project.	Interested in providing expert advice for the project team to ensure the development of a quality DT product that is useful.
Naval Postgraduate School (NPS)	Secondary	Provide productive educational environment to DOD workforce.	Interested in improving the skills of DOD personnel.
Naval Supply Systems Command (NAVSUP)	Secondary	Understanding the logistical processes feeding into supportability.	Manages the global supply chain which includes spare parts, replacements, and consumables.

1. Primary Stakeholders

The primary stakeholders are Naval Surface Warfare Center Port Hueneme Division (NSWC PHD) Code 00T, ISEAs, RMCs, and sailors aboard the surface vessel. They are all interested in furthering the development of CBM/PHM. The DT architecture and model developed by Team Gemini met their needs for CBM/PHM with the use of real-time data from a system to better predict maintenance needs. Improving maintenance predictions allows for parts to be replaced before failure occurs and transitions away from relying on TBM, which is still common with the RCM process, improving system Ao for the sailors. Additionally, the DT utilizes data from sensors in the system to generate alerts sent to the sailors that inform them to perform maintenance tasks. Both the ISEAs and RMCs are interested in real-time data and DT predictions because this information can be analyzed to optimize probability algorithms for when maintenance will be required before a failure occurs. Code 00T, Office of Technology, is responsible for the research that led to the DT capstone project. The information from this research drove the system requirements and was vital to the formation, scope, and boundaries of the system architecture.

2. Secondary Stakeholders

The secondary stakeholders are Dr. Douglas Van Bossuyt, NPS, and NAVSUP. Dr. Van Bossuyt is the primary advisor of the capstone project as well as one of the authors, along with Code 00T, of the DT research article that inspired this project. His goals aligned with NPS such that they both want to ensure the development of a quality, useful, and research-based DT product. Additionally, a successful capstone that leads to improved overall effectiveness for the DOD, reflects highly on both the NPS program and Dr. Van Bossuyt. Another secondary stakeholder, NAVSUP, is responsible for controlling the entirety of the global supply chain for the Navy. One of the goals of this capstone is improving supportability by decreasing logistics delays, so NAVSUP has a vested interest because of the potential for increased efficiency. Additionally, NAVSUP is interested in the DT's ability to identify improvements for parts procurement so that the sailors aboard the vessels have parts readily available when necessary.

B. REQUIREMENTS ANALYSIS

As mentioned earlier, the primary and secondary stakeholders helped with driving the system's desired functionality. With the functional need established, the team formulated the "operational scenario" for the DT through defining operational requirements. The previous sections mentioned the established need and technical approach. The scope narrowed the DT development requirements specifically to functional, nonfunctional, and external interfaces. This section focuses primarily on functional and external interface requirements. The team decided not to highlight the nonfunctional requirements, see Appendix B for a list, because these requirements are derived from restrictions through standards, timing constrictions, and processes on services and functions provided by the entire system, therefore do not require an analysis to be performed. Nonfunctional requirements specify or constrain the system as a whole, describe how a system should be, are derived by examining quality attributes, such as: reliability, performability, serviceability, interoperability, safety, and security that apply to the entire system (Sommerville 2016). It is also important to note that the tables within this section only contain high-level descriptions. Further decomposed functional, nonfunctional, and external interface requirements can be found in Appendix B.

The team designed the DT to gather data from the physical host, process the data into real-time health and scheduled maintenance predictions, and calculate a probability of system mission success. These three broad vignettes focused the system's initial requirements development. The team needed to establish the primary customer services from the system and the operational constraints. Initially, the high-level stakeholder needs complimented the foundational requirements from an abstract view as seen in Figure 11. Overall, eight stakeholder needs emerged. The term "stakeholder need" refers to the primitive needs established by the stakeholder which are described using normal language and act as the highest unrefined parent requirement. The top row in Figure 11 shows broad objective needs that solve the original problem posed regarding the need for real-time system health performance feedback to inform maintenance decisions, decrease life cycle costs, improve Ao, and decrease logistics delays. The bottom row represents the areas dedicated to functional, nonfunctional, and external interface requirement decomposition. These three stakeholder needs (SN-6, SN-7, SN-8) provided the areas for further requirement decomposition.

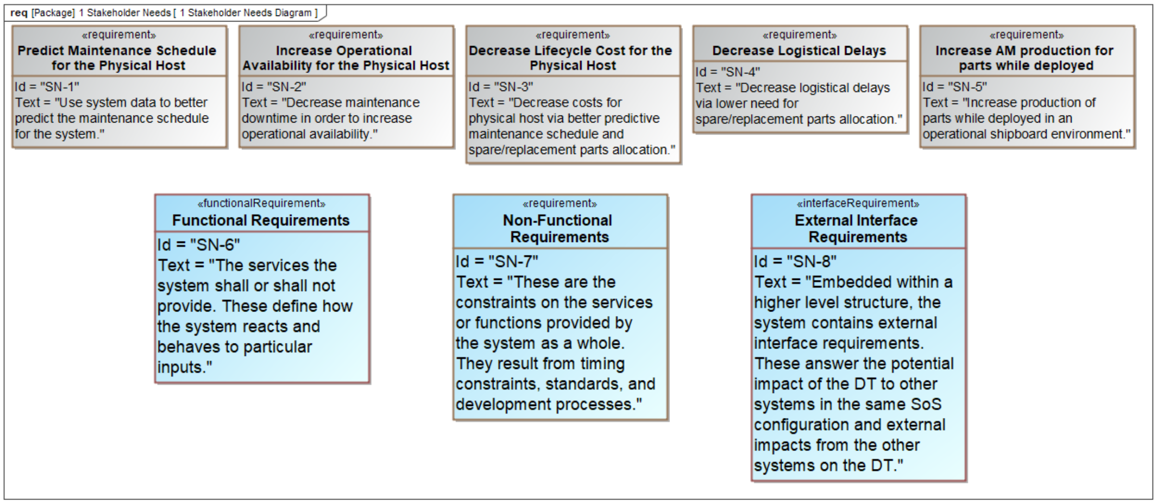

Figure 11. High-Level Stakeholder Needs Diagram. Adapted from Sommerville (2016).

1. Functional Requirements

Functional requirements express the "statements of services the system should provide, how the system should react to particular inputs, and how the system should behave in particular situations" (Sommerville 2016, 91). The DT needs to collect data from two key areas: the ship's environment and the 3D printer. Sensors outfitted on the DT and ones that are built-in to the ship provide the collection of ship space environmental data, like compartment temperature, humidity, and vibration. The 3D printer provides its inherent physical system outputs through new and existing sensors. These two forms of data, combined with uploaded hybrid cloud raw and historical data, provides the basis for further processing functionality. The processing function of the DT provides the overall end-user product: CBM+ reports, PHM status, and probability of printer part success.

The DT's functional requirements explained a simple sequence of steps in order to achieve the overall goal. The DT shall take data from a physical asset and the environment, manage environmental sensors, record the data into a database, manage environmental faults, process the data through functional algorithms, and communicate the data in the form of status reports. While there are more defined and refined aspects of the DT's functional requirements shown in Appendix B, Table 2 highlights the primary goals needed for follow-on design.

Table 2. High-Level Functional Requirements Table

SN-6	Functional Requirements	The services the system shall or shall not provide. These define how the system reacts and behaves to particular inputs.
FR-6.1	Receive 3D Printer Data	The DT shall receive raw data from embedded sensors.
FR-6.2	Manage Ship Space Environmental Sensors	The DT shall maintain sensors able to record environmental data external to the physical host.
FR-6.3	Collect Ship Sensor Data	The DT shall receive data from ship sensors external to the 3D printer physical asset.
FR-6.4	Record Data	The DT shall record data from embedded and external sensors.
FR-6.5	Manage Ship Space Instrument Faults	The DT shall manage faults from environmental instrument sensors.
FR-6.6	Process Data	The DT shall process data for current and predictive system effectiveness and suitability.
FR-6.7	Communicate Data	The DT shall transmit data through the ship communication system

As shown in Table 2, there are seven primary functional requirements represented as FR-6.1 through FR-6.7. The following subsections are a detailed description of the seven functional requirements:

a. FR-6.1: The DT shall receive 3D printer data

This functional requirement represents the DT capability of sampling live stream data from embedded sensors on the 3D printer in a manner that can be processed by the DT. Received sensor data shall include, but is not limited to, amount of time the printer is in-use, laser unit power, laser drive motor position, collimator beam size, laser circularity, printer compartment gas pressure, metal powder material type, printer component faults, inert gas purity, printer bed air flow, and cooling water composition. Ultimately, the DT shall pass the sensor data to the processing function and data recording function.

b. FR-6.2: The DT shall manage ship space environment sensors

This functional requirement represents the DT capability of managing the function and sample rates of external instrument sensors located in a controlled ship's space that houses the 3D printer. Environment sensors shall include, but are not limited to, thermometer, hygrometer, accelerometer, and gyrocompass. The function shall also run a self-test on all instrument sensors. The function shall dictate how/when a sensor passes data to the data processing function and data recording function. Along with the physical host data, these sensors compliment the physical host data for current and predictive analysis.

c. FR-6.3: The DT shall collect ship sensor data

This functional requirement represents the DT capability of sampling live stream data from both sensors inherent to the ship itself and sensors installed in a controlled ship's space that houses the 3D printer. Sensor data received for the ship space shall include, but is not limited to, temperature, humidity, vibration, and attitude. Sensor data received from inherent ship sensors shall include, but is not limited to, ship propulsion settings and ship sea state. Much like a hospital's vital sign monitor, the DT applies the environment data to the host data to provide a similar analysis to the 3D printer. The DT shall pass data to the data processing function and data recording function.

d. FR-6.4: The DT shall record received and processed data

This functional requirement represents the DT capability of recording sampled data from all embedded and external sensors. In addition to sensor data, the DT shall record uploaded historic data pertaining to 3D printer component accuracy, precision, and tolerance. The DT shall record computer-aided design (CAD) specifications for 3D-printed components. The DT processing function shall access recorded data, which are stored in a hybrid cloud, to conduct a performance analysis.

e. FR-6.5: The DT shall manage ship space instrument faults

This functional requirement represents the DT capability of recording sensor faults. The ability to log instrument faults acts more towards self-reliability management. The DT shall produce a sensor fault log as well as provide the recorded faults to the processing data function for analysis. Ultimately, DT fault management eases the historically labor-intensive monitoring of system sensors.

f. FR-6.6: The DT shall process data

This functional requirement represents the DT capability of analyzing the sampled live sensor data, historical data, and the fault log. The DT shall use the data provided to make predictive CBM decisions for the physical host. The DT shall predict printer failure rates as a combination of each component of the physical host's failure rates and the probability of success for printed part. The DT shall provide probability of success for a printed part based on performance analysis of laser beam, scanning mirror, and powder bed considering environmental values from the ship for temperature, humidity, vibration, attitude, and propulsion settings.

g. FR-6.7: The DT shall communicate data

This functional requirement represents the DT capability of communicating data outside the DT. The DT shall transmit the following information to the hybrid-cloud to be accessed by ship personnel and shore support personnel: DT instrument sensor maintenance report, physical host maintenance report, current prognostic health of physical host, CBM for physical host, and probability of success for part production.

2. External Interface Requirements

The DT acts as an embedded piece within an external environment of systems. Team Gemini realized the SOS components have a major impact on successful DT applications. The external environment's primary actors include the users, 3D printer, and hybrid cloud. Based on these primary actors, the team identified five primary external interface requirements, which are shown in Table 3 as EIR-8.1 through EIR-8.5.

Table 3. High-Level External Interface Requirements

SN-8	External Interface Requirements	Embedded within a higher-level structure, the system contains external interface requirements. These answer the potential impact of the DT to systems in the same SOS, as well as impacts to external systems.
EIR-8.1	Graphical User Interface	The software shall contain a user interface web portal providing access through a web browser application available to the shore support community or maintenance laptop.
EIR-8.2	Hardware Interface	The system shall be able to physically connect to external systems.
EIR-8.3	Software Interface	The system shall be able to send compatible strings of code and decode messages with the external systems.
EIR-8.4	Communications Interface	The system shall contain a working interface with the physical host and ship's communications system for transmitting and receiving data.
EIR-8.5	Data Storage Redundancy Interface	The system shall provide an interface with the hybrid cloud for data storage redundancy (such as RAID configurations)

The external interface requirements consist of how these actors interact with the DT and define the necessary interfaces that the DT shall have. These interfaces include a graphical user interface (GUI), hardware interface, software interface, and communications interface. Team Gemini determined that designing a fully functional GUI for the DT proved beyond the team's scope; however, a fully functional GUI is essential to the users, which includes both operational maintainers and system engineering analysts. A functioning GUI serves as the primary means to decrease many of the administrative delay times associated with deciphering system maintainability. These users require an interface which remained paramount to the team's projected recommendations and a primary focus for DT integration. Therefore, the DT relied heavily on leveraging the 3D printer host interface and integration into a communicative hybrid cloud. In addition to these interfaces, the last external interface requirement, EIR-8.5, involves how the system shall provide a data storage redundancy interface using a redundant array of independent disks (RAID).

The requirements analysis and requirements engineering provided within this section was the necessary segue into the following sections. Establishing requirements allowed for further operational concept development of specific use cases, additional behavioral analysis for the system environment, and measures of effectiveness.

C. FUNCTIONAL DESCRIPTION

The functional description provides an operational concept for the overall DT system. This section serves to create a description of the system using the requirements analysis and the identified stakeholders' needs. It consists of the system context diagram, use cases, and scenarios.

1. Context Model

The system context diagram illustrates the users and external systems that interact with the DT system, shown in Figure 12. The surface vessel (SV) is the primary external system that interacts with the DT. The SV houses the system of primary focus for the DT, the 3D printer. Additionally, the SV provides environmental data to the DT which informs the conditions that the system of focus is operating within. The DT system collects raw system sensor and usage data from the 3D printer as well as environmental data from the SV. The DT processes that data to provide reliability and maintenance predictions to the users.

The users include the SV's personnel, shore support community, and tactical mission support. The ship's personnel include all the sailors assigned to the SV that houses the DT and the system of focus for the DT. The sailors are responsible for interacting with the DT and acting when the DT provides alerts, either performing maintenance or ordering components for the 3D printer. The shore support community is composed of NAVSUP, ISEA, and RMC, who act upon maintenance, parts, and reliability predictions provided by the DT. Additionally, the shore support community consists of personnel responsible for development, maintenance, and improvement of the DT. These DT support personnel are concerned with providing maintenance and support for the DT. They are also concerned with all the historical data the DT maintains, both raw sensor data and predictions that were made, so they can improve the prediction algorithms using machine learning. Figure 12 illustrates machine learning as a future capability for the DT because it is out of scope for this capstone project. The last user is tactical mission support which consists of the DON and the officers responsible for planning and executing missions. This user is identified in orange in Figure 12 because they are only concerned with tactical decision predictions provided by the DT, which is identified as a future DT capability because it is out of scope for this project.

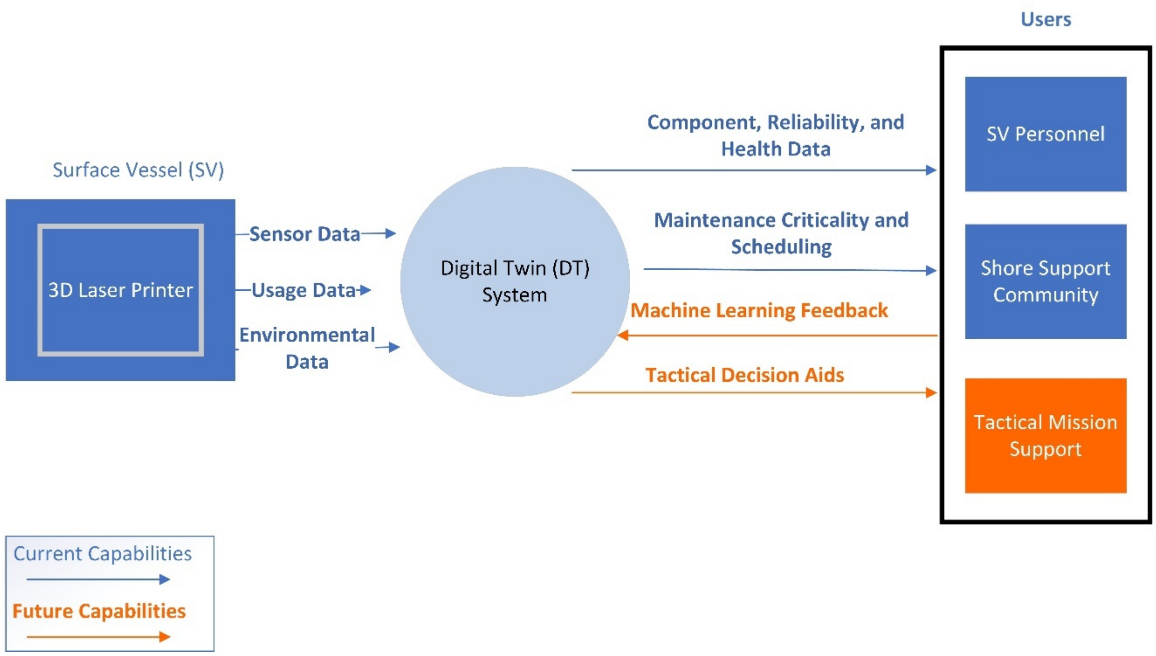

Figure 12. System Context Diagram

2. Use Cases and Scenarios

The use cases characterize the functionality that a system needs to achieve the goals of the users (Friedenthal, Moore, and Steiner 2011). Table 4 lists all the DT use cases, an overview of what the use case covers, and the scenario that describes the use case in more detail. The uses cases are used in SysML to augment the requirements and further refine the definition of the functional requirements (Friedenthal, Moore, and Steiner 2011). These use cases are developed from the perspective of the users of the DT, which include all the DT external interfaces defined in the system context diagram. Additionally, the system goals described in the use case represent the functionality that the system must support (Friedenthal, Moore, and Steiner 2011). The use cases are critical for the next section which consists of the functional analysis and allocation of the system.

Table 4. DT Use Cases and Scenarios

Use case	Overview	Scenarios
Send sensor data via local connection	The SV, 3D printer, and ship’s environment sensors send sensor data to the DT system	The SV, 3D printer, and ship’s sensors are energized and online. Local connection is established with the DT system, enabling sensor data reporting to the DT. The SV, 3D laser printer, and ship’s sensors report data to the DT system for storage and analysis, and the DT system receives and stores sensor data for processing.
View data locally	Sensor and prediction data are displayed on the DT system local interface.	The user connects to the DT system interface. The user authenticates by entering their username and password. The user requests to view data. The DT system displays available data containing sensor information or data prediction. The user disconnects from the DT system interface when finished.
Provide DT system maintenance	Maintainers run DT system local diagnostic tests to verify overall DT system health and performance. The maintainers provide any necessary maintenance, data storage optimization, or schedule any maintenance such as hardware replacement	The DT system is online and operational. Maintainers connect to the DT system interface. The maintainers authenticate by entering their username and password. Maintainers run diagnostic tests and optimize data storage. The DT system remains operational, and there are no faults. Maintainers disconnect from the DT system interface.
		The DT system is online and operational. A DT system maintenance alert is displayed on the DT system interface. The user/maintainer connects to the DT system interface. The user/maintainer authenticates by entering their username and password. The user/maintainer runs diagnostic tests and detects any system failures. The user/maintainer schedules any necessary maintenance. The user/maintainer disconnects from the DT system interface when maintenance is complete.
Request data via local connection	The user requests sensor and prediction data using the DT system local interface	The DT system is online and operational. The user connects to the DT system interface. The user authenticates by entering their username and password. The user requests data analysis that contains historical sensor data, reliability, health, and performance information. The data is available to the user for display and/or downloading. The user disconnects from the DT system interface when finished.
Receive alerts via local connection	The user receives DT system alerts containing SV subsystem prediction data via the DT system local interface	The DT system creates a prediction alert from anomalous MSV subsystem sensor data. The alert is displayed on the DT system interface and saved for historical data storage.
Upload updates via local connection	The user uploads software updates and prediction algorithms using the DT system local interface	The DT system is online and operational. The user and/or maintainer authenticate by entering their username and password. The user and/or maintainer interfaces with the DT system interface and uploads software and prediction algorithm updates. This action results in having the most up-to-date software and prediction algorithm version. The user and/or maintainer disconnects from the DT system interface when finished.
Perform DT Functions	The DT system performs data processing, storage, and sends alerts.	The DT system establishes communications with shipboard environment sensors and the 3D printer. The DT system receives data from the SV, 3D printer, and ship’s environment sensors. The data is stored and processed by the DT system. The processed data is stored and analyzed, and any necessary alerts are sent to the user.

3. Measures of Effectiveness

The previous sections discussed essential decomposition of both requirements and use cases for the DT system. These areas of design and development produce specific system outputs that must be evaluated. First, the team explored "what" specific measurements provided a proper evaluation of the system. As a reminder, the system's main product remains increased CBM+ and PHM for its physical host. The areas for "how" to gather these measurements occurs later in development. The best definition for a measure of effectiveness (MOE) is:

> A measure of the ability of a system to meet its specified needs (or requirements) from a particular viewpoint(s). This measure may be quantitative or qualitative and it allows comparable system to be ranked. These effectiveness measures are defined in the problem-space. Implicit in the meeting of problem requirements is that threshold values must be exceeded. (Smith and Clark 2004, 4)

To evaluate a successful mission for the system, the team designed measures for analyzing this result. MOEs decompose further into measures of performance (MOP) and measures of suitability (MOS). A DT design contains familiar aspects to that of a sophisticated computer, which rendered MOS development to be detracting from the project's objectives. The team focused DT development on high level MOEs to answer questions for the stakeholders' problems and needs. Figure 13 shows a simplistic comparison to calibrate the DT into "doing the right things" though accomplishments. The data inputs driven by the functional requirements and activities provide qualitative and/or quantitative information to feed the evaluation of the system's MOEs.

MOE	MOP	Indicator
Answers the question, "*Are we doing the right things?*"	Answers the question, "*Are we doing things right?*"	Answers the question, "*What is the status of this MOE or MOP?*"
Measures purpose accomplishment	Measures task completion	Measures the data inputs to inform MOEs and MOPs
No hierarchical relationship to MOPs	No hierarchical relationship to MOEs	Subordinate to MOEs and MOPs
Often formally tracked in formal assessment plans	Often formally tracked in execution matrices	Often formally tracked in formal assessment plans
Typically challenging to choose the correct ones	Typically simple to choose the correct ones	Typically as challenging to choose as the supported MOE or MOP

Figure 13. Assessment Measures and Indicators. Adapted from Joint Staff, J-7 (2011).

As mentioned earlier, evaluation of the team's DT did not involve specific SUT MOSs. However, the DT uniquely possessed the performance goal of improving its physical host's MOS. Therefore, many of the metrics chosen through development contain a focus on increased maintainability for the 3D printer. These parameters ultimately feed into system maintainability design (Blanchard and Fabrycky 2011). As established earlier during the problem definition, the less down time for the physical host, the greater the availability.

For specific DT goals as they relate to MOEs, the team organized three categories of measuring purposeful accomplishments:

- Increment 1: Improving the maintainability of the 3D printer.
- Increment 2: Improving the logistical supportability of the printed part.
- Increment 3: Improving the probability of success for a printed part.

These goals encompassed the areas for DT MOE development to feed into, not only, SUT design, but physical host design. Ultimately, through these metrics, the DT provided a predictive and real-time service for physical host heath improvement. Figure 14 shows the specific MOEs for further discussion.

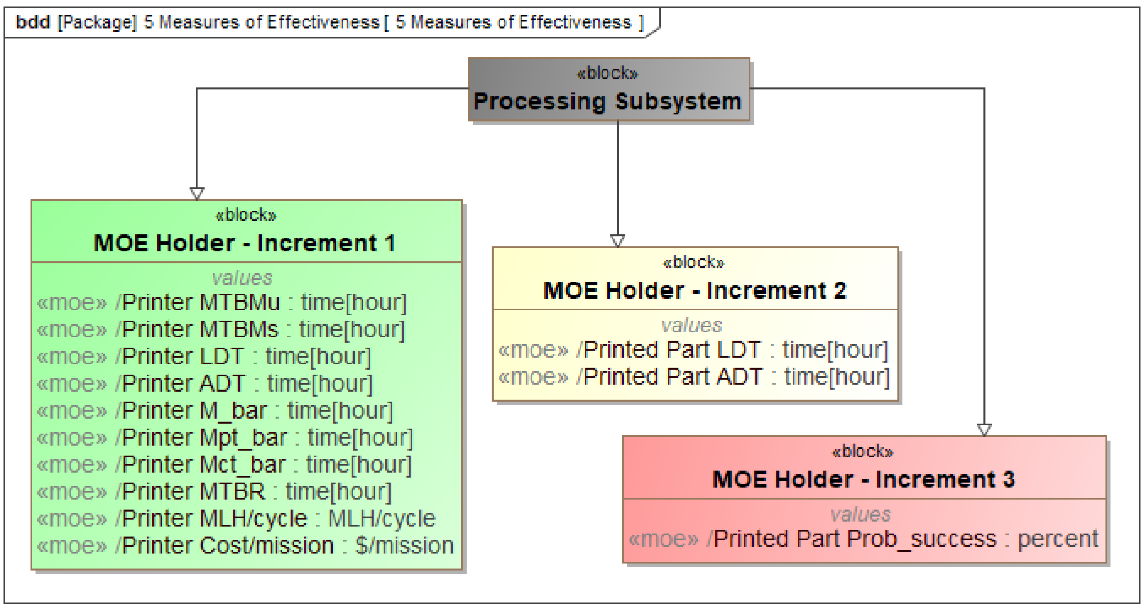

Figure 14. DT Measures of Effectiveness

a. Increment 1: Improving the maintainability of the 3D printer

The availability of a system depends on up time versus downtime. Downtime depends on several factors; the team focused on specific maintainability measures due to the time allotted to complete the project. Increment 1 intended to serve the near-term efforts for Team Gemini. All other increments provided conceptual background for future development and design.

Blanchard and Fabrycky (2011) easily explained and decomposed system maintainability into a convenient review of common SE knowledge. The important aspect to remember is that while these metrics are typical MOS, they still feed into the DTs MOEs. This poses the unique relationship between DT and host. As defined by Blanchard and Fabrycky (2011) the mean time between maintenance contains both unscheduled

(MTBMu) and scheduled (MTBMs) measures that consists of the mean, or average, time between all maintenance actions (corrective and preventative). They also define maintenance downtime (MDT) to include mean active maintenance time (M_bar), logistical delay time (LDT), and administrative delay time (ADT). Additionally, M_bar includes mean corrective maintenance (Mct_bar) and mean preventative maintenance (Mpt_bar) while considering the failure rate (λ) and preventative maintenance rate (fpt) (Blanchard and Fabrycky 2011). Further modeling and simulation referenced the following equations:

$$Ao = \frac{MTBM}{MTBM + MDT}$$

$$MTBM = \frac{1}{\frac{1}{MTBMu} + \frac{1}{MTBMs}}$$

$$M_{bar} = \frac{(\lambda)(Mct_{bar}) + (fpt)(Mpt_{bar})}{\lambda + fpt}$$

$$MDT = M_{bar} + LDT + ADT$$

The last MOEs incorporated the mean time between replacement (MTBR) for item replacements and considered the potential cost impacts for further analysis, which was maintenance labor hours per cycle of system operation (MLH/cycle). Table 5 shows the high-level specifics behind each MOE. From a test and evaluation aspect, these do not include the necessary condition and data requirement matrices for a full data collection plan (DCP) that traditionally belong to the test and evaluation enterprise. They merely show the intent for high level DT evaluation for effectiveness.

Table 5. High Level Measurements of Effectiveness (Increment 1)

MOE ID	Description	Trajectory	Value	Threshold
1.1	MTBMu of the 3D printer	Increase	Time (hours)	Positive improvement based on historical
1.2	MTBMs of the 3D printer	Increase		
1.3	LDT of the 3D printer	Decrease		
1.4	ADT of the 3D printer	Decrease		

MOE ID	Description	Trajectory	Value	Threshold
1.5	M_bar of the 3D printer	Decrease		printer measurements constitutes the threshold.
1.6	Mct_bar of the 3D printer	Decrease		
1.7	Mpt _bar of the 3D printer	Decrease		
1.8	MTBR of the 3D printer	Decrease		
1.9	MLH/cycle of the 3D printer	Decrease	MLH/cycle	
1.10	Maintenance cost per mission of the 3D printer	Decrease	$/mission	

b. Increment 2: Improving the logistical supportability of the printed part

With the DT paired to the 3D printer, further MOEs derived from the unique physical host mission. The idea stems from a DT's ability to improve the physical host and subsequently improve the physical host's mission. For an athlete, improving the body's health naturally acts as a catalyst for their success on the field. This concept paves an important steppingstone into many of the Navy's peaking interests for unique and complex weapons systems. For the case of the 3D printer, the DT improves the already paramount AM strategy for the DOD as discussed in the scope and literature review sections.

From an AM lens, the 3D printer's production of a printed part alleviates the stressors on their inherent logistical supportability measures. Specifically, these measures target the logistics included for spare part storage, off-site production of replacement parts, and the accompanying transportation/distribution fallout (Blanchard and Fabrycky 2011). The printer achieves further prosperity from the DT due to the predictive and real-time system health diagnostics. Through system integration, the DT achieves AM "success by association" while attached to a 3D printer.

c. Increment 3: Improving the probability of success for a printed part

The final increment for achieving the DTs goals includes the quality and performance of the printed part. Continuing with the unique attachment benefits, the DT enables the printer's produced part performance. Again, from a solution agnostic mindset, the DT attached to any complex weapon system stands to improve its overall mission performance. For a radar system DT example, an MOE could include probability of detections with an increase in range and accuracy as the end goal.

In the case of the team's printer, the accuracy, precision, and tolerance of the printed part remained valid MOEs able to evaluate an end goal for applying effective AM within a unique and challenging environment on an SV. These would be measured against the military standard (MIL-STD) specifications for that part. Additionally, the printed part's life cycle performance while installed and executing its own duties would be measured. If a 3D printed part showed data trends of premature structural anomalies, causing early replacement, the DT's analysis of these negative performances would show in transparent reporting to the users.

The probability of success for a printed part considers numerous factors, conditions, and response variables. Each 3D printer component adds to the overall aggregate of success percentage. For the project's allotted time, Team Gemini provided this brief conceptual discussion as a branch into the performance success of any complex system that stands to benefit.

d. Refine Requirement Matrix (RRM)

Lastly, each MOE needed a relation to the previously discussed functional requirements and activities. The expanded RRMs show MOE refinement for the specific requirements and activities. The detailed lines, for each matrix, reside in Appendix C. These MOE relations contribute to the system's functional development and design loop. The high-level requirements and activities were derived from the stakeholder's needs and concept of operations. The MOEs ensure refinement of each requirement and activity such that each possess a form of measurement to relate the overall system's effectiveness.

D. FUNCTIONAL ANALYSIS AND ALLOCATION

A vital activity performed early in the conceptual and preliminary design phase was the development of system functional descriptions, which served as the base to determine the system resources that were necessary to accomplish the mission (Blanchard and Fabrycky 2011). This section examines the functional requirements and use cases derived in the previous sections to generate behavior and structure diagrams for the Perform DT Function activity. Of the three types of SysML diagrams that capture dynamic behavior, this capstone chose to use an activity and state machine diagrams which are discussed in the following subsection, functional analysis. Using the functional analysis, the team further decomposed the Perform DT Function activity using a functional decomposition diagram to display all sub-functions. This section ends with the logical subsystems communications which depicts the input and output relationship for all hardware associated with the DT system.

1. Functional Analysis

The functional analysis details the top-down process of translating system-level requirements into performance design and detailed functional criteria. Defining the top-level architecture ensures all required system functions are properly integrated. Team Gemini used an activity diagram to detail this top-down process, shown in Figure 15. The activity diagram details the DT system's control flow and breaks down how the data is processed. The shipboard environmental data and the 3D printer data are passed into the DT and processed separately. Both sets of primary data are stored on the DT before being processed and analyzed by the DT system. Once processed, the data is sent to the hybrid cloud for storage and any applicable alerts are created.

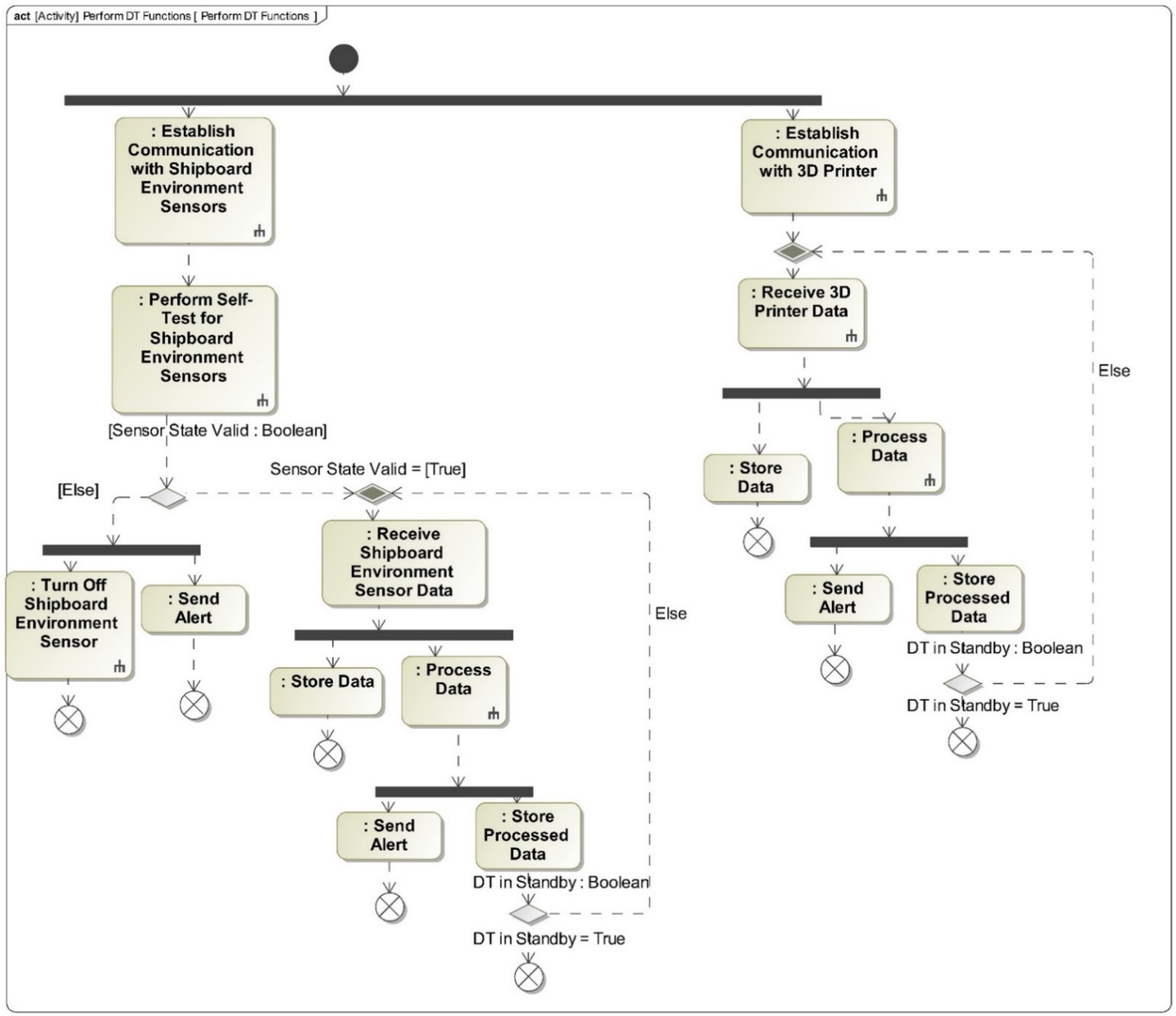

Figure 15. Perform DT Functions Activity Diagram

The state machine details the various states, transitions, and events of the DT system. To define system behavior more clearly, Team Gemini separated the events detailed in the activity diagram into events that cause a state change and events that exist as operational states. Then used these categorized events to create the state machine diagram shown in Figure 16. Team Gemini used this information to establish a simplified order of actions the DT takes during the startup process. Once the system is turned on, communication is established with all connected components and sensors. Diagnostics are run to ensure all components and sensors are operating as expected, at which point, the DT system switches into standby mode while it awaits new data from the sensors. The introduction of new sensor data into the DT initiates the process of shifting the DT from the standby state, into the full operation state.

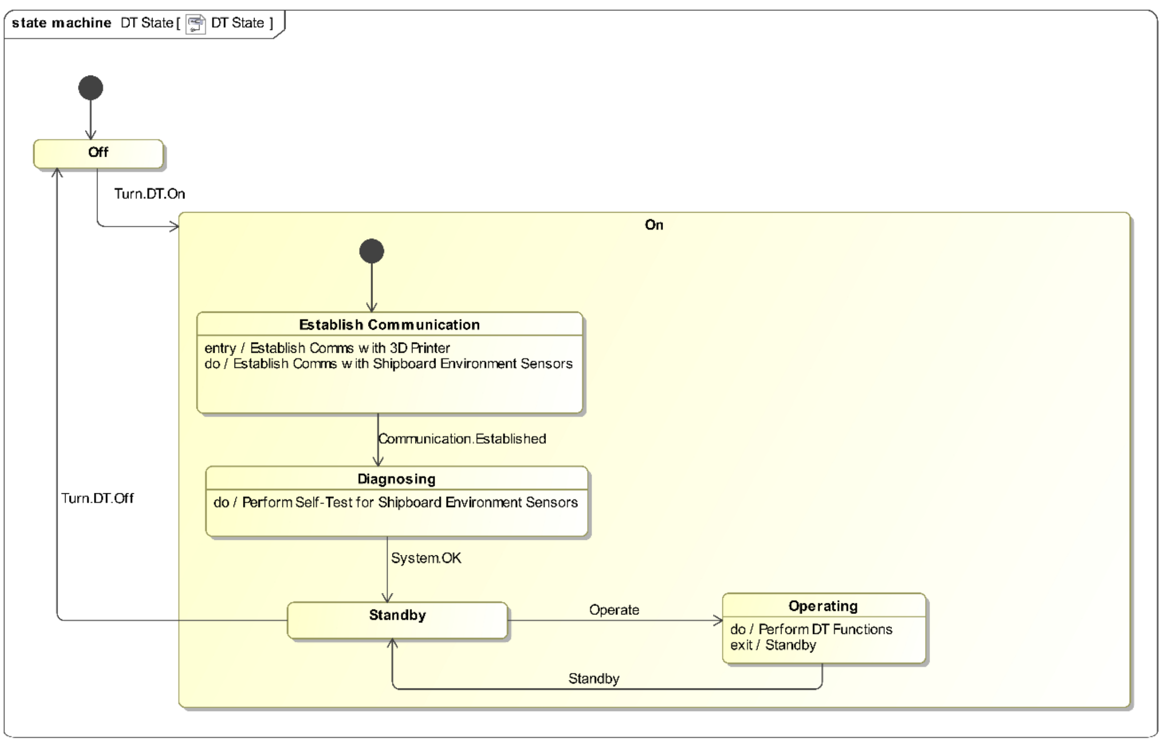

Figure 16. DT State Machine Diagram

2. Functional Decomposition

The functional decomposition analyzes the overall functions and breaks them into their respective sub-functions (Aleksandraviciene and Morkevicius 2018). As part of the white-box perspective of the problem domain following the MagicGrid method, the functional analysis decomposed every function listed within the use case. A functional decomposition diagram was generated based on the activity diagram from the functional analysis performed in the previous section. The functional decomposition diagram for the Perform DT Function activity, showing all the required sub-functions, can be seen in Appendix D. The figure details sub-functions for Process Data and Perform Self-Test for Shipboard Environment Sensors, which were not presented in the Perform DT Functions activity diagram. These sub-functions detailed activities such as executing built-in tests for shipboard environmental sensors as well as calculating aggregate probabilities of success, performing data extraction, and performing CBM analysis for individual components. The functional decomposition, in conjunction with the functional analysis, was conducted to identify the logical subsystems, shown in the following section.

3. Logical Subsystems Communications

The functional analysis and decomposition performed in previous sections helped identify logical subsystems specified within this section. Logical subsystems are considered as groups of interconnected and interactive parts consisting of one or more functions for the system of interest (Aleksandraviciene and Morkevicius 2018). Moreover, logical subsystems are represented by generic components that are necessary to perform DT system functions specified in the activity diagram. The result of modeling the logical subsystems' communications produces inputs and outputs of the DT system as well as defines logical subsystems. These logical subsystems of the DT system demonstrate interactions between other logical subsystems and external systems.

Blocks defined for the system context within the black-box perspective of the problem domain following the MagicGrid method were used to define inputs and outputs of the DT system. Inputs and outputs for the block definition diagram (BDD) are DT system interfaces. These interfaces were identified based on the activity diagram or through analysis of the system context diagram. The identified inputs for the DT system are sensor data, control signals, and energy, in the form of electrical power. The DT system outputs consist of sensor/processed data, fault/maintenance information, and system commands. The DT system contains three ports that are defined by type, which are data, energy, and I/O (input/output) interface blocks. Figure 17 illustrates the BDD that defines inputs and outputs along with designated flow properties for each interface block of the DT system.

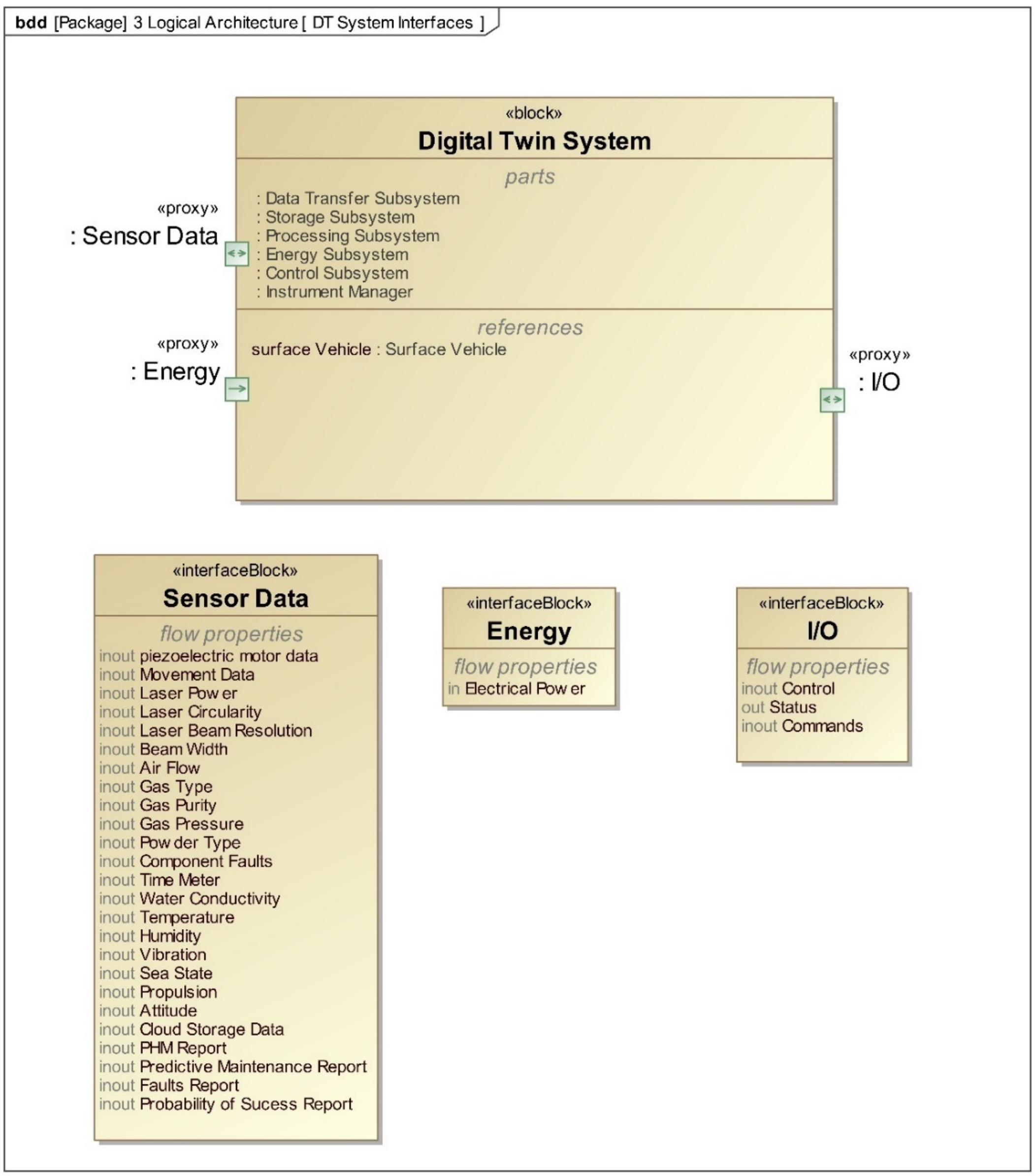

Figure 17. Block Definition Diagram of DT System

An internal block diagram (IBD) can specify logical subsystems of the DT, as well as interactions amongst them. IBDs are used to define the internal structure of a single block and show the connections between internal parts of a block and interfaces between them (Delligatti 2013). The logical subsystems contained in the IBD are defined as part properties and are derived from the Perform DT Function activity diagram. The IBD depicted in Figure 18 consists of six subsystems: instrument manager, energy, data transfer, processing, control, and storage. The instrument manager subsystem manages external instrumented sensors, or sensors that are not internal to the 3D printer, as well as managing sampling rate for these sensors. The energy subsystem provides power to all logical subsystems within the DT system. The data transfer subsystem receives and transmits data to internal and external systems. The processing subsystem provides computational resources to perform DT system functions such as processing sensor data, providing component reliability and health data, as well as maintenance criticality and scheduling. The control subsystem governs the other subsystems within the DT and receives system status from each. Lastly, the storage subsystem receives both raw and processed data and stores it for historical artifacts.

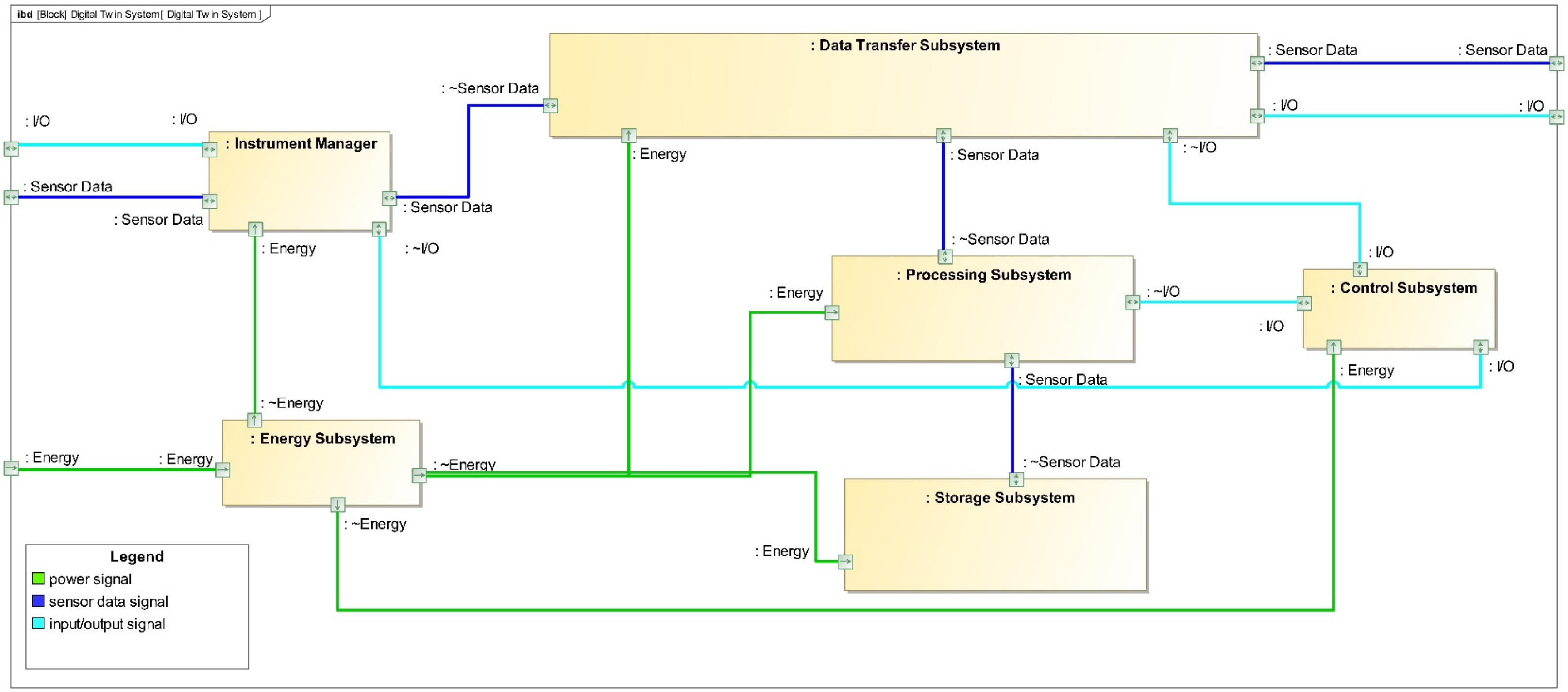

Figure 18. Internal Block Diagram for DT System

E. CHAPTER SUMMARY

Extensive research into stakeholder identification compiled a list of stakeholder needs. These needs were the basis for the development of the DT's high-level requirements. The high-level requirements were then expanded upon to develop the functional requirements. Each functional requirement provided insight into which components and environmental statuses required monitoring. This insight translated to specific sensors which are discussed in the first section of the next chapter. The requirements also defined the specific interactions between the DT, embedded and external sensors, and the users through the development of use cases. These use cases were then decomposed and used to discuss the common tasks that the DT was expected to perform in the functional analysis. Finally, this chapter finished with using the functional analysis to conceptualize the logical subsystems and internal structure of the DT required to perform the various defined functions. The next chapter further discusses the DT architecture developed and defined within this chapter.

IV. ARCHITECTURE ASSESSMENT

This chapter continues to expand on the architecture established in Chapter III. Chapter IV consists of the assessment of the architecture. It begins with an analysis of alternatives that helped determine what components and factors the DT model will consist of. The next sections explain the actual modeling of the DT and the simulation results. Chapter IV concludes with a cost analysis and technological risk assessment for the DT.

A. ANALYSIS OF ALTERNATIVES

According to Blanchard and Fabrycky the analysis of alternatives, or trade-off analysis, consists of a well-defined process:

> One must first define the problem and then identify the design criteria or measures against which the various alternatives will be evaluated …, select the appropriate evaluation techniques, select or develop a model to facilitate the evaluation process, acquire the necessary input data, evaluate each of the candidates under consideration, perform a sensitivity analysis to identify potential areas of risk, and finally recommend a preferred approach. (Blanchard and Fabrycky 2011, 93)

Team Gemini considered the various components of the 3D printer and other environmental factors that have a potential for affecting the reliability of the printer and the success of the print. The components and factors that were considered for modeling and monitoring were broken down by major subsystems in the following subsection.

1. Alternatives Generation and Description

All the components that feed data into the DT are identified and described below. To determine which components were used for monitoring and modeling, the component interrelationships and basic operations were defined first. These components are composed of the 3D printer itself and the ship's space.

a. 3D Printer Internal Environment

During the printing process, when the laser is melting the powder, the print area consists of an inert environment mostly composed of nitrogen gas with air flowing over the part being created. To keep the air flowing over the print at optimal parameters, the air filters cannot be clogged. To keep the laser cool and prevent overheating, a DI water radiator is used requiring the DI water purity and fluid level to be monitored to ensure optimal cooling occurs. The printer provides airflow and cooling to keep the laser cool, prevent any temperature fluctuations with the melted powder, and remove any foreign object debris (FOD) that accumulates on the print bed.

b. Laser System

The laser system is responsible for the DMLM process; therefore, it has many components and factors that were considered:

- Servo-controlled galvanometers control the laser and drive the steering of the laser beam on the printed area. Any deviation between the desired and actual location of the laser will affect the quality and success of the print.

- The laser's power output influences the amount of energy that is being directed at the powder that causes it to melt. Any major power fluctuations can create issues with the DMLM process and, in turn, the print.

- A layer of glass, called the protective glass, sits between the laser beam and the build plate which acts as a protective barrier. Cleanliness of the optical surfaces such as the protective glass interface is a concern; a dirty interface impedes the laser output power and laser focal size, which influences the quality of the melted powder and the fusing of the particles.

- A few components influence the laser beam's accuracy. A collimator focuses the laser light to ensure the beam is parallel, which in turn affects the focal length of the optics involved. These factors correlate to the beam size and circularity. The beam size affects the beam's dimensional accuracy and that the correct area of the powder is melted, and the beam's circularity affects the melt pool size as well as accuracy of the fused material.

c. Print Bed and Material

When the printer operates, the printed part is built up on a build plate where the material is fused. After each print, the part must be cut off the build plate; the plate is subsequently ground down and needs to be considered for levelness and flatness. Additionally, the choice of material, or rather powder, must be considered for grain size, grain purity, and sphericalness. All these factors affect the quality of the print.

d. Recoater Blade

The recoater blade moves the material from the powder supply pool across the build plate, deposits a new and even layer of material, as well as removes any excess powder. The recoater blade completeness, or lack of imperfections, is the most important factor to consider. Any irregularities with the blade can cause streaking in the powder on the build plate, which causes imperfections in the melting of the material during the printing of the part.

e. Ship's Space

Since the 3D printer is aboard a surface vessel, there are additional variables that were considered. These variables include the ship's motion and vibration which are affected by the sea state and propulsion settings. In addition, there are optimal conditions for the printer to operate under; therefore, the equipment space the printer is located in has a different temperature and humidity requirement than the rest of the ship. The propeller settings and transitioning of helm controls in the ship's pilothouse ideally affects the overall vibrations within the skin of the ship. These factors all affect a sanitized and serene environment for the printer's mission.

2. Feasibility Screening

The team discussed the aforementioned components and factors with material scientists from NSWC PHD Code 00T department, to determine which would be best suited for modeling. The selected factors and components were determined to have the greatest impact on the success of the print and are ideal candidates to transition from TBM to CBM. In this section, the components and factors are described for why they were or were not selected for modeling, a summary of which can be seen in Table 6.

Table 6. Components Considered for Modeling

Component	**Modeled**
Printer’s inert environment	No
Air flowing over print bed	No
Air filters	Yes
DI water conductivity	Yes
DI water level in radiator	Yes
Laser drive motors	Yes
Laser power output	No
Laser protective glass	No
Laser collimator and focal length	No
Print bed flatness	No
Metal build powder	No
Recoater blade	No
Ship’s space	No

a. 3D Printer Internal Environment

The inert nitrogen gas environment is maintained inside the 3D printer to reduce the possibility of flames and fires. When printing, the onboard computer monitors the environment and will abort the print if the purity of the gas is out of operating parameters. Air flows across the print bed to remove residue caused by printing, and laminar flow is not easily modeled due to the number of sensors required. However, the printer’s air filters that capture contaminants are prime candidates for modeling since air flow information can be obtained from them and maintenance can be moved away from TBM to CBM.

Another component that was a prime candidate for modeling is the radiator water used for cooling the laser. There are two factors for the radiator water, the first being salinity, which is needed to maintain a specific conductivity, and the water level, which ensures there is enough water circulating throughout the cooling system.

b. Laser System

Since positional accuracy for the material that is melted and fused is critical to the success of a printed part, the servo-controlled galvanometer that drives the laser beam was heavily considered as a candidate for modeling. The printer utilizes galvanometer scanners to direct and control the laser beam throughout the printing process. The motor system for the galvanometer scanners utilizes magnets that enable a high degree of accuracy, which facilitates fast and precise mirror positioning. Additionally, the motor system contains axially pre-loaded precision ball bearings that allow for low friction, high stiffness, and a backlash-free rotor design. While calibration is required during the initial setup process, these scanners are designed to run maintenance-free. However, there are always possible chances of failure. The repair or replacement of a failed or damaged motor system requires a manufacturer's representative. The extensive lead time to schedule a technical visit and the extended downtime the repair requires would have a large impact on the availability of the 3D printer. The team determined that placing a sensor on the laser drive motor system would benefit the DT system for CBM because of the criticality of this component to the printing process. The laser power output is difficult to measure against expected values and is outside the scope of the project given the time constraint for finishing.

To ensure and maintain optical cleanliness, the protective glass is wiped down at the beginning and end of each print to remove any residue or build up. This task is relatively quick and preventative, hence was not a good candidate for CBM. The calibration for the collimator, beam size, and the circularity of the laser beam are all annual maintenance tasks which require specialized, proprietary training. Therefore, these tasks are best suited to be performed by technicians from the manufacturer.

c. Printer Bed and Material

While a process exists to recycle and clean the powder for reuse, the equipment occupies space that could be better utilized for other equipment. It is easier for material to be supplied from the shore and have the used powder recycled at a shore support facility. When printing, the parts that are being made are fused to the build plate. The build plates require specialized machinery to machine the plates flat. With the space being a constraint, the shore facility would be better suited to machine the plates flat and provide the ship with new build plates that meet the levelness specifications. Therefore, these tasks are best suited to be performed by a shore facility, not on the ship.

d. Recoater Blade

There are two possible types of blades that are used with the printer: rubber and ceramic. The most common and least expensive blade is the rubber one, which is replaced at the beginning of every print job to avoid using a damaged or pitted blade. This item was not considered for modeling since it is a consumable component. Ceramic blades are not typically used because they are more expensive and are still subjected to the same issues with pitting and damage as the rubber recoater blade; therefore, this item was also not selected for modeling.

e. Ship's Space

There are a few factors that play a significant role in the success of a print such as sea state, temperature, and humidity. While they are possible predictors of the success of a print, they are not a reliable predictor for required maintenance. Therefore, these factors were not included for modeling.

B. MODELING AND ANALYSIS

In the analysis of alternatives, the ideal candidates for modeling were identified. The components and factors selected for modeling were DI water levels, DI water conductivity, air filters, and laser drive motor system. The team modeled these components and analyzed the results of different maintenance distributions. A detailed description of the modeling process, data elements, and results are found in this section.

1. Modeling Approach

To create a baseline of expected results for modeling, the team's first model was constructed using Excel. Without the availability of historical data or detailed information on the performance of the 3D printer and its components, the values used in the model were derived from various sources and some educated assumptions. General information pertaining to the 3D printer was provided by NSWC PHD Code 00T material science engineers that work with the 3D printer at the Fathomwerx facility. Additionally, maintenance information and schedules were provided in the 3D printer's manual, as well as from GE 3D printer technicians.

In the Excel model the mean time to failure (MTTF) was estimated for individual components. In the case where the manufacturer provided a maintenance schedule, a conservative assumption was made that the provided schedule periodicities represented three standard deviations from the actual MTTF. This ensured that the component would be serviced before a failure occurs, 99.7% of the time. A standard deviation was assigned, multiplied by three, and added to the maintenance interval to estimate the component's MTTF. Additionally, values for maintenance, logistic, and administrative delay times, for both preventative and corrective maintenance, were estimated. These values were estimated for both a TBM schedule and a CBM schedule. The component's usable life was assigned a value from 100 to 0, with 100 representing a new or newly serviced component and zero indicating the need to replace or service the component. The Excel model reduced the usable life of the component by a random amount each time segment based on a normal distribution using the estimated MTTF and assigned standard deviation. Once the usable life reached zero, an alert was recorded, and the usable life was reset to 100. The model was run for a two-year period and the resulting CBM Ao was compared with the Ao resulting from a TBM schedule. Since the MTTF for the laser drive motor system was orders of magnitude larger than the other components it was not modeled with excel.

The components were then modeled using ExtendSim, which allowed for a more robust model and use of various distributions. For the ExtendSim model, the previous MTTF values, which were calculated on a continuous flow of time, were adjusted to be based on actual time spent printing. The laser drive motor system was added to the ExtendSim model; however, in order to ensure the laser drive motor system would fail at least once during the runtime of the model, an artificially low MTTF was used. The model used normal distributions for random number generation. The ExtendSim model results were verified against the Excel model. The model was presented with varied random print job arrival times; and the print time of each print was modeled using a random normal distribution. Just like the Excel model, the ExtendSim model compared the use of CBM and TBM. For CBM, the model calculates the reduction of usable life for each component after each print. Once a single component's usable life was reduced to zero, the printer was taken offline for the appropriate amount of maintenance time and the usable life for that component was reset to 100.

By adding up total maintenance time, the availability of the system was calculated. For TBM, the model added printer offline time based on a scheduled periodicity. The usable life of the component was calculated the same as with CBM; however, if the component reached a usable life of zero before the scheduled maintenance, the printer was offline for a longer period of time to account for the corrective maintenance times. The ExtendSim model runs both variations simultaneously and the resulting availabilities were compared.

2. Data Elements

Based on meetings with stakeholders, several elements of the 3D printer were recommended for assessment using a model. These elements included monitoring DI water level, conductivity of DI water, air flow through the filters, and the laser drive motor with respect to positional accuracy. The following section provides specific details about the components that were needed to accurately model these elements and provides a further breakdown of the component.

a. Monitoring DI Water Levels

The laser radiator of the 3D printer requires a certain amount of DI water to prevent overheating of the laser. The radiator is susceptible to high temperatures because the laser uses large amounts of power to be able to melt and fuse the printing material, which generates a lot of heat. If the water level is not optimal, the radiator would not be able to dissipate the heat fast enough, and both the radiator and laser could become damaged by the melting of important components. There are numerous reasons for a low water level. The primary reasons are evaporation, due to the heat of the radiator, or leakage within the system. A leak could be from the radiator itself or from any hoses, or connections, that are attached to the radiator. Currently, the water is refilled after every four or five prints.

Additionally, a water level indicator, located on the back of the printer, is checked weekly. The cost of DI water is exponentially lower than having to replace a radiator or laser; therefore, this small check potentially saves hundreds, or even thousands, of dollars.

b. Conductivity of DI Water and Effects on 3D Printer System

The 3D printer uses a DI water cooling system to remove heat generated by the laser system. DI water is considered the optimal choice as a coolant for laser systems due to both its chemical and electrical properties. Conductivity is the measurement of the medium's ability to conduct an electric current, and DI water is considered to have low conductivity due to its lack of cations and anions. The use of DI water prevents mineral deposits from forming, which improves cooling efficiency and system operation. Additionally, the low conductivity of DI water makes it suitable for a closed-loop cooling system due to its inability to accumulate static charge as a result of fluid circulation. This prevents any potential damage that would be caused by electrical arcing of sensitive electrical components contained in the 3D printer system. However, it should also be noted that, if conductivity is too low the DI water has the potential to become corrosive due to its lack of ions, resulting in a non-equilibrium state between the fluid and contact surface. It is imperative that components that come into contact with the coolant are corrosion-resistant and compatible with DI water. Ultimately, the 3D printer system's optimal conductivity for the DI water is between 2 – 3 μS/cm and should be maintained to maximize Ao of the system.

c. Air filters

The DMLM printing process is performed in an enclosed assembly area with an inert gas atmosphere. The results of the manufacturing process are fumes and fine dust, which partially consists of extremely tiny nanoparticles. To maintain a stable construction process, the entire system must provide a uniform flow of inert gas over the build bed, capturing fume and particles but not the metal powder material. Due to the small particle sizes, the dust itself can be highly reactive. The dust particles also pose a significant health risk to anyone who encounters them. A filtration system removes and collects the fume and particle byproduct of the printing process. Filter cartridges collect particles on their surfaces, and these particles can be removed periodically with a blast of inert gas to prolong the life of the filter. Eventually, the filter will need to be replaced once it reaches its saturation point. If printing continues past the point of filter saturation, quality of the print will degrade, and the risk of hazardous material contamination of the 3D printer environment is possible. The purity of the inert gas blown over the printer bed needs to be greater than or equal to 99.5% by volume. To maintain the sufficient removal of fumes and particles from the printing area, the air flow should be approximately 1.0-1.5 cubic meters/hour (m^3/hr).

d. Laser Drive System (Galvanometer)

The laser drive system is the fundamental component to the 3D printing process. By precisely directing a high-powered laser to the exact point on the print bed, the printer is able to produce highly accurate and detailed print designs. Galvanometer scanners are motorized mounts that are ideal for processes that require precision and accuracy, while also being able to move quickly. The scanners are powered by limited rotational direct current motors. These are built to extremely high standards and are designed to run error free over long use times. The mirror system used by the laser drive system enables system customization of apertures ranging from 6mm to 30mm. Lastly, precision ball bearings are used to ensure a no recoil rotor, high stiffness, and low friction.

3. Results and Limitations

Based on analysis of both simulation model results, the CBM approach clearly benefited the user by providing higher overall Ao. The basic Excel model showed that a CBM approach provided an Ao of 96.21% compared to the TBM Ao of 90.64% which shows an increase in Ao of approximately 6%. The more realistic and detailed ExtendSim model showed an increase in Ao between 1.5% and 5% depending on the utilization of the 3D Printer. These results, along with a comparison between the number of maintenance tasks performed between the Excel and ExtendSim models during the 2-year simulation, provided the verification for the ExtendSim model. The largest benefit resulted when the mean time between each print was small. Figure 19 and Figure 20 depict the average availability for the printer over 100 runs where the mean time between prints varied ranging from 18 to 58 hours over a two-year assessment period. Figure 19 shows the results when the simulation was run with the laser drive motor system sensor, and Figure 20 shows the results when the simulation was run without the laser drive motor system sensor. Additional simulations ran were for when the MTTF values varied for three of the four components, for three values. The additional MTTF values were ±20% of the calculated MTTF. Since the MTTF for the laser drive motor system was already artificially low, it was not altered; however, simulations were run with and without the laser drive motor system sensor. The results of these additional runs can be found in Appendix E.

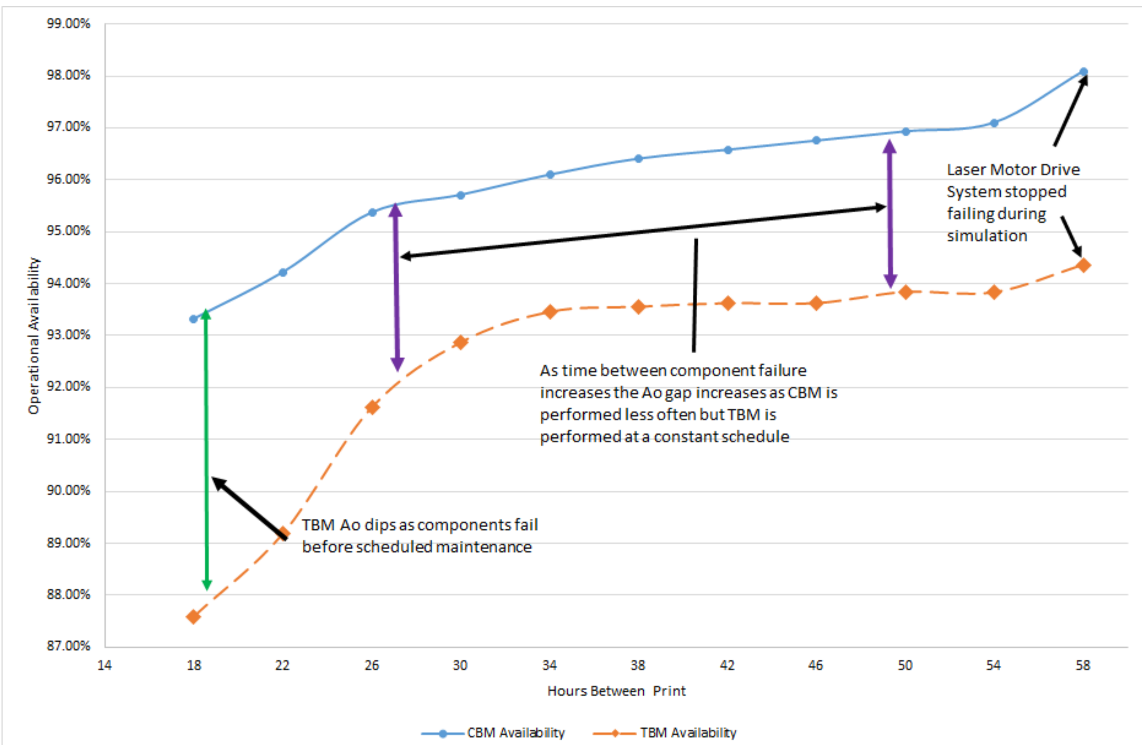

Figure 19. Ao for CBM and TBM with Laser Drive Motor System

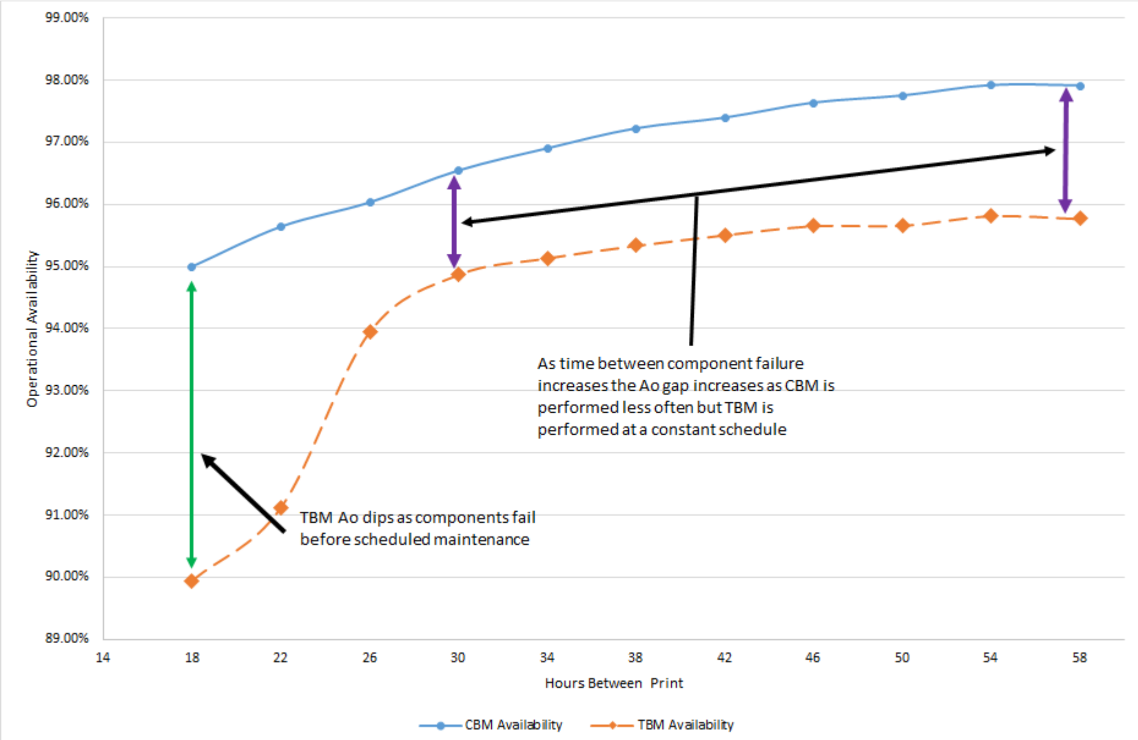

Figure 20. Ao for CBM and TBM without Laser Drive Motor System

All the simulation runs' graphical results have a common shape. As the mean time between each print increases, the number of component failures before the scheduled maintenance reduces close to zero, resulting in the smallest gap between CBM Ao and TBM Ao. As the mean time between each print continues to increase, the gap between CBM and TBM starts to slowly increase. When the mean time between prints was small, the gap between CBM Ao and TBM Ao was greatest because components failed before the TBM was performed, resulting in large corrective maintenance downtimes, decreasing the overall system availability.

Using the TBM approach, where preventative maintenance is performed on a set schedule unrelated to the actual condition of the component, makes it so the TBM availability becomes a product of the schedule maintenance performed. The TBM Ao reaches a plateau and cannot be increased without changing the TBM periodicity. On the other hand, the CBM approach has no set schedule for maintenance. Maintenance is only performed when required; therefore, as the mean time between each print increases, the component's remaining life decreases at a slower rate. This results in maintenance being performed less and less frequently, which caused CBM Ao to continue to slowly increase.

The system that incorporated a DT using a CBM approach had a higher Ao because the DT negated the need to perform preventive maintenance because it predicted the need for maintenance, which eliminated the need for corrective maintenance. The CBM approach decreased LDT and ADT, as well as reduced preventive maintenance time to zero. Ultimately, the model demonstrates that having a DT, or transitioning to a CBM approach, presents substantial benefit to the user regardless of usage of the 3D printer.

There were several limitations and constraints applied to the model throughout the process. Limitations on the model included assuming maintainability parameters for several of the components based on research, which potentially reduces the accuracy of the results. Another limitation was that availability of the system was limited to the four components that were examined. The results did not indicate availability of the entire 3D printer system, which could be significantly different from the analysis performed within this capstone.

C. COST ANALYSIS

The cost analysis focused on the comparison of the printer sustainment costs using TBM versus CBM. The sustainment costs were derived from the maintenance tasks described in the data elements section, which were re-filling the radiator tank, monitoring DI water salinity, replacing the air filters, and laser calibration.

Re-filling the radiator tank is considered a weekly check with the estimated time to complete the task being 30 minutes. There is a monitor on the back of the printer that shows the DI water level of the tank that must be manually checked. By using the DT, it would send an alert when the tank needs to be filled, eliminating the need to perform the weekly check. When it comes to monitoring DI water conductivity, it is a weekly check as well. Checking the tank level and DI conductivity is a part of the same monitoring task; however, if the conductivity is not within specifications, the tank needs to be flushed and completely replaced. This entire process takes 60 minutes and is scheduled to be performed at least once every 180 days, according to the manufacturer (General Electric Additive 2019).

Replacing the air filters is done after every 30 days, using TBM. Using CBM, the estimate extends to around 45 days. TBM can be overly cautious and replaces parts earlier than required. The air filters were used 50% longer when using the DT to monitor them. In a given year, the air filters would normally need to be changed 12 times, but that number decreased to nine times when using a DT. The estimate to replace the filters is 26 hours; therefore, 78 labor hours would be saved as well as $4500 for the cost of the filters themselves.

Laser calibration is different from the rest of the maintenance tasks in that there is no preventative task associated with them. On average, the sensor driven galvanometer scanners are replaced every 3000 days; however, there is no clear way of knowing when to replace them other than examining print accuracy. The DT sensor for laser calibration has the most cost benefit because it would decrease LDT from 30 days to 4 days.

The costs of the DT and its sensors were not the primary focus of the cost analysis, however, the primary cost for the DT would be the maintenance of the hybrid cloud. Using the AWS Snowball, that was mentioned in Chapter II literature review hybrid cloud section, as an example for cost, a three-year contract would be $38,325. This contract includes data transfers and other service fees, as well as an extra charge of $0.03 per GB for outgoing data from Amazon. The maintenance of the DT sensors would involve operational checks and replacement of faulty sensors.

The primary cost benefit from the CBM process would be increased Ao. For the TBM approach, the Ao is 90.56% but increases to 96.15% with the use of a DT. With this increased Ao, the printer would have more time to print parts instead of waiting for repair parts or doing unnecessary maintenance.

D. CHAPTER SUMMARY

The analysis of alternatives narrowed down the components to the four most salient that are related to maintenance. The four modeled components – DI water level, DI water conductivity, air filters, and laser drive motor system – show that switching to a CBM approach for maintenance vice a TBM approach increases the overall system Ao. The modeling started in Excel to provide a baseline of expected results. The components were then modeled in ExtendSim where the results were verified against the Excel model to ensure the model performed as intended. Various distributions, arrival times, and failure rates were introduced into the ExtendSim model to better reflect reality. The comparison between CBM and TBM demonstrated that the use of CBM will save time and money.

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V. RECOMMENDATIONS AND CONCLUSIONS

This chapter offers recommendations for areas of future work and investigates additional topics for consideration regarding the development of the DT. The DT model developed for this report focused on sensors best suited to provide a comparison between the Ao in a TBM or a CBM environment. Future work explores the benefit of performing a design of experiments, as well as monitoring additional 3D printer components and ship environmental conditions. The ability of the additional sensors to aid in the prediction of print quality and suitability of the printed part needs to be investigated. Additional areas of consideration include machine learning, mission planning and performance, hybrid cloud expansion, and cybersecurity. DTs are a powerful tool for the DOD to exploit CBM, save money, and increase the lethality of the warfighter.

A. AREAS FOR FUTURE WORK AND ADDITIONAL CONSIDERATIONS

The scope of this capstone focused on how to improve Ao using CBM+. Therefore, various sensors and topics were not explored. The DMLM process would benefit from additional sensor and environmental data feeding into the DT. These additional sensors, when combined with machine learning, would help to better predict required maintenance, individual print quality, and aid mission planning and performance. The DT benefits from a historical section of data collection, leveraging historical performance, real-time assessments, and predictive maintenance. Team Gemini provided basic modeling for CBM+ suitability for the 3D printer attached to a DT. Further analysis warrants connecting data collection plans that involve more internal and external sensors. Additional topics explored are hybrid cloud integration into the fleet and securing data transfer.

1. Design of Experiments

The team's methodology involved the use of primitive suitability measures to model Ao metrics for the 3D printer. These suitability measures involved collecting data from four sensors embedded within the physical host (DI water conductivity, DI water level, air filters, and laser drive motor system). Additionally, the team used basic methods to model conditions that prompted maintenance, which were generic failures of the components. The modeled generic failures did not focus on specific conditions that the components would exhibit when they were close to failure. Project constraints limited the team's ability to explore the full effect of internal and external factors on the 3D printer's Ao. These constraints also limited the team's ability to explore expanding the conditions the model used to prompt the need for maintenance. Creating a model that includes conditions rather than general failures would allow for deeper insights into how much the DT can improve Ao.

An aspect outside of suitability that could be analyzed for future work is the quality of the printed parts. Collection of environmental data (vibration, temperature, humidity) and 3D printer parameters could be analyzed to determine the potential effect each variable has on the quality of a print. Previous MOE discussions explored decreasing logistical delay time and increasing the probability of the printer part's success. The DT requires expansion to include external ship-sensor data to assist in determining the success rate for a printed part. This expanded DT can only succeed using machine learning (ML).

The baseline modeling approach encompassed subject matter expert (SME) elicitation. Another aspect to consider for future work involves a full design of experiments (DOE) to provide comprehensive consideration for design and analysis. This DOE would incorporate multi-level and factorial considerations while leveraging historical response data. This important step provides statistical confidence for any model using inputs (factors) to produce an output (responses). The DOE methodology provides data analysis able to provide insight for identifying main factors and interrelationships between those factors. Further development for 3D printers would compare the team's four chosen components against a full DOE analysis able to provide the proper power and confidence in these factors while introducing a high "probability of declaring a factor matters when it truly does" (JK Analytics, LLC 2021). In the end, the responses filtered through the DT would provide looped feedback into refinement of the DOE cycle.

To fully understand how environmental factors and the 3D printer affect performance metrics, future work should include an analysis of variance (ANOVA). The combined efforts of data analysis and historical data fed into standard DOE methodologies combine the response variables and key factors able to inform this ANOVA for 3D printers onboard SVs. The ANOVA needs to include all the factors that could potentially affect mean Ao of the 3D printer, such as MTTF, MTTR, time in between print, etc. An ANOVA will determine if there is any statistically significant correlation among different variables that could affect Ao for a 3D printer. This expanded analysis provides true insights into the types of conditions required for a 3D printer deployed onboard an SV and should be explored.

2. Additional DT Sensors

The ship's sensor data was not added for monitoring by the DT because the project focused on components that required maintenance. However, the DT would benefit from input from those sensors (i.e., sea state, vibration, and ship compartment temperature and humidity). The DT could use the ship's environmental data, along with embedded sensor data, to determine how the ship's environment impacts the success of the printed components and the 3D printer's health. The DT could also use the environmental data to help determine if anomalies recorded in the printed component were due to the components degrading health or an environmental factor.

Another component not added for monitoring by the DT was the power output of the laser. Providing the DT power output measurements for the laser would allow the DT to ensure the metal powder is being fully melted. An alternative to directly measuring laser output power would be to monitor the melted powder to identify correlations to the expected performance of the laser. Either method would help determine if the next layer is ready to be "printed" since having an existing molten pool of metal when the printer is adding another layer of metal powder to be melted is not conducive to the printing process.

Positional accuracy is another important factor the DT should monitor. An accurate position for the laser is critical to the print's success. No current method ensures the laser is in the correct position while printing. Since the printer may be subjected to vibrations and shock while the ship is at sea, having a way to check the positional accuracy of the laser could prove invaluable. Adding a sensor to serve as a check for monitoring the valve positions could be useful. If the valves are closed when they should be open, or vice versa, it could lead to a printed part failure and require unscheduled maintenance to clean the printer, which defeats the purpose of being able to predict required maintenance.

3. Machine Learning Predictions

One of Team Gemini's areas of future work includes the integration of ML into predicting maintenance and reliability of the system that affects the overall success of the print. ML refers to any algorithm applied to a section of data to discover patterns that can be exploited to make predictions or decisions (Madni, Madni, and Lucero 2019). Therefore, as the systems that the DT interfaces with become more complex, the need to expand the DT to use neural network-based ML algorithms to make predictions will be essential. As system complexity increases, so does the number of variables for which the DT will need to make predictions. The increasing number of variables cause the predictions to divert from a simple linear relationship between inputs and outputs, therefore, making the DT's need for machine learning essential to deal with the multiple data streams and relationships (Madni, Madni, and Lucero 2019).

Machine learning algorithms can be applied to the DT system to better understand probability of success for a printed part and factors that would affect a part's failure rate. This process will develop a feedback loop that involves real-time collection of 3D printer data, user input of failure data for a printed part, and analysis of historical data to determine factors internal and external to the 3D printer that affect the quality of a printed part. The ML algorithm will be leveraging the DT system's collection of real-time data, therefore additional features that would have to be included into the DT system would be the ability to receive user input that ties failure rate and mode of a part to a specific print job and the ability for the algorithm to cross reference historical data to determine factors that affect the quality of a printed part. Ultimately, as the amount of historical and failure data that is collected increases and is analyzed, the DT system will be able to predict the expected life of a component. The added value of this feature includes better planning for logistical spares as a result of knowing a printed part's estimated useful life. In addition, the system the printed part was made for should have improved availability due to a reduction in logistical delay time. This feature requires a large amount of failure data required to determine how the condition of a 3D printer and environmental factors affect the quality of a print. This can be alleviated by use of a hybrid cloud, which would promote sharing of information across a fleet of 3D printers.

Another area of future work involving the DT and ML would be leveraging cloud computing to implement ML algorithms. There are numerous ML solutions offered by cloud computing for organizations that do not want to build, test, and integrate their own ML algorithms from scratch. Additionally, various platforms that integrate cloud computing with ML do not require advanced skills. Implementing ML in the cloud offers many benefits including lower barriers for entry and workload scalability as well as reduced costs since it would not require large computer hardware for processing power (Cook and Hummel 2019).

4. Mission Planning/Performance

Delving into mission planning and performance was outside the scope of this capstone but is still an important aspect for future work with the DT. Since the DT's primary goal is to improve the host system's overall Ao, the DT will inherently influence mission performance and planning, regardless of the system the DT is connected to. If the DT can better predict when a failure will occur within a system, then the personnel planning missions that involve that system can identify both how many assets are available and when they will be down for maintenance. By adding mission profile information into the DT, which states what the system requirements are for completion, then the DT could make predictions based on the health of the system for the probability of success of the mission. There may be scenarios where completing the mission will be more important than bringing the system down for maintenance. Therefore, by adding machine learning algorithms into the DT, it will allow the DT to not only make maintenance predictions but also report risk associated with deferring the maintenance, as well as how it would affect overall mission success.

5. Hybrid Cloud Expansion

Future work for Team Gemini's DT system includes the possibility of integrating a fleet of DTs within a hybrid cloud to provide increased storage and processing capabilities. One configuration for this fleet of DTs would be having multiple mobile data devices connected to the hybrid cloud, which would provide more data for the DT to develop insights and predictions. Another type of configuration would consist of connecting the fleet of DTs in parallel clusters, or in a parent-child connection, providing improved scalability and modularity. This proposed configuration would consist of individual DT datasets, each connected to specific systems, subsystems, and equipment, forming a network of DTs. The benefit of this configuration is that single DT data units with specific sensors attached to individual subsystems would provide dedicated processing power and storage. Each data unit may be configured with specific artificial intelligence and ML algorithms directly related to the applicable sensor data and subsystems they are connected to. The outputs of individual DT datasets may connect to a principal unit, or to the hybrid cloud, where it correlates and processes all the data acquired from the subsystems using unique algorithms to provide key insights. All the processed data can then be analyzed and used for PHM and CBM+ predictions. Additionally, the processed data can be used to refine the ML algorithms, resulting in improved maintenance scheduling, decision making, and system availability.

Another important factor to consider as an area of future work is expanding on how users of the DT can benefit from the advantages that hybrid clouds offer. The advantages of on-premises, private cloud, and public cloud services provide the flexibility of storing sensitive sensor data on-premises. This means that any sensitive data from the system sensors, algorithms, and CBM and PHM insights can be securely stored on premises (down to the physical layer) where the ship has full control while storing other large amounts of less sensitive data via private or public cloud services. The users can choose where to place workloads and data, based on risk, sensitivity, and other security requirements. Cloud services would facilitate data migration via encrypted application programming interfaces (APIs) and technologies that isolate applications (Red Hat 2019). These types of services would allow the DT system's users to run critical workloads on premises and less critical workloads on public clouds. Many platforms and technologies integrate with existing clouds. It is important to consider interoperability and security at the beginning of the architecture design phase.

Hybrid clouds can also help to address the many security considerations for protecting DT system information, such as limiting data exposure through encryption. Sectors like the government and military require additional security compliance and governance considerations, discussed in the following section. These considerations include knowing how to properly secure distributed workload environments, implement policies, and safeguard critical information (Red Hat 2019). Another important factor to consider is the use of trusted vendors for the hybrid cloud that provide quality software management, patches, and updates to their products. This consideration will minimize risks of adopting multiple vendor technologies for hybrid clouds that may not comply with industry standards.

6. Cybersecurity

A memorandum from the Director, Operational Test and Evaluation (DOT&E) (2018) outlined specific procedures to apply cybersecurity policies for all operational testing throughout the DOD. The letter highlights "any electronic data exchange (however brief and regardless of format, means of transmission, or physical 'air-gap') provides an opportunity for a cyber-threat to deny, degrade, disrupt, destroy, deceive, or manipulate information critical to military operations" (Behler 2018, 2). Cyber assessments fall under a scope defined by early decomposition through a system's life cycle. Further development of a DT requires understanding the full mission context and the critical components paramount to their performance. Additionally, each DT pairs with a physical host containing unique system attributes and specialized components. The problem with this agnostic array of system configurations potentially creates severe cybersecurity attack vectors.

Team Gemini's DT paired relatively risk-free to a 3D printer. There are substantially more systems attached to an SV posing greater risk with valuable data and performance metrics. However, further DT development could latch onto physical hosts involved with higher classification levels. Many systems of interest delve into sensitive and transferable data via hardware, software, and radio frequency (RF). Because the DT integrates so closely with multiple components of the SOS, the need for early cybersecurity requirements proves even more vital.

The added benefit for the DT mission is to provide cybersecurity health for the physical host. Much like the suitability assessments discussed in-depth throughout this capstone, the ability to detect, report, and prevent cyber-attacks to a physical host should be an additional objective for the DT. Today's modern trajectory shows system suitability and cyber survivability acting in parallel importance to the effectiveness of any system. The greater complexity and capability offered by the weapon system, the higher the vulnerability. As a real-time prognostic monitor, the DT serves as the primary sentinel for system integrity against cyber vulnerabilities.

B. CONCLUSION

The current maintenance philosophy the USN employs requires continual or responsive maintenance strategies to sustain Ao of complex defense systems. Particularly, these maintenance strategies are performed using TBM which affects Ao because of system downtime. Additionally, DOD systems need to have the ability to provide accurate, real-time, system health performance feedback during their entire life cycle. However, once a system reaches the fleet, opportunities for operational performance assessment are limited. This means leadership lacks the necessary real-time data or post-mission analysis to truly measure mission effectiveness.

The primary goal of this capstone project was to develop an architecture and rudimentary model for a DT to explore a transition in maintenance strategy from TBM to CBM+ while leveraging existing PHM technology. To explore the concept of utilizing a DT onboard a naval surface vessel, which answered the objectives of the Navy's Digital Transformation Strategy, Team Gemini examined DT capabilities currently available (or under development) and systems that may benefit from the use of a DT. The project scope, defined in Chapter I, was constrained with a classification level not to exceed CUI, which excluded emphasis on weapon, combat, and radar systems. In addition, actual performance data for naval systems below a classification level of CUI were not available, so the CONOPS for the DT was developed based on research of openly available information. As a result of the constraints and to address a topic of great interest to the Navy, AM, the team explored the application of a DT system for a 3D printer onboard an SV. Additionally, creating a DT architecture for a 3D printer provided invaluable insights regarding sensitive, high-precision systems in dynamic environments unique to naval operations.

In Chapter III Team Gemini developed the DT architecture, showing the required functions and interfaces needed to maximize the benefit of utilizing a DT through a functional description and analysis. The functional description of the system was illustrated through the development of a context diagram, use cases, and scenarios. The system context diagram illustrated users and external systems that interact with the DT. The use cases characterized the functions necessary for the DT to achieve stakeholders' goals. The primary use case the team focused on for the development of the DT architecture was the Perform DT Functions. This use case covers the DT receiving sensor data from the environment and the 3D printer, processing that data, sending raw and processed data for storage, and providing predictions as well as alerts. In addition, several measures of effectiveness were defined that benefit the DON. These included improving maintainability of the 3D printer, improving logistical supportability of a printed part, and improving probability of success for a printed part.

The functional analysis consisted of a top-down process of translating system level requirements to define the DT architecture which ensured all required system functions were accounted for. First, this was detailed in an activity diagram that described control flow and data processes. Next, various system states, transitions, and events of the DT system were defined using a state machine diagram. The determination of system actions and states helped to identify logical subsystems communications through the identification of generic components that are essential for the system to perform the necessary functions. A BDD was created to establish inputs and outputs for the DT system, which included sensor data, control signals, and energy sources.

In Chapter IV, the team determined which components of the 3D printer would benefit from the application of a DT for performing maintenance operations. Those components/factors were DI water level, DI water conductivity, air filters, and laser motor drive system. The initial model the team created in Excel, which was used as a proof of the concept for the follow-on model, showed that applying a DT system to a 3D printer increased the Ao from 90.56% for TBM, to 96.15% for CBM. This increase in availability was due to a decrease in the amount of preventive maintenance performed over a two-year period. The follow-on ExtendSim model was created to allow examination of Ao while allowing parameters, such as time between prints and mean time to repair, to be modified. Comparing the results between TBM and CBM indicated that for TBM, Ao was significantly affected for shorter times between each print due to components of the 3D printer failing more frequently while still having to perform scheduled maintenance. As time between each print increased for TBM, the effect of component failures appeared to taper off since scheduled maintenance was performed consistently while failure of each component was reduced. In contrast, the Ao for CBM was approximately 5% higher for a shorter time between each print due to maintenance only being performed when a component failed. In addition, as the time between each print increased, the Ao using CBM increased at a steady rate due to not having to perform preventive maintenance.

The effect of implementing a DT system on a 3D printer demonstrated that transitioning to a CBM approach improved the current maintenance methodology utilized by the Navy through a reduction in system downtime. The transition from using TBM to CBM, using a DT system, essentially changed the maintenance philosophy from proactive to reactive through enhanced knowledge of system conditions and performance. The cost analysis performed in Chapter IV complemented the model and determined the cost savings that could be achieved by implementing a DT system. Using the maintenance manual as a guide, it was determined that over a two-year span, the cost savings associated with replacing just the air filters was an approximate reduction of 78 hours of labor and $4500 in maintenance costs. The modeling and simulation efforts, in conjunction with cost analysis, determined that implementing a DT system on a 3D printer demonstrated an improvement in system availability while reducing costs associated with maintenance.

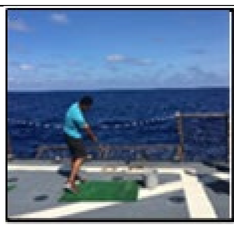
APPENDIX A. TEAM GEMINI ORGANIZATION

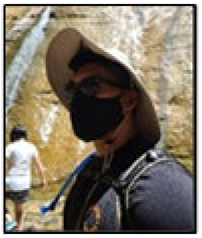
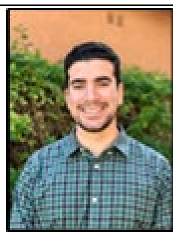
Team Gemini is composed of eight MSSE students from NPS. This team is composed of a group of diverse individuals, each contributing their unique experiences and expertise to the capstone project. First a brief background for each team member is provided, followed by a discussion of the organizational structure. Finally, this appendix ends by describing the roles and responsibilities.

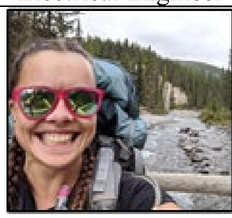
A. TEAM MEMBERS

Team Gemini has both civilian and military team members. Most of the team members work at NSWC PHD. Table 7 identifies each team member and includes information about what organization they work for and current position.

Table 7. Team Member Identification and Organization

Team Member	Background
 Ray Ashworth NSWC PHD, Code L71 Naval Fire Control SE and T&E Mechanical Engineering	Ray Ashworth graduated from University of Central Florida with a bachelor's degree in mechanical engineering with an emphasis in mechanical system. Since June 2015, Ray has been part of the naval fire control systems engineering branch, starting as an intern through the Naval Acquisition Development Program. Ray currently serves as the Gun Weapon System Combat System Ship Qualification Trail Lead onboard United States Navy, United States Coast Guard and Foreign Military vessels. Other responsibilities include technical documentation development, data analysis for test events and fleet support through tech assists.
 LCDR Zachary Capacete COMOPTEVFOR OTC, Code 511 F/A-18 WSO	CDR Zachary "Cap'n" Capacete is an F/A-18 E/F Weapon Systems Officer (WSO) and Operational Test Coordinator (OTC) assigned to Commander Operational Test and Evaluation Force. Zach is a former TOPGUN course graduate with over 2,600 hours in the F/A-18 and over 600 carrier landings. He currently oversees operational test for the F/A-18 Software Configuration Set (SCS), Infrared Search and Track (IRST), AIM-9X Block II Sidewinder, and AIM-120 AMRAAM missile. Zach graduated with a B.S. in Systems Engineering from the U.S. Naval Academy.

 Matthew Casim NSWC PHD, Code A61 Electrical Engineer	Matt Casim graduated from Cal Poly Pomona with a bachelor’s degree in electrical engineering. Shortly after graduation, he started working at NSWC PHD in 2016 as an engineer for SPY radar. Responsibilities included performing grooms, troubleshooting the system, and supporting ORDALTs. He moved to the SPY-6 group after a couple of years to provide government oversight in test events, perform RCM analysis and review documentation.
 Garrett Dong NSWC PHD, Code A56 Launcher Support Equipment Mechanical Engineer	Garrett Dong earned his bachelor’s degree at Cal Poly San Luis Obispo in mechanical engineering and is currently a master’s student at NPS in Systems Engineering with a focus in systems and project management. He currently works at NSWC PHD as a mechanical engineer in the MK41 Launcher Support Equipment Team. Garrett enjoys traveling, hiking, and challenges which is why he pushes himself to his limits such as summiting Kilimanjaro (highest peak in Africa at 19,341’) and Mt Whitney (highest peak in CA) which has spawned his own travel blog; www.adventuredinosaur.com. He hopes to apply the lessons he has learned through the master’s program to his job and take on more challenges to better support to the warfighter.
 Joshua Gutterman NSWC PHD, Code A48 Camera & Video Systems Computer Engineer	Joshua Gutterman graduated from the University of California, Santa Cruz with a bachelor’s degree in computer engineering where he designed and built autonomous robotics. He is currently pursuing a master’s degree in systems engineering at NPS. Since 2018 he has worked at NSWC PHD as a computer engineering for the camera and video systems branch. As ISEA responsibilities include onsite and remote tech assists, future equipment integration and technical documentation development.
 Carlos Rios Mora NSWC PHD, Code A63 SPY Signal Processor and Antenna Electronics Technician	Carlos Rios Mora is a United States Navy Veteran and Senior Electronics Technician working at the Naval Surface Warfare Center Port Hueneme Division (NSWC PHD). He is currently part of the AEGIS SPY-1 Signal Processor and Antenna Engineering Branch where he provides combat systems and radar technical support and training to military and civilians.

 Jeffrey Smith NSWC PHD, Code A51 ESSM All Up Round Electrical Engineer	Jeffrey Smith holds a BS in electrical engineering from Cal Poly Pomona and a MS in telecommunications from Colorado University at Bolder. He is currently pursuing a MS degree in systems engineering from NPS. Jeff works at NSWC PHD as an engineering team lead for the Evolved Seasparrow Missile All up Round branch. He coordinates fleet operational and maintenance processing documentation and is the principle AUR engineer for ESSM JUWL integration and testing for the DDG 1000 program.
 July Thomson NSWC PHD, Code A63 SPY Signal Processor and Antenna Electronics Engineer	July Thomson holds a BS in electrical and computer engineering from Oregon State University. She is currently pursuing a master's degree at NPS in systems engineering. July works at NSWC PHD as an electronics engineer for the SPY-1 Radar Signal Processing and Antenna branch. Before working at NSWC PHD, she worked as an F-15 and UH-1 systems engineer for the 896th Test Support Squadron at Eglin Air Force Base. Before that, she worked as an electrical engineer for non-nuclear electrical systems for 688 Class Submarines at Pearl Harbor Naval Shipyard.

B. ORGANIZATIONAL STRUCTURE

The members of Team Gemini identified roles needed to accomplish the capstone project, seen in Figure 21. In addition to the students, there are two advisors assigned to guide the team, as well as stakeholders and a primary sponsor who provided invaluable insight into the capstone project topic. The organizational structure is shown in Figure 21. To ensure successful completion of the capstone project, each role has been assigned one student as the lead (shown in orange) and another student as the deputy (shown in light orange). The lead assumed primary responsibility for the role and the deputy was assigned to assume the responsibilities as lead in the event was necessary.

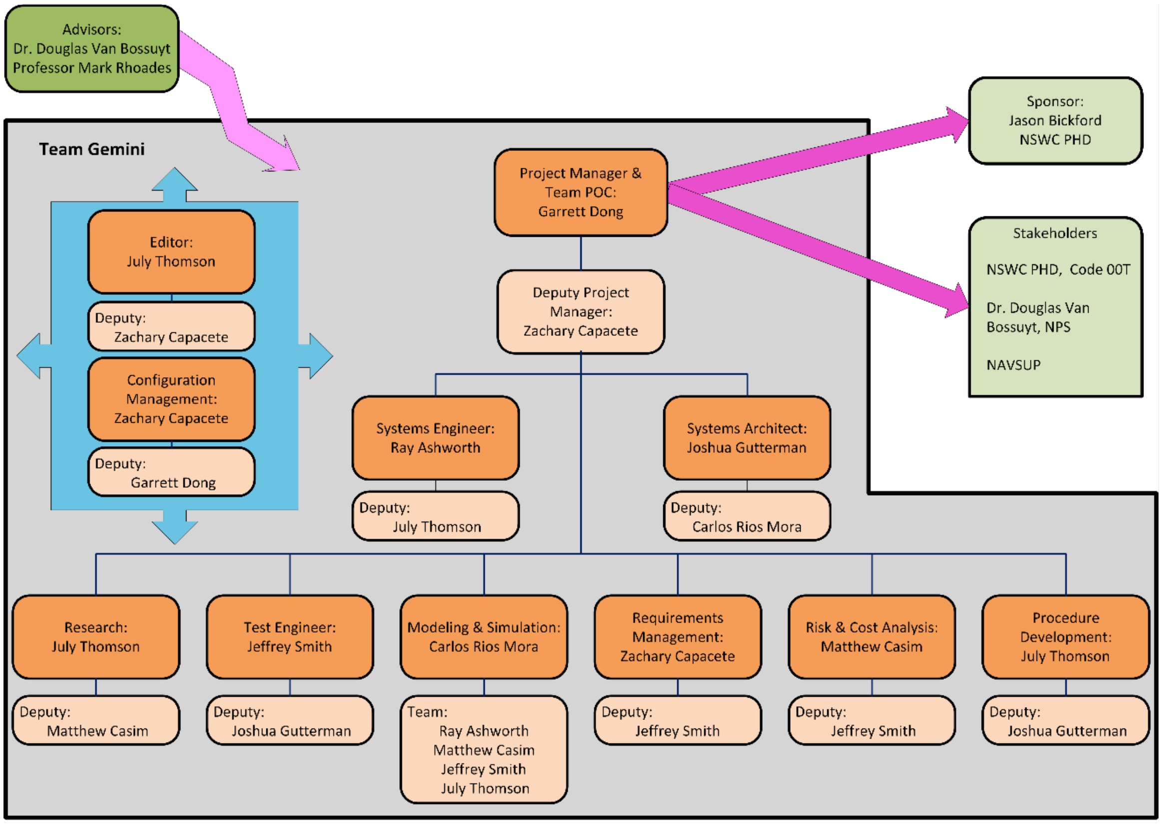


Figure 21. Team Member Roles

C. ROLES AND RESPONSIBILITIES

Table 8 expands on the roles assigned in Figure 21 by detailing the responsibilities of everyone. The roles and responsibilities table includes the capstone advisors and project sponsor.

Table 8. Team Member Roles Description

Role	Members	Description
Advisors	Dr. Van Bossuyt Prof. Rhoades	Project advisors were responsible for advising the team. They were responsible for guiding the team to ensure the project stayed on track, provided recommendations, performed internal reviews of documentation, and answered any questions.

Sponsor	Jason Bickford	The sponsor was responsible for guiding the team by reducing the scope of the project. Additionally, the sponsor was there to provide expertise on the subject and address questions from the team regarding the project.
Project Manager (Team POC)	Garrett Dong	The project manager (PM) was responsible for planning, developing, and leading the team throughout the course of the project. They were responsible for keeping the team on track to meet deliverable dates and being the primary liaison between sponsors, advisors, and other stakeholders. Additionally, they maintained meeting notes (which included key takeaways), the schedule, and kept their "fingers on the pulse" of the group by being informed of any changes or life events affecting team members and planning around that.
Deputy Project Manager	Zachary Capacete	The deputy PM assumed project manager responsibilities when necessary. They acted as an executive officer for the program and assisted the project manager as needed.
Systems Engineer	Ray Ashworth	The systems engineer (SE) was responsible for overseeing the technical and engineering aspects of the project. In addition, the SE was responsible for researching potentially applicable solutions/products, and providing technical assistance and backup for System Architect, Test Engineer, and Risk/Cost Analyst.
Systems Architect	Joshua Gutterman	The systems architect was responsible for overseeing the development of required project architecture, application of heuristics, and the definition of operational needs.

Editor	July Thomson	The editor **w**as responsible for going through the various team developed documents to maintain continuity of voice throughout and check for grammatical errors.
Configuration Management	Zachary Capacete	The configuration management lead was responsible for ensuring any version changes required for documentation was performed. Additionally, they were responsible for maintaining the backups of all the documentation.
Research	July Thomson	The lead researcher was responsible for maintaining and organizing all research documents. As well as identifying gaps in the research and finding documentation to fill those gaps.
Test Engineer	Jeffrey Smith	The test engineer was responsible for oversight of the development of testing necessary for validation and verification of the model.
Modeling & Simulation	Carlos Rios Mora	The modeling and simulation (M&S) lead was responsible for oversight on all M&S projects, in addition to performing M&S work. They were responsible for delegating tasking to the deputy M&S team, ensuring the tasking matched the individual's capabilities.
Modeling & Simulation Team	Ray Ashworth Matthew Casim Jeffrey Smith July Thomson	This team was responsible for performing and coordinating work on M&S projects, as well as reporting status to M&S lead. As necessary, one of the deputies assumed the role of lead.

Requirements Management	Zachary Capacete	The member oversees the requirements change board (RCB) process and maintains the requirements database. This record contains a history of all previously changed core requirements in addition to new proposals.
Risk & Cost Analysis	Matthew Casim	The risk and cost analysis lead were responsible for overseeing the development of cost estimates and risk management plan. The risk management plan included risk assessments as well as risk mitigation plans.
Procedure Development	July Thomson	The procedure development lead was responsible for overseeing the development of any procedures necessary for the project.

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APPENDIX B. DETAILED REQUIREMENTS

Table 9. Detailed Functional Requirements

SN-6	Functional Requirements	The services the system shall or shall not provide. These define how the system reacts and behaves to particular inputs.
FR-6.1	**Receive 3D Printer Data**	**The DT shall receive raw data from embedded sensors.**
FR-6.1.1	Receive printer time meter readings	The DT shall receive the printer's operational use in mm:ss.
FR-6.1.2	Receive laser unit power	The DT shall receive the laser unit's power output in watts to compare with the expected value.
FR-6.1.3	Receive galvanometer data	The DT shall receive the galvanometer scanner motor data for laser steering.
FR-6.1.4	Receive collimator beam size data	The DT shall receive the collimator data for laser beam spatial resolution in micrometers.
FR-6.1.5	Receive laser circularity data	The DT shall receive the circularity of the laser.
FR-6.1.6	Receive printer compartment gas pressure	The DT shall receive the type of inert gas and gas pressure in mmHg.
FR-6.1.7	Receive powder material type	The DT shall receive the type of metal powder material for printing.
FR-6.1.8	Receive printer component faults	The DT shall receive the faults from any component on the printer.
FR-6.1.9	Receive inert gas purity	The DT shall receive the inert gas (nitrogen) purity for the printing chamber for the duration of the print.
FR-6.1.10	Receive printer bed air flow data	The DT shall receive the printer bed air flow in ___units for the duration of the print.
FR-6.1.11	Receive water conductivity data	The DT shall receive conductivity error.
FR-6.2	**Manage Ship Space Environment Sensors**	**The DT shall maintain sensors able to record environmental data external to the physical host.**
FR-6.2.1	Run self-test on instrument sensors	The DT shall command the instruments to run a self-test.
FR-6.2.2	Manage ship space thermometer	The DT shall manage the thermometer for temperature readings.
FR-6.2.3	Manage ship space hygrometer	The DT shall manage the hygrometer for humidity readings.
FR-6.2.4	Manage ship space accelerometer	The DT shall manage the accelerometer for vibration readings.
FR-6.2.5	Manage ship space gyrocompass	The DT shall manage the gyrocompass for attitude readings.
FR-6.3	**Collect Ship Sensor Data**	**The DT shall receive data from ship sensors external to the 3D printer physical asset.**
FR-6.3.1	Collect ship space temperature	The DT thermometer shall collect the ship space's average temperature for the duration of the print in degrees C.
FR-6.3.2	Collect ship space humidity	The DT hygrometer shall collect the ship space's average humidity for the duration of the print in grams per cubic meter.
FR-6.3.3	Collect ship space vibration	The DT accelerometer shall collect the ship space's vibration data in frequency (Hz), amplitude (m), and acceleration (meters per second squared).
FR-6.3.4	Collect ship space attitude	The DT gyrocompass shall collect the ship's maximum and average attitude readings in the x, y, and z-axis in degrees for the duration of the print.
FR-6.3.5	Receive ship propulsion settings	The DT shall receive the ship's propulsion command settings for the duration of the print in nautical standard nautical terms (one-third, two-thirds, full, etc.).
FR-6.3.6	Receive ship sea state	The DT shall receive the ship's reported sea state for the duration of the print in wave height (m).

FR-6.4	**Record Data**	**The DT shall record data from embedded and external sensors.**
FR-6.4.1	Record embedded printer data	The DT shall record embedded printer data.
FR-6.4.2	Record external ship space data	The DT shall record external ship space instrument data.
FR-6.4.3	Record historic uploaded part accuracy data	The DT shall record uploaded part accuracy data from the hybrid cloud.
FR-6.4.4	Record historic uploaded part precision data	The DT shall record uploaded part precision data from the hybrid cloud.
FR-6.4.5	Record historic uploaded part tolerance data	The DT shall record uploaded part tolerance data from the hybrid cloud.
FR-6.4.6	Record CAD specifications for parts	The DT shall record CAD specifications and tolerances for printed parts
FR-6.5	**Manage Ship Space Instrument Faults**	**The DT shall manage faults from environmental instrument sensors.**
FR-6.5.1	Record instrument faults	The DT shall record all instrument faults.
FR-6.5.2	Provide instrument maintenance report	The DT shall provide a maintenance status report for the instruments.
FR-6.6	**Process Data**	**The DT shall process data for current and predictive system effectiveness and suitability.**
FR-6.6.1	Provide predictive CBM for physical host	The DT shall provide CBM for the physical host.
FR-6.6.1.1	Predict printer failure rates	The DT shall predict failure rates
FR-6.6.1.1.1	Predict failure rates for the laser component	The DT shall predict failure rates for the laser component
FR-6.6.1.1.2	Predict failure rates for the scanning mirror	The DT shall predict failure rates for the scanning mirror
FR-6.6.1.1.3	Predict failure rates for the recoater arm	The DT shall predict failure rates for the recoater arm
FR-6.6.1.1.4	Predict failure rates for the powder dispenser	The DT shall predict failure rates for the powder dispenser
FR-6.6.1.1.5	Predict failure rates for the powder dispenser piston	The DT shall predict failure rates for the powder dispenser piston
FR-6.6.1.1.6	Predict failure rates for the build piston	The DT shall predict failure rates for the build piston
FR-6.6.1.2	Predict printer operational availability	The DT shall predict printer operational availability
FR-6.6.1.2.1	Predict printer downtime	The DT shall predict printer downtime
FR-6.6.1.2.2	Predict printer uptime	The DT shall predict printer uptime
FR-6.6.1.3	Predict printer CBM for parts	The DT shall predict preventative maintenance data for printer components.
FR-6.6.2	Provide probability of success for printed part	The DT shall calculate a probability of success as a function of component performance and environmental data.
FR-6.6.2.1	Predict based on laser power	The DT shall calculate the probability of success based on laser power.
FR-6.6.2.2	Predict based on scanning mirror	The DT shall calculate the probability of success based on the scanning mirror deviations.
FR-6.6.2.3	Predict based on laser beam	The DT shall calculate the probability of success based on the laser beam accuracy, precision, and tolerance.
FR-6.6.2.4	Predict based on powder bed layer size	The DT shall calculate the probability of success based on the powder bed layer size.
FR-6.6.2.5	Predict based on environmental temperature	The DT shall calculate the probability of success based on environmental temperature.
FR-6.6.2.6	Predict based on environmental humidity	The DT shall calculate the probability of success based on environmental humidity.
FR-6.6.2.7	Predict based on environmental vibration	The DT shall calculate the probability of success based on environmental vibration.
FR-6.6.2.8	Predict based on ship’s positional attitude	The DT shall calculate the probability of success based on the ship’s positional attitude in roll, yaw, and pitch.

FR-6.6.2.9	Predict based on environmental propulsion settings	The DT shall calculate the probability of success based on environmental propulsion settings.
FR-6.7	**Communicate Data**	**The DT shall transmit data through the ship communication system**
FR-6.7.1	Transmit DT instrument sensor maintenance report	The DT shall transmit an instrument sensor maintenance report.
FR-6.7.2	Transmit physical host maintenance report	The DT shall transmit a physical host maintenance report.
FR-6.7.3	Transmit current prognostic health of physical host	The DT shall transmit a current prognostic health of the physical host.
FR-6.7.4	Transmit CBM for physical host	The DT shall transmit a recommended CBM schedule for the physical host.
FR-6.7.5	Transmit probability of success for part production	The DT shall transmit a probability of success for the part being produced.

Table 10. Detailed External Interface Requirements

SN-8	**External Interface Requirements**	**Embedded within a higher-level structure, the system contains external interface requirements. These answer the potential impact of the DT to systems in the same SOS, as well as impacts to external systems.**
EIR-8.1	**Graphical User Interface**	**The software shall contain a user interface web portal providing access through a web browser application available to the shore support community or maintenance laptop.**
EIR-8.2	**Hardware Interface**	**The system shall be able to physically connect to external systems.**
EIR-8.2.1	Data Connection Port for maintenance laptop	The system shall contain a data connection port for manual software updates and data commands via maintenance laptop connection using the GUI.
EIR-8.2.2	Data Connection Port with physical host	The system shall contain a data connection port for prognostic health and maintenance monitoring via maintenance laptop connection using the GUI.
EIR-8.2.3	Data Connection Port for ship space environment and ship instrument sensors	The system shall contain a data connection port for collection of all ship space environment and ship instrument sensor data.
EIR-8.3	**Software Interface**	**The system shall be able to send compatible strings of code and decode messages with the external systems.**
EIR-8.3.1	Software interface with maintenance laptop	The system shall contain a software interface with the maintenance laptop.
EIR-8.3.2	Software interface with 3D printer host	The system shall contain a software interface with the 3D printer host.
EIR-8.3.3	Software interface with hybrid cloud server	The system shall contain a software interface with the hybrid cloud server.
EIR-8.4	**Communications Interface**	**The system shall contain a working interface with the physical host and ship's communications system for transmitting and receiving data.**
EIR-8.5	**Data Storage Redundancy Interface**	**The system shall provide an interface with the hybrid cloud for data storage redundancy (such as RAID configurations)**

Table 11. Detailed Non-functional Requirements

SN-7	Non-Functional Requirements	These involve the constraints on the provided services or functions of the system as a whole. These constraints are defined from timeline, standards, and development processes.
NFR-7.1	**Reliability**	**The reliability requirements pertain to the SUT hardware and software components.**
NFR-7.1.1	Error Rate	The software shall have a probability of failure on demand (POFOD) of _____ (time range)
NFR-7.1.2	Fault Check Execution	The software shall execute fault checks to the system hardware every _____ (time unit).
NFR-7.1.3	Fault Notification	The software shall notify the shore support community of a system fault within ____ (time unit).
NFR-7.1.4	Network Connectivity Check	The system shall execute connectivity to the physical host's communication system every ____ (time unit).
NFR-7.1.5	Collection Instrument Reliability	The embedded sensor hardware shall have a reliability of ______ (percentage).
NFR-7.2	**Performability**	**The performability requirements pertain to the time to accomplish tasking.**
NFR-7.2.1	Time to Process Data	The system shall process data inputs within _____ (time units per size).
NFR-7.2.2	Time to Load Processed Data	The system shall load processed data to the physical host communication system within _____ (time units per size).
NFR-7.3	**Serviceability**	**The serviceability requirements pertain to system reconfigurations and updates.**
NFR-7.3.1	Modular Reconfiguration	The system shall contain modular software reconfiguration capability.
NFR-7.3.2	Dynamic Reconfiguration	When in a fault status, the system software shall have a safe mode to perform reconfiguration.
NFR-7.3.3	Update Request Frequency	The system shall perform an update query ____ (time unit).
NFR-7.3.4	Update Time	The software shall perform an update in _____ (time unit).
NFR-7.4	**Interoperability**	**The interoperability requirements pertain to how the system interacts with the operators or other equipment.**
NFR-7.5	Software Development	The software shall be developed using an object-oriented approach with agile processes.
NFR-7.6	Usability	Operator Use: The software shall be easily usable by operators after completing a training course.
NFR-7.7	Software Environment	Equipment Identifiers: Digital Twins and instrument sensors shall be assigned identifiers for a unique communication address.
NFR-7.8	**Safety**	**The safety requirements pertain to protecting the system and the users from harm.**
NFR-7.8.1	Data Collection System Temperature	The data collection system shall not exceed ____ (temp unit).
NFR-7.8.2	Electric Safety	The software shall adhere to Occupational Safety and Health Administration (OSHA) requirements to prevent risk of electrocution or arcing at electrical databases and workstations.
NFR-7.9	**Security**	**The security requirements pertain to protecting the data and the system.**
NFR-7.9.1	Support Community System Login	The software shall require secure login information from the users.
NFR-7.9.2	Data Corruption	The software shall safeguard against data corruption.
NFR-7.9.3	Data Encryption	The software data shall employ encryption protocol for transmission of commands to and from the shore support community.

APPENDIX C. REFINE REQUIREMENT MATRICES (RRM)

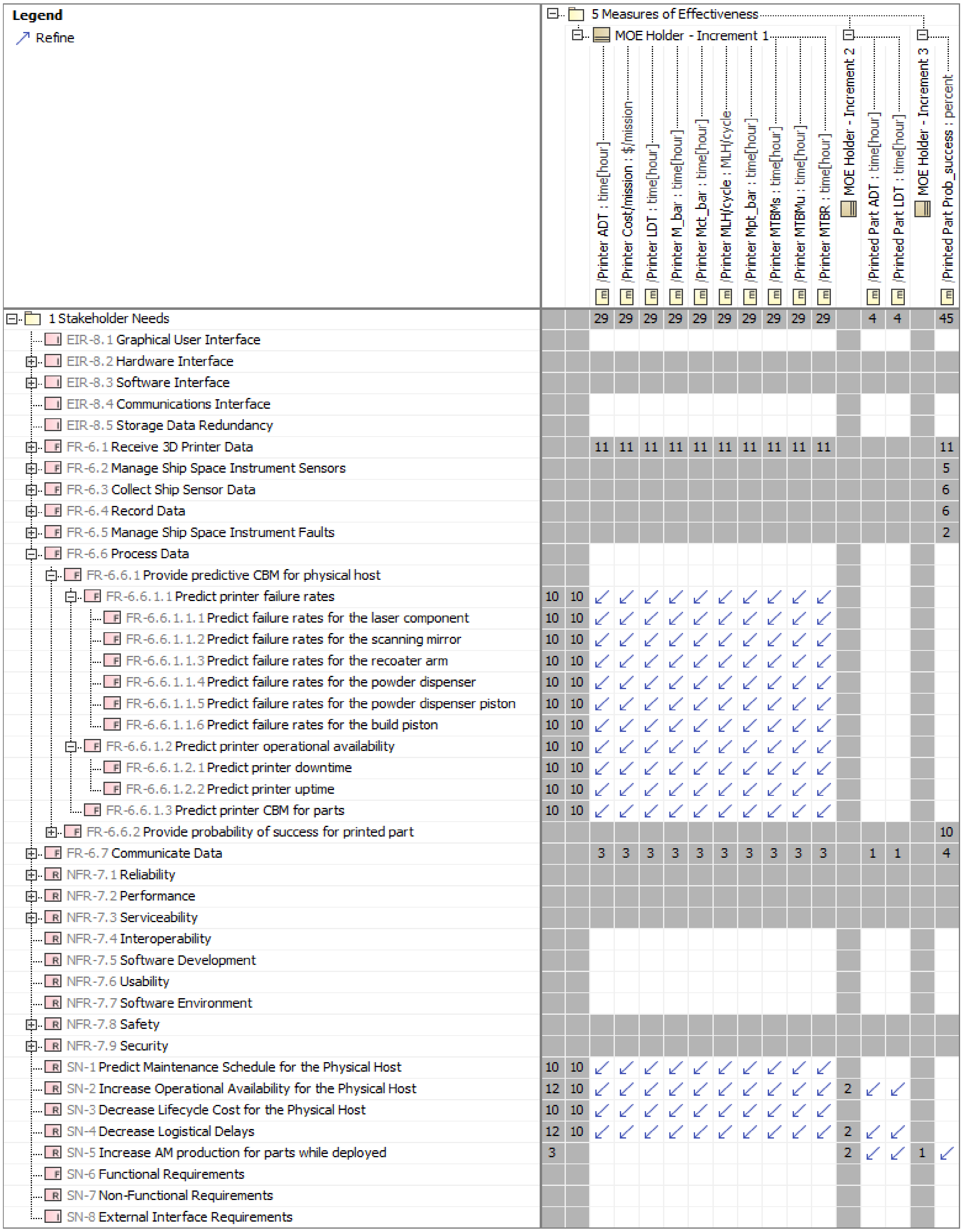


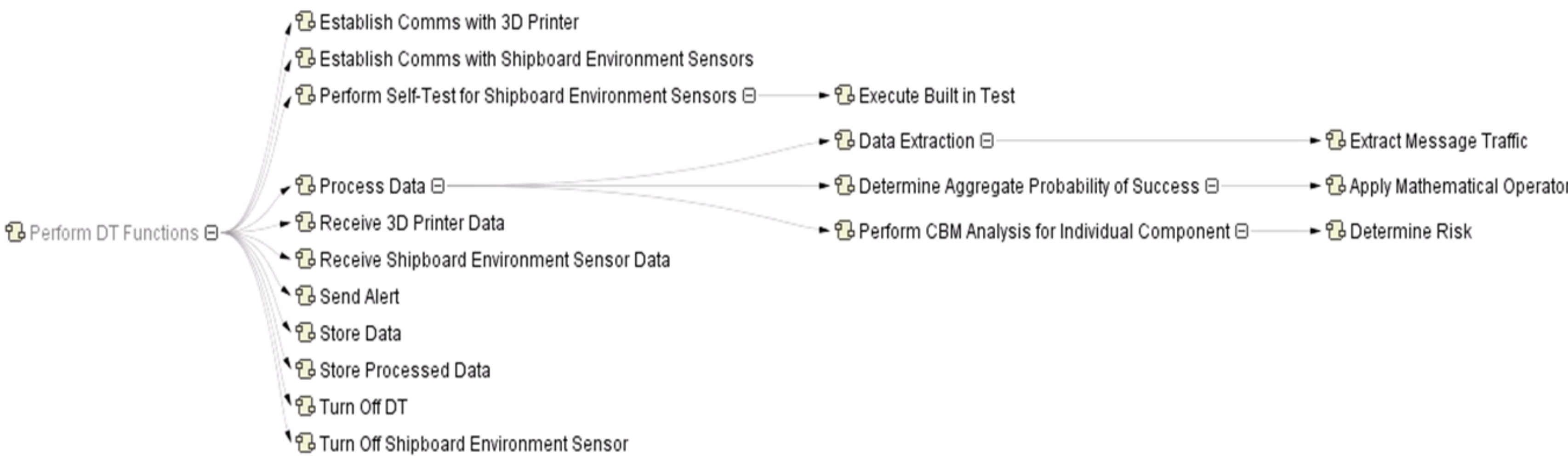
Figure 22. MOE to SN (RRM)

Legend
↗ Refine

Perform DT Functions	5 Measures of Effectiveness	MOE Holder - Increment 1	/Printer ADT : time[hour]	/Printer Cost/mission : $/mission	/Printer LDT : time[hour]	/Printer M_bar : time[hour]	/Printer Mct_bar : time[hour]	/Printer MLH/cycle : MLH/cycle	/Printer Mpt_bar : time[hour]	/Printer MTBMs : time[hour]	/Printer MTBMu : time[hour]	/Printer MTBR : time[hour]	MOE Holder - Increment 2	/Printed Part ADT : time[hour]	/Printed Part LDT : time[hour]	MOE Holder - Increment 3	/Printed Part Prob_success : percent
Perform DT Functions			10	10	10	10	10	10	10	10	10	10		7	7		10
Apply Mathematical Operator(context Digital Twin (DT) [	13	10	↙	↙	↙	↙	↙	↙	↙	↙	↙	↙	2	↙	↙	1	↙
Data Extraction(context Digital Twin (DT) Domain)	13	10	↙	↙	↙	↙	↙	↙	↙	↙	↙	↙	2	↙	↙	1	↙
Determine Aggregate Probability of Success(context Dig	1															1	↙
Determine Risk(context Digital Twin (DT) Domain)	13	10	↙	↙	↙	↙	↙	↙	↙	↙	↙	↙	2	↙	↙	1	↙
Establish Comms with 3D Printer(context Digital Twin (DT																	
Establish Comms with Shipboard Environment Sensors(c																	
Execute Built in Test(context Digital Twin (DT) Domain)																	
Extract Message Traffic(context Digital Twin (DT) Domai																	
Perform CBM Analysis for Individual Component(context	10	10	↙	↙	↙	↙	↙	↙	↙	↙	↙	↙					
Perform Self-Test for Shipboard Environment Sensors(c																	
Process Data(context Digital Twin (DT) Domain)	13	10	↙	↙	↙	↙	↙	↙	↙	↙	↙	↙	2	↙	↙	1	↙
Receive 3D Printer Data(context Digital Twin (DT) Doma	11	10	↙	↙	↙	↙	↙	↙	↙	↙	↙	↙				1	↙
Receive Shipboard Environment Sensor Data(context Di	11	10	↙	↙	↙	↙	↙	↙	↙	↙	↙	↙				1	↙
Send Alert(context Digital Twin (DT) Domain)	13	10	↙	↙	↙	↙	↙	↙	↙	↙	↙	↙	2	↙	↙	1	↙
Store Data(context Digital Twin (DT) Domain)	13	10	↙	↙	↙	↙	↙	↙	↙	↙	↙	↙	2	↙	↙	1	↙
Store Processed Data(context Digital Twin (DT) Domain)	13	10	↙	↙	↙	↙	↙	↙	↙	↙	↙	↙	2	↙	↙	1	↙
Turn Off DT(context Digital Twin (DT) Domain)																	
Turn Off Shipboard Environment Sensor(context Digital																	

Figure 23. MOE to Activities (RRM)

APPENDIX D. FUNCTIONAL DECOMPOSITION FOR PERFORM DT FUNCTIONS



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APPENDIX E. SIMULATION RESULT GRAPHS

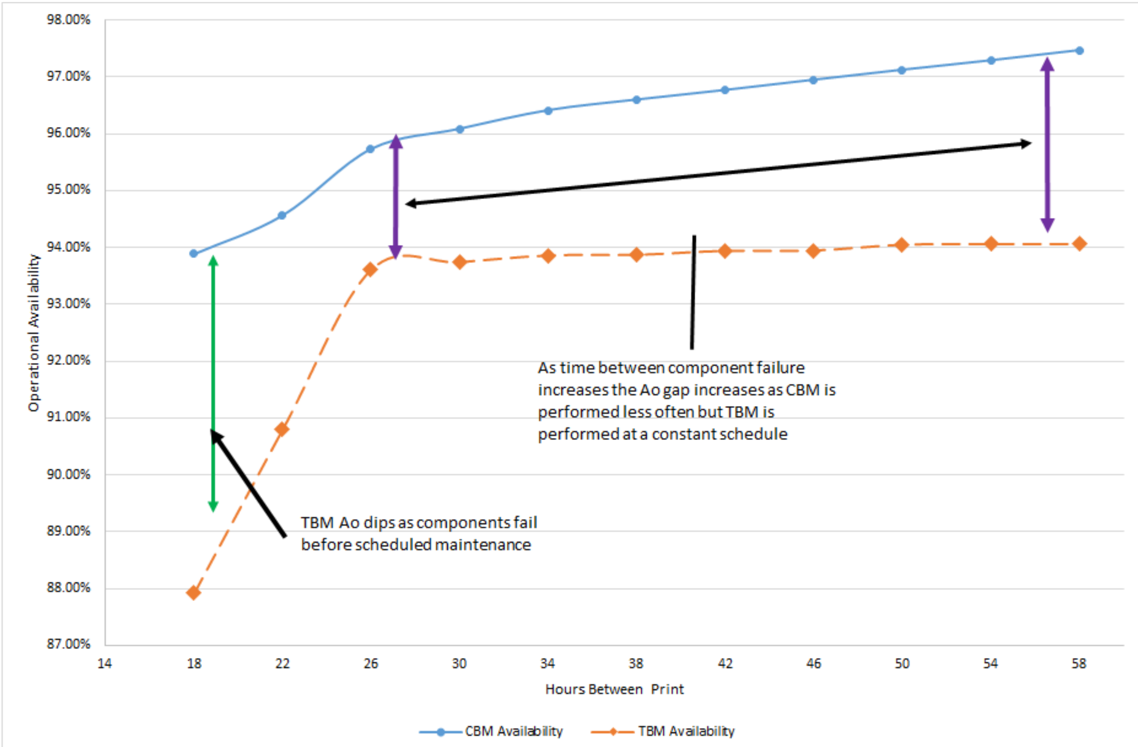

Figure 24. Ao for CBM and TBM with Laser Drive Motor System (+20% MTTF)

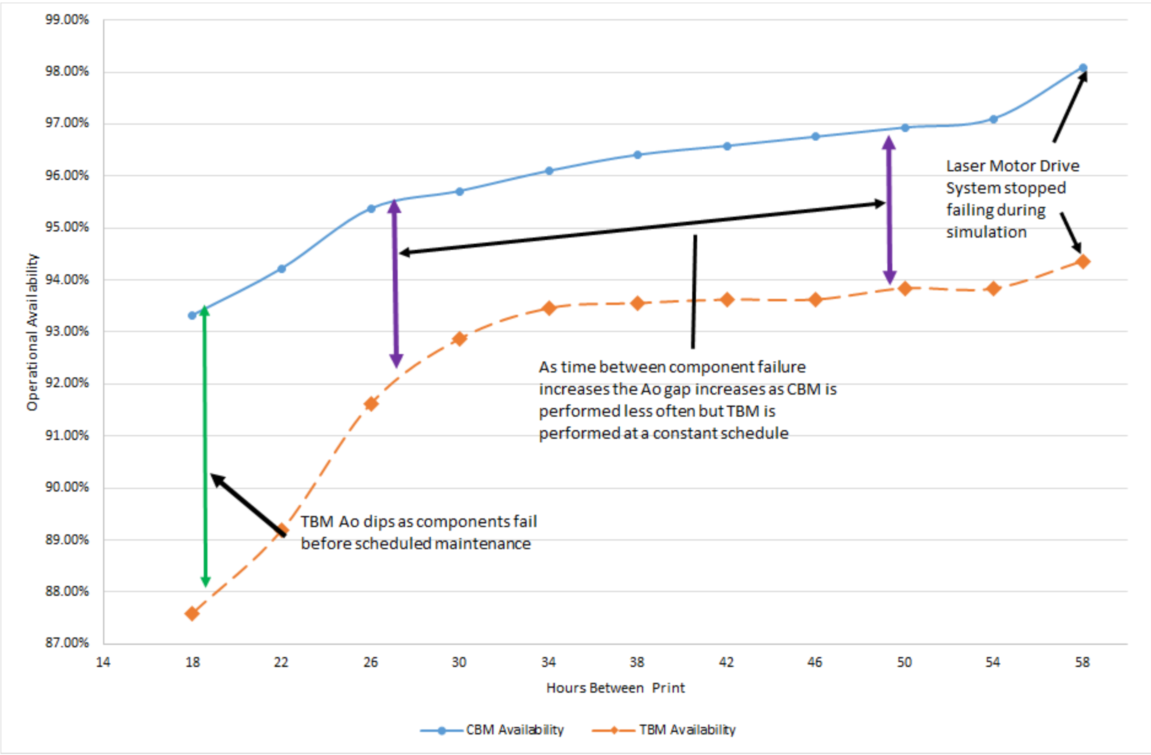

Figure 25. Ao for CBM and TBM with Laser Drive Motor System

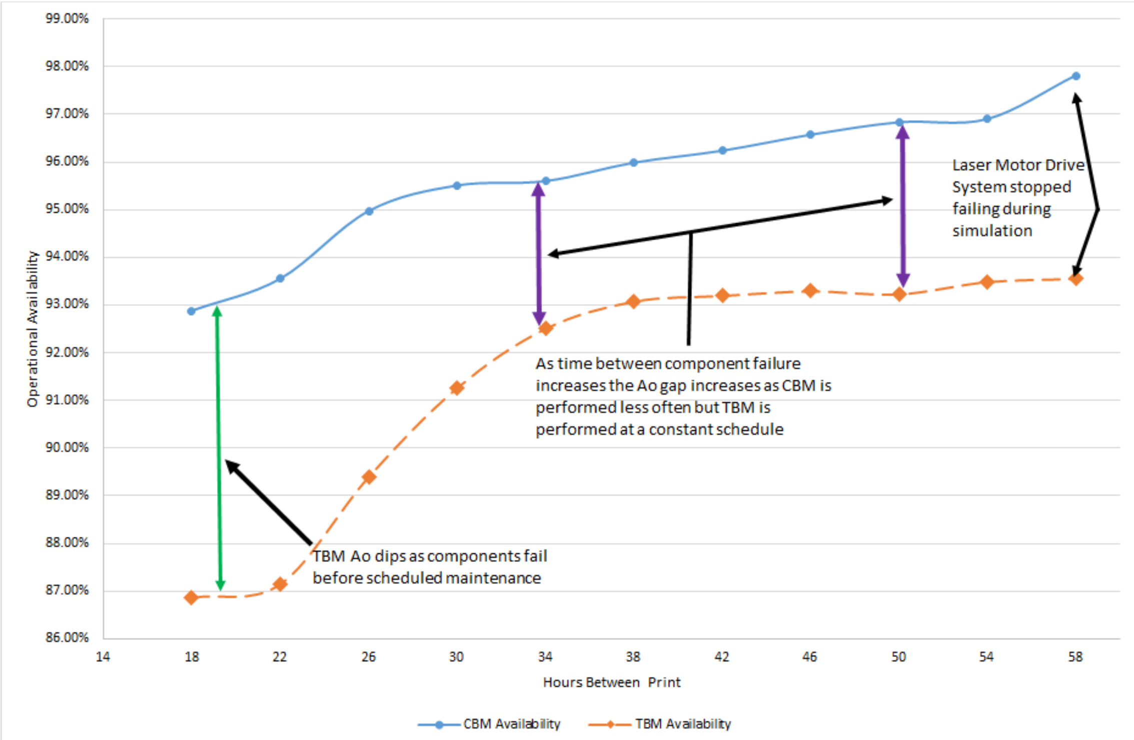

Figure 26. Ao for CBM and TBM with Laser Drive Motor System (-20% MTTF)

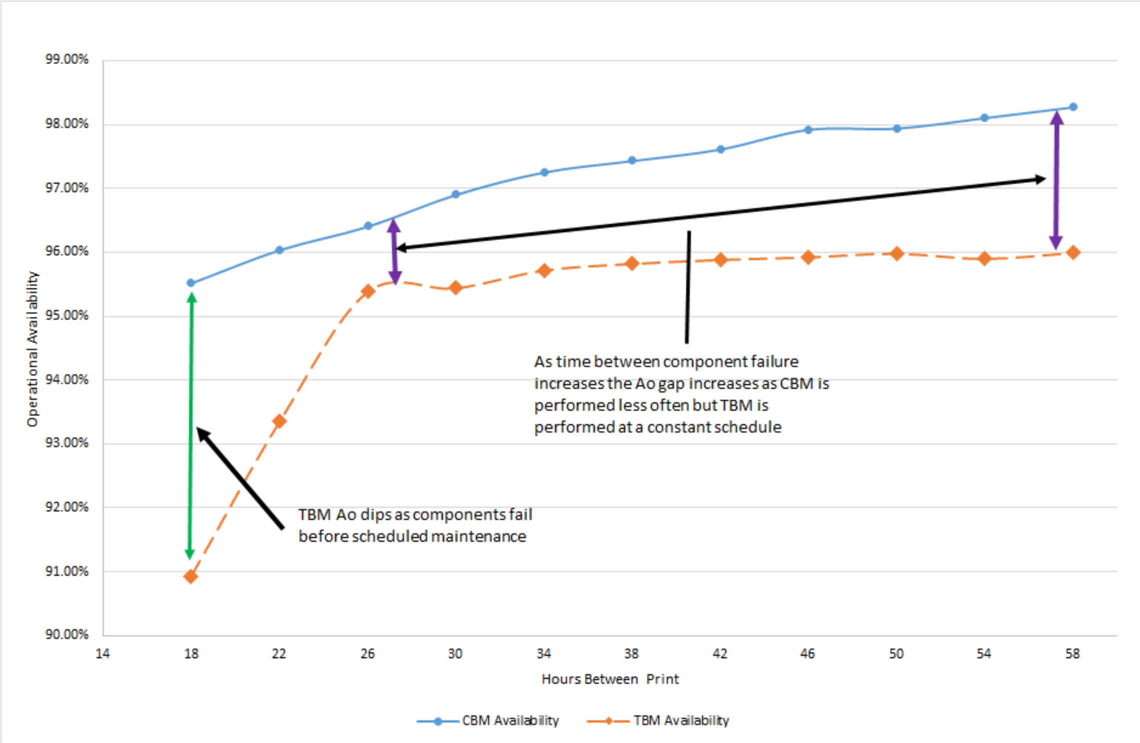

Figure 27. Ao for CBM and TBM without Laser Drive Motor System (+20% MTTF)

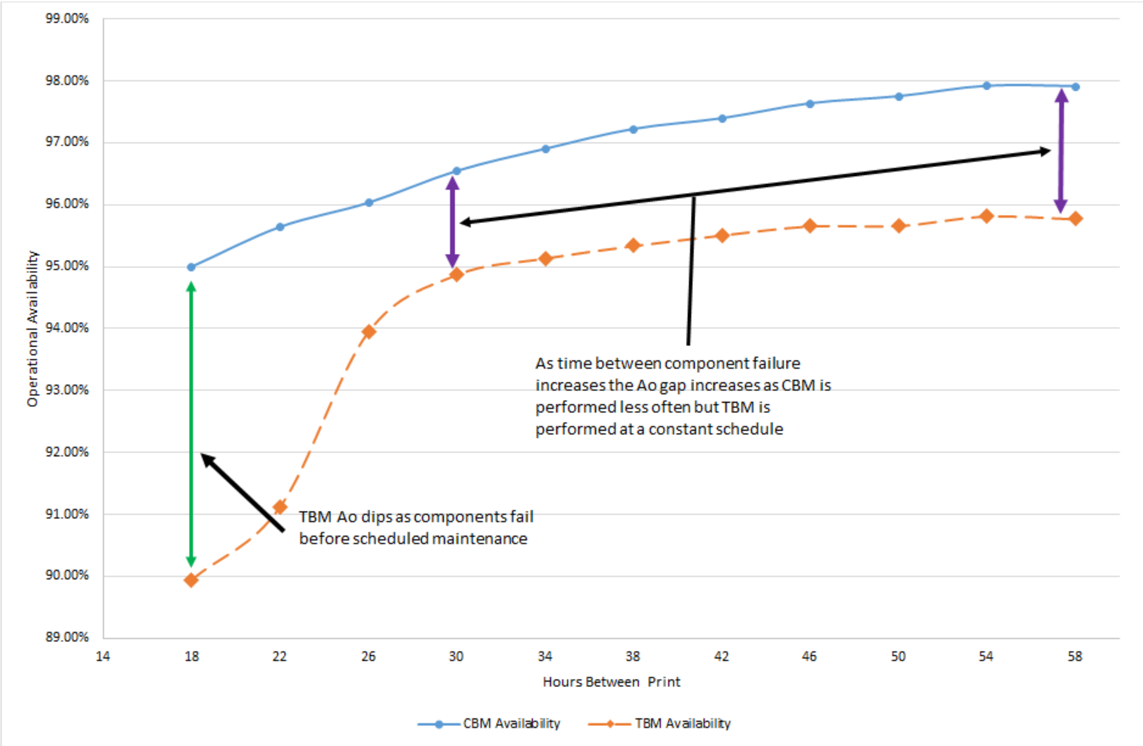

Figure 28. Ao for CBM and TBM without Laser Drive Motor System

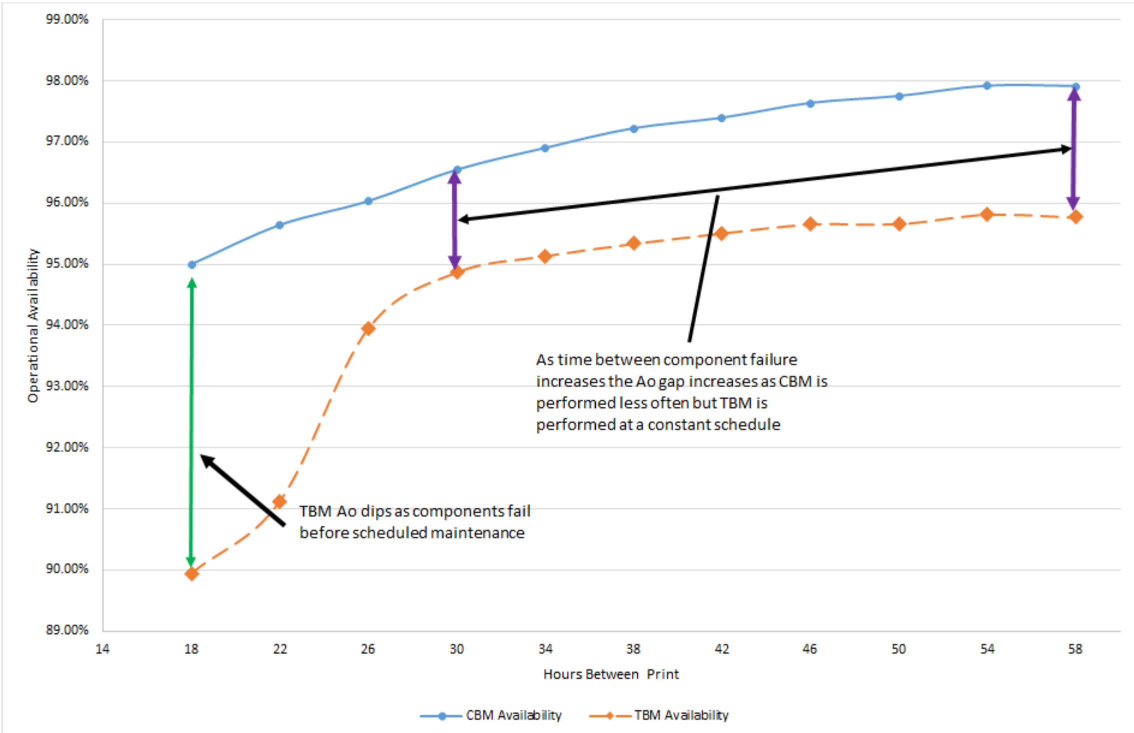

Figure 29. Ao for CBM and TBM without Laser Drive Motor System (-20% MTTF)

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