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Improving System Sustainment Through an Integrated Modeling Schema Coupled With Effective Execution of the Life Cycle Sustainment Plan

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Improving System Sustainment Through an Integrated Modeling Schema Coupled With Effective Execution of the Life Cycle Sustainment Plan

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Abstract

Title 10 § 4324 tasks the Product Support Manager (PSM) to "(B) ensure the life cycle sustainment plan is informed by appropriate predictive analysis and modeling tools that can improve material availability and reliability, increase operational availability rates, and reduce operation and sustainment costs." Advances in modeling and simulation offer the opportunity for PSMs to bring new approaches to long-standing challenges, particularly using AI and machine learning models. This paper examines how one PSM has used a series of traditional and AI-based models to develop predictive analytics that can advise the platform life cycle with the expectation of improved Operational Availability (Ao) and Material Availability (Am).

There are many challenges, including: (1) most models are built to suit the particular user community, without any intention of connecting the model to others, (2) each model is often built with a set of algorithms that are custom adapted to the problem set, giving rise to composability questions, and (3) many models are built to different time scales, or even independent of any time representation.

Life cycle sustainment of submarines, particularly during service life extension, has been met with challenges that have led to inefficient use of time and personnel resources. While maintenance availabilities include various service, planned, corrective and alteration jobs that maintain or increase readiness of the Navy's deterrent fleet, these facilities encounter cost and schedule overruns caused by constraining factors including personnel, equipment, facilities, supplies, material, weather, or other uncontrollable factors. The COLUMBIA Submarine Program has developed several models to assist in decision making. We describe two models, one a discrete event simulation of the approved and alternate life cycles and the other a manpower forecasting model for the repair facilities and how these models have led to new insights in improvements that will improve Ao and Am.

We also describe a future state where currently disconnected models are integrated together, allowing decision makers insights to see the complete loop from a 3D product model used to design, build, and sustain the platform to the end user applications.

Introduction

We have previously reported on the application of governance to the sustainment effort on COLUMBIA (Baker et al., 2019). In this work, we described the Complex Governance System, its alignment with the nine directed responsibilities of the PSM, and how it could fill in the governance gaps from the Product Support Manager's Guidebook. We also discussed the application of several governance meta-functions to the program situation. One meta-function (Learning and Transformation M4*) was touched upon lightly but presaged our work in modeling and simulation. Currently, an explicit gap exists in the Title 10 responsibilities; we note that

> *The Learning and Transformation (M4*) meta-function, although not emphasized in the Title 10 responsibilities, is a critical element for governance. Learning facilitates the evolution of product support but also involves transformation of the DoD components if their business processes do not satisfy program requirements, or if their way of doing business comes at the cost of viability of another organization or a set of organizations (M4*). Governance through M4* implies continual adaptation and design of the underlying system and business processes through fundamental double-order learning to improve future execution.* (Baker et al., 2019, pp. 13–14)

The continued exploration of Learning and Transformation leads to several questions complemented by the governance perspective of having a model of the current system and potential future systems:

- How can a Product Support Manager (PSM) take advantage of the rapid advances in modeling and simulation to develop an integrated, through life cycle ecosystem of models and simulations to develop otherwise hard to find improvements that lead to cost sensible improvements in Fleet Availability and Operational Availability?
- What considerations might a PSM evaluate as the ecosystem is developed from a collection of siloed simulation instances?
- Can the learnings from this effort be applied to other current or future acquisition programs?

In this paper, we look at how one program is using modeling and simulation to improve the key parameters of A_o, A_m and C/DA specified in DODI 3110.05, first from an individual model perspective, then combining the models into an ecosystem. We begin with an introductory section that lays the foundation of the legal and regulatory basis for the work, describes our evolving concept of an ecosystem, and discusses the fundamental science of the models and simulation. We then transition to a methodology section describing the technical approaches taken in the computational models. A discussion of some of the insights learned and results from our work to date follows, along with some conclusions. We wrap up with a discussion of future work on our vision of expanding the modeling boundaries across the organizational ecosystem and some of the challenges we are sure to confront.

Background

Product Support Management Guidance in USC Title 10 and DoD/USN Supporting Instructions

The Product Support Manager (PSM) is a position designated in law to deliver and implement product support strategies for covered systems. This position is required to develop and maintain the life cycle sustainment plan, approved by the milestone B decision authority. The life cycle decision plan has eight significant elements. The PSM also has nine specific responsibilities, including "(B) ensure the life cycle sustainment plan is informed by appropriate predictive analysis and modeling tools that can improve material availability and reliability, increase operational availability rates, and reduce operation and sustainment costs" (NDAA, , 2021). This section is relatively new and represents the evolving understanding of the tools available to the PSM and the growing responsibilities. For instance, Public Law 111-84 of 2009, which introduced the Product Support Manager (Chapple & Faire) called out only five responsibilities for the PSM, none of which specified requirements for modeling and simulation. The responsibility to conduct modeling and simulation arrived in public law in Section 2337 (renumbered from 805) in the National Defense Authorization Act for Fiscal Year 2013, which began the explicit enumeration of requirements for the PSM to "use appropriate predictive analysis and modeling tools that can improve material availability and reliability, increase operational availability rates, and reduce operation and sustainment costs" (NDAA, 2013).

While Congress was providing legislative direction, OSD and the services were providing regulatory direction for PSMs to execute the law. Department of Defense Instruction 3110.05 has had several iterations, with the latest issuance in April 2024. It specifies three "superordinate metrics that will allow decision makers at all levels across the DoD enterprise to assess the effectiveness and efficiency of weapon system sustainment using a standard structure and consistently applied methodology." An additional nine metrics are specified in 3110.05. While the instruction specifies several characteristics and methods of calculation, it makes no comment on models or simulations (DoD, 2024b).

From a Navy perspective, a new Memorandum was signed out in 2024 that similarly focuses on key measures like Operational Availability (A_o) and Material Availability (A_m). Following the DODI format, instructions are provided to calculate specific measures and reporting intervals (OPNAV letter, 2024).

The COLUMBIA PSM had been working on various models and simulations, to be discussed in detail later, but the recognition had grown that the thread of the guidance combined with rapid advances in modeling and simulation offered the opportunity to begin connecting these models in an ecosystem embedded within the larger Project Blue ecosystem.

Application of "Ecosystems" as a Pervasive Lens

The rise of industry 4.0 and digital solutions has identified a new complexity, in that many of the technologies are interrelated and themselves complex, with few providers able to provide the complete suite with the requisite speed and flexibility. Benitez et al. (2020) had noted that

> *Before the advent of Industry 4.0, technology providers had mostly worked in a dyadic relationship for the development of their solutions in the supply chain (Marodin et al., 2017, 2018), while technology implementation was based on the exchange of units (Lusch and Vargo, 2014). This means that each actor contributed with specific technology modules to the supply chain, which were developed independently from other technology parts and based mainly on transaction as a mechanism of exchange.*

The PSM and his staff set out to create an ecosystem centered around delivery of sustainment to COLUMBIA, all within the scope of the PSM guidebook direction to employ Product Support Integrators (PSI) to facilitate the product support strategy through formal arrangements (e.g., Memorandums of Understanding/Agreement, formal contracts, teaming agreements) with designated Product Support Providers (PSP). The formal arrangements document mutual agreements for the scope of PS and resources provided and constrained in each individual arrangement.

We retain the earlier definition of governance as "occurring within a "meta-system" responsible for design, execution, and evolution of those meta-system functions ("meta-functions") necessary to provide communication, control, coordination, and integration for the complex system (Keating & Bradley, 2015)" (Baker, 2019). This paper addresses the specific need to develop models of the system, both current and desired future, and how COLUMBIA has developed and used models to meet the statutory and regulatory guidance, as well as intended path for a system of models covering the physical span from design through operations and the temporal span of the entire class lifetime.

Modeling Perspectives

This section discusses the current modeling approaches for the life cycle and repair facility manpower. The PSM has explored earlier modeling techniques, not reported here, as part of an exploration of "the art of the possible." The remainder of this section discusses each approach, software choices made and some detail on how each model was designed and implemented.

Discrete Event Simulation (DES)

Discrete Event Simulation (DES) models evaluate operation of a system or System of Systems (SoS) as sequential discrete time periods where each time period is distinguishable by a marked change that is clearly identifiable. In DES, abstract system models use a continuous but bounded time base where only a finite number of relevant events occur. These events cause state changes within the system which are then evaluated within the model to determine the effects on the overall system. In DES models, events occur at a discrete point in time that signifies a change to a system's status. Between two successive status changes, the system remains static. DES is a method that steps through time, skipping static periods where no changes occur (Griendling & Mavris, 2011). In continuous simulations, a system is allowed to change continuously over time (Banks et al., 2004). In DES, however, models are designed to specifically deal with discrete changes through either time-triggered or event-triggered activities whose stochastic output can be used for making decisions. Any continuous time period can be discretized into discrete time periods using cut points. DES evaluates a continuous time period by analyzing and quantizing attributes within discrete time segments before recombining them into a single result that spans the original continuous time period. DES results quantify results for the discrete time periods analyzed within the model. Thus, any continuous time period under examination must be discretized.

Discretization segregates data into discrete units. It replaces an infinite sequence into finite-dimensional problems that can each be solved individually through mathematics before being recombined to represent the solution in the original infinite sequence. Discretization methods produce data whose values can be counted (Yang et al., 2010). The discretization process establishes discrete data values that exist in intervals across a continuous range (Liu et al., 2002). Continuous results can be achieved by examining smaller and simpler results in discrete-time processes (Jacod & Protter, 2012). Partitioning a continuous time segment using cut points is a simple way to discretize any continuous time period. Any continuous time segment can be separated into "k" partitions using k-1 cut points. The process consists first of determining the number of discrete intervals (i.e., partitions) followed by demarcating the boundaries of the intervals (Kotsiantis & Kanellopoulos, 2006). There is no theoretical limit to the granularity of discretization. Mathematically, discretization methods are approximations, but as granularity of the discretization becomes smaller and smaller, the approximation becomes closer to the actual solution of the original infinite sequence (Stetter, 1973). However, there is a practical limit that is determined by the period of observation or the ability to measure or record values associated with discrete time values or cut points. A continuous range can be discretized by using cut points to dissect the range into partitions or intervals. Phases, modes and states have been defined as clearly distinct and different partitions of an operation and a system's functional operations (Wasson, 2014). Although a lack of a standardized taxonomy has resulted in much conjecture and confusion as to the distinction between phases, modes and states (Olver & Ryan 2014), they present an appropriate method for segmenting a life cycle into discrete periods that can be examined through DES.

Phases, modes and states of operation are integral to defining a system even though the distinction between modes and states may be relatively arbitrary (Wasson 2014, 2016). A submarine's life cycle is a continuous period from conception to disposal. A ship's Life Cycle Model (LCM) is the assemblage of unambiguous and specific phases, modes and states and the assigned product baseline. There is not much difference between modes and states, but it is primarily how a user defines modes and states in the context in which it is being used (Wasson, 2016). Any DES must be discretized. DES, as used in the COLUMBIA Submarine Program, requires discretizing each submarine's continuous life cycle into discrete periods that can be quantized. Modeling a submarine using DES requires segmenting the life cycle into discrete time periods. Decomposing a submarine's life cycle into phases, modes and states provides the cut points in the LCM and discretizes a submarine's life cycle.

Each submarine's life cycle is a sequence of phases: Research and Development (R & D), design and construction (including delivery), Operations and Sustainment (O & S) and disposal. DES within COLUMBIA's IPS is primarily concerned with the O & S phase which begins with the submarine's delivery and ends with decommissioning. Decommissioning is the event signaling the transition from the O & S phase to disposal phase. The O & S phase is comprised of alternating modes of operations and sustainment (Lemerande, 2020, p. 8). The operations mode decomposes further into various states, each defined by a configuration of constituent systems and equipment that must meet pre-defined criteria to be considered in the operational mode. A Functional Profile (FP) segregates a mission into periods for specific functions to be performed rather than performing all functions simultaneously. FPs includes all events performed during a mission (USN, 2002). States can correlate to mission segments and be paired with specific equipment and specific configurations assigned to mission segments as unique periods to be assessed (Wasson 2014, 2016; Esary & Ziehms, 1975; Burdick et al., 1977). The sustainment mode is comprised of any period where the submarine is undergoing intermediate or depot level maintenance. A submarine's LCM is the assemblage of specific phases, modes and states. Phases, modes and states provide the cut points for discretizing an SSBN's life cycle. The SSBN fleet life cycle is an agglomeration of the life cycles of the constituent submarines. The COLUMBIA Class LCM consolidates all the phases, modes and states of the SSBN fleet into a single model. DES is a state-driven model that uses probabilistic characteristics for submarines' O & S Phase's modes and states to evaluate and assess scenarios and quantify outcomes across all submarines included in SSBN force data models.

Naval Sea System Command (NAVSEASYSCOM) initiated Model Based Product Support (MBPS) as a digital transformation program to consolidate and update Integrated Product Support (IPS) activities across the fleet. A core aspect of MBPS is the Navy Common Readiness Model (NCRM) that will provide "predicted, optimized and sustainable readiness" for ships and submarines. Systecon's Opus Suite is the chosen software for producing NCRMs in MBPS (NAVSEASYSCOM, 2022). SIMLOX, one of three software programs within Opus Suite, is DES software that has the ability to illustrate how outcomes vary over time, taking into account changing operational demands as well as changing resource availability, maintenance operations and logistics transportation operations. "SIMLOX is an event driven simulation tool that enables detailed analyses of how technical system's performance vary over time given different operational and logistics support scenarios" (Systecon, 2021, p. 17). Systecon developed SIMLOX to evaluate scenarios through simulations to help users understand the implications of various logistics and support conditions on the identified operational requirements. COLUMBIA's PSM became an early adopter of Opus Suite and has been developing SSBN models in SIMLOX to drive improved IPS in the COLUMBIA Submarine Program.

Artificial Intelligence and Machine Learning

AI and ML-driven approaches have the potential to significantly improve fleet management by increasing availability and operational performance. One area of improvement involves adequately sizing the workforce required to perform necessary maintenance. This occurs at both the facility and trade levels. Workforce sizing exercises have been performed in similar circumstances. Turan et al. (2021) provided a case study involving the Royal Australian Navy that combined system dynamics simulations with the use of a sorting genetic algorithm to generate plausible workforce planning scenarios, which are then passed to further simulation models for evaluation. Witteman et al. (2021) applied time-constrained variable-sized bin packing approaches to calculate workforce requirements under optimal operational maintenance conditions for an entire aircraft fleet owned by a European airline. Potential modifications to these workforce sizing algorithms can include the incorporation of models for resignations, retirements, recruitments, promotions, and even annual leave (Akyurt et al., 2022).

While workforce sizing is an appropriate technique to summarize the requirements across an entire facility, complex systems require analysis at the trade level to ensure that all aspects of maintenance can be covered by the workforce. Applying skillsets to the individual workers creates a variation of the Multi-Skilled Resource Constrained Project Scheduling Problem (MS-RCPSP), which attempts to optimize work schedules while considering worker skillset (namely, each worker can only work on tasks for which they are skilled) and material availability constraints. MS-RCPSP has been frequently tackled across a variety of industries using techniques such as parallel scheduling schemas (Almeida et al., 2016), genetic programming (Lin et al., 2020; Zhu et al., 2021; Snauwaert & Vanhoucke, 2023), binary integer programming (Zhang et al., 2023), mixed integer linear programming (Snauwaert & Vanhoucke, 2023), Benders decomposition (Balouka & Cohen, 2019), and variable neighborhood searching (Chakrabortty, 2020).

MS-RCPSP has been proven to be an NP-hard problem (Blazewicz et al., 1983). The consequence of this finding is that known methods are incapable of producing a solution to the MS-RCPSP problem in polynomial time, meaning that the computation required to produce the optimal solution scales at least exponentially as the inputs become more complex. Submarine maintenance requires hundreds of workers tackling hundreds, if not thousands, of jobs during any maintenance period. Even under idealized conditions, the scope of the submarine maintenance environment renders existing MS-RCPSP techniques computationally impractical. Techniques that attempt to simulate operational conditions, such as the stochasticity induced by Isah and Kim (2021) or the mid-project job delay forecasting by Awada et al. (2020), improve the realism of the modeling and simulation process but exacerbate the computational complexity of the problem. As a result, entities have asked whether other numerical, data science, artificial intelligence, or machine learning techniques can achieve results faster while appropriately considering the operational conditions (Washko, 2019).

Another area where AI and ML can improve maintenance facility performance involves prediction of unplanned work, which is known to contribute significantly to maintenance delays. The Government Accountability Office (GAO, 2020) notes that unplanned maintenance causes a 36% underestimation of workforce size, directly leading to over 4,000 days of maintenance delays in the aircraft carrier and submarine fleets during Fiscal Years (FYs) 2015–2019. This number accounts for 47% of all delays across the nuclear-powered fleet during that time span (GAO, 2019). Unplanned work generally arises after maintenance begins and can result from equipment breakdowns, inspection and/or test failures, discovery during maintenance of other parts, or other reasons. As a result, unplanned work is difficult to project. Data science efforts can identify patterns in unplanned work and attempt to apply the results to other machinery, allowing synthetic work packages to be developed for equipment that does not yet have maintenance history.

Methodology

In this section, we detail the two specific models that were developed for the life cycle model and the repair facility manning.

Discrete Event Simulation

DES in the COLUMBIA Submarine Program uses SIMLOX to demonstrate how simulation outcomes vary over time with varying inputs, resources and constraints. SIMLOX is designed to account for operational demands, maintenance requirements, resource availability and transport schedules to produce results that characterize operational and maintenance demands. SIMLOX models simulate mission scenarios according to predefined operational profiles while considering maintenance and support and the consequences resulting from logistics constraints and on operations throughout the scenario. Data related to maintenance schedules and resources, operational schedules/profiles and maintenance strategy are loaded into SIMLOX templates to produce a Database Model (DM). Each SIMLOX DM is generated by importing curated data tables from a Predictive Data Model (PDM) directly into SIMLOX using Open Database Connectivity (ODBC) functionality inherent in Opus Suite.

The PDM creates conditions and curates data needed to conduct DES in SIMLOX. The PDM was developed within the Navy Marine Corps Intranet (NMCI) using common applications available in the USN's Information Technology (IT) infrastructure. It is a development environment that collates submarine LCM and pertinent product support information into the requisite tables for importation into SIMLOX. The PDM developed for SSBNs uses MS Excel and MS Access to create, condition and curate data tables that comprise a comprehensive data model. Synthetic data was created and conditioned in MS Excel and curated in MS Access before importation into designated SIMLOX data tables for processing in a DES. The PDM's data architecture is a collection of data tables that allows flexibility in the composition of individual submarines and their life cycle phases, modes and states and the necessary product support environment (i.e., model entities and resources). The PDM is modularly constructed to allow for incremental improvements to increase model fidelity and usefulness. The PDM's output is curated data collated into tables that exactly match SIMLOX tables. Curated data tables in the PDM are imported directly into SIMLOX via ODBC. Data integrity is maintained between MS Excel, MS Access and SIMLOX to ensure data quality remains intact throughout the model. The PDM's continued development and improvements remain unclassified while using synthetic data. However, the PDM is portable to the USN's classified network to allow classified modeling when actual fleet data will be used. Using a standardized PDM allows separate DMs to be developed independently before being assimilated into a single model and run as a consolidated simulation with multiple ships. Moreover, the standardized PDM allows any quantity of modes and states to be included in a single DM. The PDM can be applied to any submarine within the fleet. Every submarine can use the same PDM to develop its own model specific to that ship. A standardized PDM ensures any DES will be executed in the same way.

PDM data tables are characterized as either common across the scenario or specific to a product (model entity). Common tables apply universally across the entire model and do not change based on submarine schedules. They consist primarily of logistics, product and organizational support resources that apply universally throughout the model. Common data tables often apply across multiple scenarios because they establish the product support environment for ships and ship operations within models. Tables specific to individual ships consist primarily of each ship's LCM data. Ship specific tables share a common structure, but the data contained within each row of data is unique. Tables in a SIMLOX DM consist of columns and rows. Each column is defined by a specific name and header and, in some cases, default values (Systecon, 2021, p. 83). Every row is a separate record in the database. In each DM, each row is either uniquely associated with an individual ship (i.e., ship specific data), or it is common and applies across the entire fleet. The order of joining is inconsequential since each row represents an individual record. Any rows common across the fleet will be duplicated and therefore must be removed, while rows specific to an individual ship are unique. Combining data tables from separate DMs is simply consolidating rows of data from individual DMs into common data tables and removing duplicate rows. SIMLOX's table structure supports piecemeal development; separate DMs can independently run individual ships' simulations separately. However, to simulate all ships in the same integrated fleet simulation, the data tables from separate database models must be combined into a consolidated DM. Individual ship DMs combined into a single model yields an Integrated Fleet DM (IFDM). Running an IFDM in SIMLOX as a DES produces results for individual ships within the confines of the product support structure and within constraints of the fleet's shared resources. SIMLOX results contain data stored as tables and graphical renderings in one common file.

SIMLOX can produce a DES for any number of submarines within a product support structure defined by the modeler. SIMLOX is scalable and can be used to evaluate any quantity of SSBNs in any configuration for all phases, modes and states. SIMLOX, as an "off the shelf" product, has some limitations but is an adequate modeling environment. Furthermore, SIMLOX is approved to be installed on Navy classified networks. SIMLOX allows for spiral development in successive models to continually improve and increase model fidelity. Features available within SIMLOX support different levels of fidelity, depending on a given model's construct. The most basic model requires specific data tables to be populated, while more complicated models must include additional tables. Once the minimum tables are populated and a basic simulation can be executed, additional features within SIMLOX can be included to add fidelity to DES results. DES in SIMLOX can be continually improved and updated with new functionality. Systecon has continually improved Opus Suite functionality with multiple releases throughout the past several years.

Artificial Intelligence/Machine Learning

Due to the overall taxpayer investment and strategic importance of the COLUMBIA class, it is important to ensure that the submarines last throughout the entire planned life cycle. The best way to achieve this standard prior to ship delivery is to thoroughly plan for maintenance throughout the ship's life cycle. Artificial intelligence and machine learning methodologies can assist with this planning by learning from historical maintenance data and providing insights on the requirements needed to sustain COLUMBIA ships. This is important because the sensitivity and hiring requirements imposed by national defense work limit the amount by which the workforce can be scaled at any one time. Furthermore, there may be changes in the structure of the workforce, particularly the number of employees skilled in different trades, due to the incorporation of new technologies onto the COLUMBIA class.

The artificial intelligence and machine learning aspect of this project addresses five key questions:

1. What sized workforce is required to perform the maintenance necessary to ensure that the COLUMBIA fleet fulfills its national security obligations?
2. Given the calculated workforce size in Question 1, what distribution of skillsets is needed to ensure the COLUMBIA fleet fulfills its national security obligations?
3. Given the results of Questions 1 and 2, what is the probability that a provided work package gets completed within a provided timeframe?
4. Can work packages be generated synthetically to improve the confidence in Answer 2?
5. How can the tools developed to analyze Questions 1–4 be efficiently packaged for use by maintenance planners?

Several assumptions regarding working conditions were made in the modeling process. It is assumed that staffing levels remain consistent throughout the period of work, meaning that daily staffing levels do not change drastically at any point during the simulated life cycle. Machinery is assumed to be of sufficient quality and quantity to avoid causing bottlenecks in the work process. Future jobs are assumed to be completed as scheduled, meaning that no individual job is deferred to future maintenance periods. Due to the nature of the data and normal operating conditions, the model inherently accounts for a base level of deferral which is assumed to be consistent over the life cycle. Maintenance periods that require use of drydock facilities are assumed to be conducted entirely in the drydock. Finally, the modeling process assumes that work at the two facilities happens independently, meaning that jobs and workers remain at their original facility and that boats do not switch homeports during their life cycle. This final assumption allows for the development of separate models for each maintenance facility, which makes sense given that the two TRF facilities operate under slightly different philosophies. A system of models (comprising of predictive modules) is proposed to address the above five key questions:

A Resource Per Day – Schedule Confidence (RPD-SC) module was developed to determine the overall workforce size. The first iteration of the RPD-SC module is trained using a corpus of all completed jobs conducted on 207 maintenance activities across all OHIO class submarines from 2010–2021. These activities include 34 docking and 77 pierside (non-docking) maintenance activities for Bangor and 19 docking and 71 pierside (non-docking) maintenance activities for Kings Bay. Daily charge data, including the number of man-hours spent on each job, is captured daily at each maintenance facility. These data were aggregated across the entire facility, then subdivided separately by maintenance activity and calendar day. Similarly sized maintenance activities were grouped together, and their daily charges were normalized to produce a generic work profile for that “type” of maintenance activity. When provided with maintenance dates and a projected scope (in man-hours), the RPD-SC module calculates the required resource expenditure needed for each day in the maintenance period to stay on track to complete the project in time. This process can be applied over each maintenance activity for each boat at a facility to produce a plot of the overall staffing needed at the maintenance facility. This plot provides the guidance needed for facility leadership to determine the required workforce size, thereby answering the first question.

The charge data that powers the RPD-SC module also bins the jobs by Work Center (WC). Hence, the second iteration of the RPD-SC module was to perform a similar analysis at a more granular level for each WC. These work centers are typically broken down by trade. For example, work center 38C conducts repairs requiring machining while work center 72A performs rigging operations. The process for generating work profiles is conducted at each of the WCs with sufficient work for analysis. This step is significant during WC analysis as some work centers only perform their work at specific times during a maintenance period. For example, 72A's work, which mostly involves the removal and replacement of equipment to improve access to other parts of the submarine, is largely conducted at the beginning and end of activities, while 38C's work is performed consistently throughout the maintenance activity. A similar plot to the overall facility plot is generated as output of the RPD-SC WC iteration, which provides the guidance needed for facility leadership to determine the number of workers at each WC and answer the second question.

Work center analysis revealed that oftentimes work is not linearly related to the estimates at the beginning of a maintenance activity. A third iteration of the RPD-SC model addresses this issue at both the facility and WC levels by incorporating a heuristic-based, non-linear model approach. Data sets are broken into three regions using the Jenks natural break algorithm (Jenks, 1967). Linear analysis is conducted in the two outer regions to provide better fits on outlier data and provide reasonable extrapolations of the work estimates. In the interior region, a gradient boosting decision tree algorithm (Friedman, 2001) is used to fit on the data. The results of each of the trees are calculated then aggregated to produce a non-linear fit in the central region. The result is a fit that better adheres to the non-outlier data while minimizing the number of degrees of freedom.

The RPD-SC module can produce raw work estimates, but when used alone, it cannot determine the likelihood that a maintenance activity is completed on time. The Resource Probability of On-Time Completion (RPC) module fills this void. RPC takes the start date, projected maintenance activity length (in days), estimated scope of maintenance, facility-wide staffing levels, and a derived value for the amount of work conducted at the facility (called load measure) as inputs. Load measure is derived from aggregated historical performance metrics gathered from the observed data. This measure is similar to the work profiles generated in RPD-SC, but it applies across the whole facility rather than for an individual maintenance activity. The underlying technology of RPC is a Gaussian Process Classification model that is trained using the aforementioned observed maintenance data and outputs a probability that a maintenance activity completes within a provided activity length, answering the third question posed. It should be noted that the RPC module only uses historical maintenance activities in its training set, so the outputs will only be accurate for new activities that somewhat resemble those in the training set.

The previously mentioned modules are each trained using observed maintenance records, but the available data may not be sufficient to ensure that the models run at peak efficiency. A synthetic data generation routine was developed to combat this issue by simulating realistic staffing/planning data using advanced machine learning techniques. The routine starts by clustering all available job data at the work center level to identify distinct job types. A job list is created for each maintenance activity, which consists of a list of job counts by cluster. A conditional variational autoencoder (CVAE) learns patterns from the job list training data and generates new synthetic job lists based on specified characteristics.

This synthetic data is instrumental in filling gaps in the existing datasets, such as projecting job distributions for maintenance activities that are not similar to those currently observed. Synthetic data allows for analysis and prediction of job compositions across different scenarios, correlates job types with input maintenance activity characteristics, and helps anticipate staffing needs more accurately. Additionally, the model can simulate future maintenance activities by leveraging shared jobs, enabling better understanding of what COLUMBIA maintenance activities will look like, particularly under newly developed circumstances foreign to existing ship maintenance plans. These simulated work packages address the fourth question posed at the opening of this section.

The RPD-SC, nonlinear RPD-SC, RPC, and synthetic work generation modules combine to produce a powerful tool suite capable of predicting maintenance needs across the entire 60+ year life cycle of the COLUMBIA class. The final package takes a nominal life cycle schedule as an input. Facility-level workloads used in the RPC module are calculated using the provided start and end dates for the maintenance activities. The RPD-SC module uses the provided maintenance scopes and profiles each activity based on the activity length and the learned workload profiles. These RPD-SC results are graphically depicted on a visualization dashboard for each activity, as well as aggregated over the entire facility to show the entire projected workload on a given date. Additionally, the scopes and dates feed into the RPC model, which estimates the probability of a successful maintenance activity. These outputs allow maintenance planners to set target rules such as a nominal workforce size, which allows for further calculations such as overtime rate during busy periods, white space during slower periods, and workforce optimization through re-assigning work on docked ships (Tse & Viswanath, 2005). The above-mentioned modeling and dashboard will allow planners to envision 'what-if' scenarios at both TRFs and adjust maintenance availabilities to over the entire life cycle of the fleet. This overall package solves the final question posed at the opening of this section.

Discussion

Each of the models provided insights to assist the PSM. The discrete event model highlighted several risks within the approved life cycle and offered alternative life cycles for consideration to reduce or eliminate those risks. The AI/ML model is an earlier model but has offered insights the ability to develop synthetic work packages for a class not yet delivered. Some specific results are discussed in the following paragraphs.

The first OHIO class SSBNs transferred into service in the early 1980s. The USN has more than 40 years of historical technical and logistics data for OHIO class SSBNs. The VIRGINIA class submarine program has about 20 years since the first of its class entered service. Although much of COLUMBIA's design incorporates legacy systems from OHIO and VIRGINIA class submarines, a portion of the new SSBNs will be new technology for which there is limited technical and logistics data for parts other than data estimated by the ship designer. Moreover, 12 COLUMBIA class SSBNs will deliver the same Sea Based Strategic Deterrence (SBSD) mission currently provided by 14 OHIO class SSBNs. O & S for COLUMBIA will necessarily be different to OHIO in order to deliver SBSD with two fewer submarines. DES provides the ability to model COLUMBIA's configuration baselines, life cycle schedules and O & S profiles as well as wider USN logistics support and TRFs' facilities and resources to forecast effects integral to IPS.

Success thus far using SIMLOX has demonstrated the usefulness of DES to IPS for the COLUMBIA Submarine Program. SSBN operations and sustainment are different to other Navy ships. SSBNs operate a "two crew" concept with each submarine routinely scheduled strategic deterrent patrols followed by in-port refit periods at a TRF. SIMLOX uses discretized life cycle schedules to simulate individual submarines' modes and states for an entire class of submarines within the same simulation. Both TRFs play the primary role in sustaining SSBNs; they will provide the majority of all in-service sustainment and husbandry for COLUMBIA class SSBNs. Within SIMLOX, the TRFs are key resources within the DES that support evaluation of submarines across their life cycles. Stochastic forecasting predicts submarines' operational successes during specific modes and states based on each submarine's configuration, technical parts data, expected failures and repair capabilities within the product support network. SIMLOX also generates parts' demands based on simulated operations and sustainment activities, to include adequacy of OBRP allocations from simulated parts failures and subsequent onboard repairs conducted Ships Force personnel, to forecast demand rates for parts. DES results have also produced availability calculations based on simulated operations and sustainment activities.

Artificial Intelligence – Machine Learning

Early analysis focused on applying reinforcement learning (RL) techniques to optimize maintenance schedules, but several shortcomings were discovered. RL is ideal for cases where jobs must be performed in a certain order, but the existing datasets do not capture this information. RL also works best when job lists for a maintenance period are known, but in many cases, these lists are fluid until the maintenance period is underway. This results in a model that is myopic in nature and incapable of producing long-term predictions. The compute time required to run RL models makes application of RL models difficult in an operational environment. This is particularly true when determining the compounding effects of deferring work to future maintenance periods since the unplanned work added to future job lists cannot be finalized until the boat performs its patrol. Finally, RL algorithms usually produce an autonomous guidance for conducting maintenance periods, which may be met with distrust and operational resistance by people familiar with conducting live maintenance.

Considering these shortcomings, the AI efforts shifted focus to traditional statistical learning approaches. The result was a suite of models that are less complex, capable of viewing long-term effects of short-term solutions, and powerful enough to provide meaningful results. Early model development directly predicted daily charged hours, but it proved difficult due to many unknowns, including the total ongoing work at the facility, how these charged hours were distributed, and other factors that might impact the workforce, such as extreme weather and extraneous conditions such as the Covid-19 pandemic. This prompted the development of models trained at the refit level on completed jobs. The workforce prediction models are trained using completed work as input and total charged hours as output. These models determine the resources required to complete a scoped work package. The trained models do not directly make daily predictions. Instead, profiles outlining the distribution of work over a maintenance activity are generated by computing statistics on historical data. By combining maintenance activity level predictions and profiles, daily workforce predictions are obtained. A requirement for this method is an understanding of how conditions affect the workforce on a daily scale. However, this model excels at making long-term predictions for the required workforce and understanding long-term trends in workforce demand.

Iterative model development practices allowed for the creation of more complex models that maintained long-term outlooks and retained predictive capability over the RL approaches. These models include the non-linear and machine learning-based approaches outlined in the Methodology section. By applying these approaches, the mean absolute errors of prediction were reduced by more than 5% for the non-linear approach when predicting resource expenditures at the western maintenance facility. Model run time does not increase significantly despite the additional complexity. Furthermore, the non-linear model was designed to give reasonable predictions in regions without data, for example, activities with very small or large work packages. This package was named Maintenance Availability and Resource Prediction (MARP) for brevity.

Model Integrations and Results

DES modeling efforts described above produce common data useful in multiple modeling environments. A standardized output file has been generated for use in cooperative modeling activities. The PDM output file contains the following data fields: submarine unique identifier (i.e., hull number), unique maintenance availability identifier, scheduled start date, scheduled completion date, planned duration and estimated scope of work in RDs. For maintenance periods where a portion of the production work will be conducted in a dry dock, planned durations of time in dry dock as well as scheduled dates for docking and undocking operations are also included. The output file is a simple MS Excel worksheet with data separated by columns with common header names. These curated data sets are common between modeling environments; they provide the source data for both the DES and the AI/ML models and any other models that could potentially be developed in the future.

Model integrations between the DES (SIMLOX) and the AI-based MARP model are carried out by passing in the output schedule of the SIMLOX model as input (in the form of a spreadsheet as described above) to the MARP model. The input schedule includes a contiguous sequence of COLUMBIA maintenance availabilities over the lifespan of the fleet (2030–2080), the scope of work, and the type of availability. The MARP model then processes the input schedule and computes resources needed and a probability of on-time completion for each maintenance availability.

Conclusions

The work to date has demonstrated the viability of our intended path to develop an interconnected ecosystem of models, including 3D product models, reliability models, supply models, and class maintenance plans, to enhance decision-making and operational efficiency. The model offers an improved ability to optimize workforce sizing and predict maintenance needs, considering factors such as resignations, retirements, recruitments, and promotions to ensure an adequate workforce. Initial efforts to use reinforcement learning illustrated the limitations in a high noise environment, enabling the decision to more traditional statistical learning approaches augmented by newer algorithms. Since the new class of submarine has not been completed, the use of synthetic data generation routines will allow for credible simulations of realistic staffing and planning, enabling better analysis and prediction of job compositions and staffing needs. Iterative model development led to the creation of non-linear and machine learning-based models, which improved long-term predictions and reduced prediction errors.

Future Research

Future work is progressing at two levels; the first is the individual model level. Future work on the AI/ML modeling side includes further enhancing and validating the RPD-SC models at a granular work center level. Future work also aims to use job level information as input. Current models use the sum of estimated man-hours across jobs to make a prediction. Using trends at the job level would provide more accurate predictions. For example, some jobs may tend to require more expended man-hours than originally estimated. Another avenue to explore is incorporating job and workload assignment practices at the facilities. This allows for flexibility in how work is distributed overtime and does not use a static profile. Using this approach, a facility could predict workload while minimizing overtime, for example.

Due to the success of the development of the first two models and the demonstrated ability to interconnect brining other models together is underway. An initial exploration of other elements of the ecosystem has been explored. Contained within our ecosystem are at least the following models and simulations: 1) the builder’s 3D product model used to design, build, and sustain the platform; 2) an intermediary viewer that permits rapid access to the 3D model data in a lightweight, easily transportable model; 3) the reliability models, primarily developed by warfare centers for the Hull, Mechanical and Electrical (HME) and combat systems; 4) the supply models populated by the construction data packages from the builder and government organizations held by both NAVSUP and DLA; and 5) the class maintenance plan. Other models and simulations exist but are ignored for this level of abstraction. A generic pictorial is offered in Figure 1.

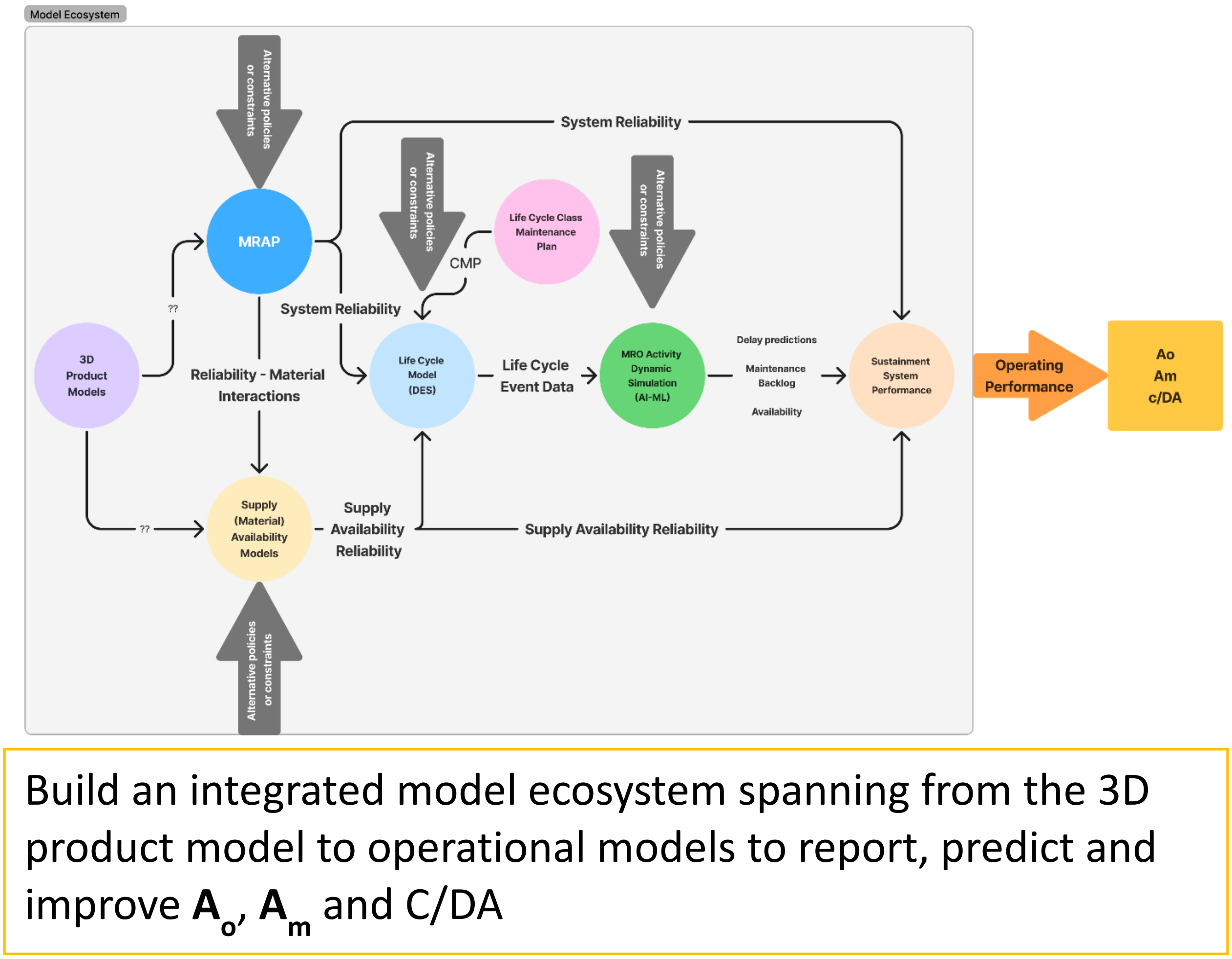

Figure 1. Abstracted Model Ecosystem

The future work will focus on developing the ecosystem. Several challenges are already understood and will require research and development. Three challenges will be discussed as part of future work. Those challenges are 1) composability, 2) verification and validation, and 3) governance of the ecosystem as an enterprise. Davis and Tolk (2007) assert that

> Strict plug-in/plug-out is unlikely to be valid for models, except in special cases, because of substantive subtleties about the component models and the assumptions that underlie them. It is much more feasible to design models in a fashion that will allow subsequent composition in short amounts of time—e.g., hours or weeks, rather than months or years.

Many of the models in our ecosystem are complex, well-developed products. However, the interaction with the other models is in a nascent stage. This highlights the problem of composability, which Davis and Tolk (2007) define as “Composability refers to the ability to select and assemble components in various combinations to satisfy specific user requirements meaningfully (NRC 2006)" (p. 860). Additional research is necessary to identify, clarify and resolve composability issues.

Related to the composability challenge is the concept of Validation, Verification and Accreditation of both the individual models and the entire ecosystem of models. Each of the individual models has a VV&A path adjudicated by the product owner (PM or equivalent). However, the ecosystem as a whole has not developed a VV&A plan. Research (Salado, 2015, 2023) offers suggestions to supplement to DODI 500.61 and MIL STD 3022 guidance.

The final challenge discussed in this paper is the topic of ecosystem (and model) governance. Several of the models are not program exclusive and are themselves evolving in conjunction with their environments. Technical advances like the advent of cloud hosting and a microservice architecture collide with monolithic models not designed as Cloud Native Applications. Whether cloud hosted or not, cyber security concerns must be integrated into the development path. Several of the model product owners have mature charters; others are nascent. The earlier reflection on the impact of Industry 4.0 creating a need for multiple participating organizations rather than a single source all create a complex system (or system of systems for those inclined). A governance system is also evolving to enable "control, communication, coordination, and integration of a complex system" (Keating & Bradley, 2015).

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