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Operationalizing digital twins through model-based systems engineering methods

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Abstract

In recent years there has been increased demand for readiness and availability metrics across many industries and especially in national defense to enable data-driven decision making at all levels of planning, maintenance, and operations, and in leveraging integrated models that inform stakeholders of current operational system health and performance metrics. The digital twin (DT) has been identified as a promising approach for deploying these models to fielded systems although several challenges exist in wide adoption and implementation. Two challenges examined in this article are that the nature of DT development is a system-specific endeavor, and the development is usually an additional effort that begins after initial system fielding. A fundamental challenge with DT development, which sets it apart from traditional models, is the DT itself is treated as a separate system, and therefore the physical asset/DT construct becomes a system-of-systems problem. This article explores how objectives in DT development align with those of model-based systems engineering (MBSE), and how the MBSE process can answer questions necessary to define the DT. The key benefits to the approach are leveraging work already being performed during system synthesis and DT development is pushed earlier in a system's lifecycle. This article contributes to the definition and development processes for DTs by proposing a DT development model and path, a method for scoping and defining requirements for a DT, and an approach to integrate DT and system development. An example case study of a Naval unmanned system is presented to illustrate the contributions.

KEYWORDS

autonomy, digital twin, health monitoring, model-based systems engineering, prognostics, systems engineering, unmanned surface vessel

1 | INTRODUCTION

Today there is a significant investment into making systems and systems of systems smarter to better aid stakeholders in the operations of equipment to improve performance or readiness. In industry, the internet of things (IOT), and user intuitive displays make system interaction and decision making far better than in the past. Today, early in a system's acquisition, stakeholders invest in models that aid in communication across stakeholders; many acquisition programs undergo some form of model-based systems engineering (MBSE) to aid in the system synthesis process.

One of the primary tenets of MBSE is the concept of system reuse throughout the system's lifecycle. Today the emergence of the digital twin (DT) as an analytics framework provides new opportunities to operationalize early investments in system models to perform analysis on the physical asset once fielded. Additionally, by leveraging

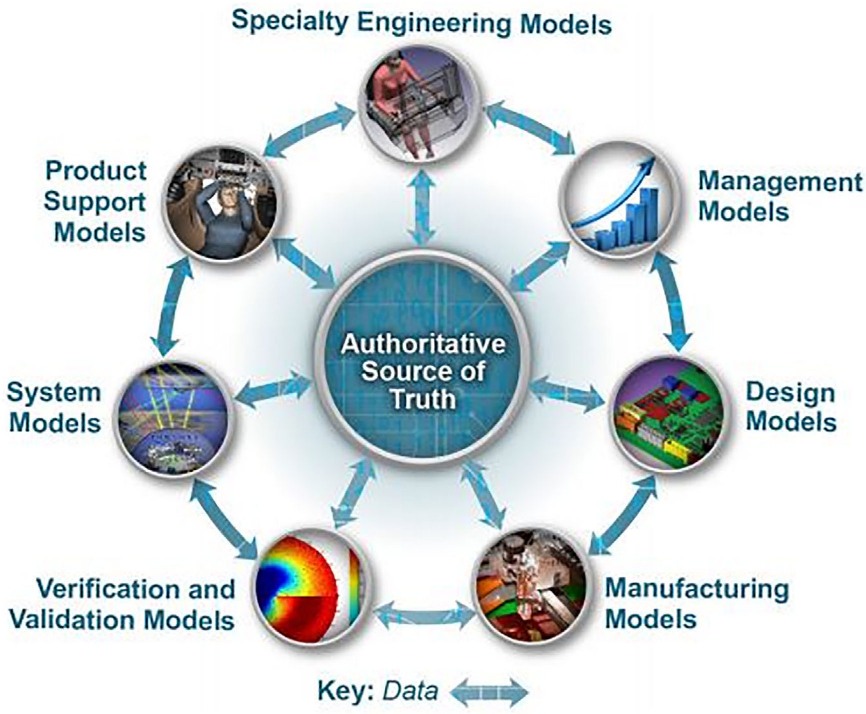

FIGURE 1 DoD digital engineering strategy—integration of models[1]

early MBSE efforts to define the DT, analytic processes used to verify system requirements and early conceptual designs can aid in the verification that fielded assets continue to meet mission objectives, or trigger user intervention when the DT predicts the system will not. In effect, an integrated modeling environment using MBSE can become the DT of the asset if that type of performance analysis is desired.

As a result DTs can be fielded much earlier in a program's lifecycle, which may have a larger net improvement on readiness, while simultaneously reducing the DT's development cost by taking advantage of modeling and stakeholder insights that define the physical asset itself. This concept ties in well with the digital transformation efforts many companies and government agencies are currently pursuing, notably by arming stakeholders across all aspects of the development, operations, and support with intuitive and common data sets to drive better decision making.

One final thought for consideration, is by pursuing a robust systems engineering approach to developing a DT, that twin itself is treated as a separate system, and therefore the physical asset/DT construct becomes a system of systems problem. This opens up a new paradigm of integrated system design and modeling.

1.1 | Digital transformation

Both the Department of the Navy (DoN) and industry are making significant investments in digital transformations to better incorporate data-driven decisions into every aspect of business operations and system lifecycles. In 2018, the Department of Defense (DoD) released the DoD Digital Engineering Strategy with objectives including formalizing the development, integration, and use of models to inform enterprise and program decision making.[1] One critical element in the DoD Digital Engineering Strategy is the leveraging of various system models throughout the lifecycle, shown in Figure 1, to aid in better decision making. For the DoN, the emergence of MBSE and model-based product support (MBPS) provide a technical framework of integrated models to achieve these goals. The current focus on digital transformation is a key concept for this article—everything stated as objectives in digital transformation publications are also key objectives in the use of MBSE to generate DTs. This article, and its contributions to the use of MBSE to drive DT development to enable condition-based maintenance (CBM), directly support the DoD Digital Engineering Strategy.

1.2 | CBM

One significant improvement to the operations and sustainment of fielded systems is the application of CBM—a strategy strengthened by modern electronics and computing systems and which will support the aforementioned DoD Digital Engineering Strategy. There are strong motivations to transition from time-based maintenance (TBM) to CBM[2–4] and leverage system modeling to drive data-driven decisions throughout a product's lifecycle. DTs are widely discussed as a natural framework for tracking and reporting a system's physical condition, and employing predictive analytics, prognostics and health management (PHM), and performance analysis tools for a deployed asset.[5–7] This article will explore alignment with the systems engineering requirements decomposition process and the implementation of a DT to inform stakeholders of the physical asset's health and performance metrics, and drive a CBM strategy.

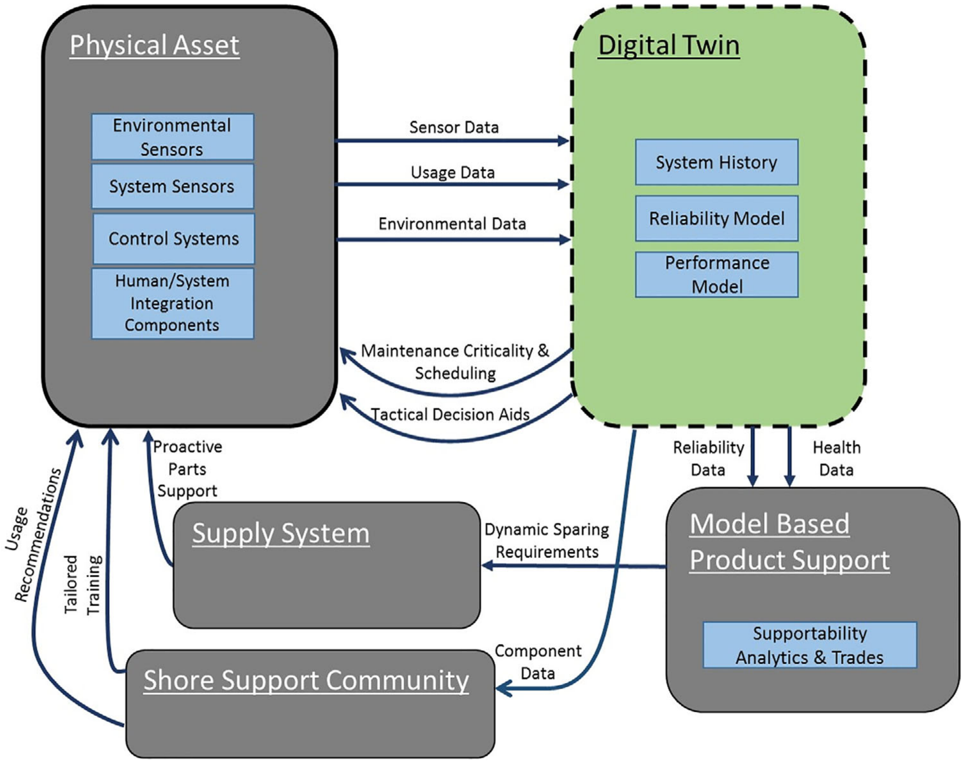

FIGURE 2 Digital twin concept of operations (CONOPS)

1.3 | DT overview

DTs are getting significant attention in both academia and industry. Gartner has identified the DT as a top 10 strategic technology for 2017,[8] 2018,[9] and 2019.[10] In the 2018 report, Gartner states: "A [DT] refers to the digital representation of a real-world entity or system." The National Aeronautics and Space Administration (NASA) provides a more detailed and technical definition. In 2012, NASA defined 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."[11] Since a DT is the virtual representation of a physical asset, it makes sense that there are varying definitions, because different stakeholders have different interests in their DT. A reliability engineer may prioritize reliability tracking. A naval officer may care about performance predictions. An acquisition program manager may care about cost and financial insights from the DT. To put it simply, the authors propose that in general terms, a DT is a model that helps stakeholders answer specific questions by providing a readily available rapidly testable digital analog to the system of interest.

In 2018, Gartner stated: "Organizations will implement DTs simply at first. They will evolve them over time, improving their ability to collect and visualize the right data, apply the right analytics and rules, and respond effectively to business objectives." The second point that DTs will be simple at first but will incrementally evolve is a natural approach given two primary considerations: (1) the cost and complexity of designing and implementing a DT can be cumbersome[5] and expensive, which limits their development, and (2) stakeholders may not know exactly what answers they will need from their DT. Developing a DT for a fielded system requires vision, expertise, and a systems engineering methodology.

There are many types of DTs outlined in Section 2.5 but for this article, the authors will emphasize one of the more complicated use cases: leveraging DTs for prognostics and health monitoring. The generalized concept of operations (CONOPS) for a PHM-centric DT can be found in Figure 2. The DT is connected and operates in parallel to the physical asset. The physical asset provides sensor data, usage data, and environmental data to the DT which then assists with maintenance planning, provides tactical decision aids, and generates health and reliability metrics. The outputs of this DT are leveraged by MBPS to deploy proactive parts supply and training to resolve issues due to the actual systems condition.

1.4 | Today's maintenance problem

Today, many assets are maintained via TBM practices.[12] In the Navy, preventive maintenance is often employed using a reliability-centered maintenance (RCM) philosophy per the Reliability-Centered Maintenance Handbook.[2] The problem with planning and scheduling maintenance based on clock or calendar time is it is inherently inefficient. There are environmental and operational factors that influence the required maintenance periodicity and when maintenance is performed purely off calendar time, those factors are not taken into account and maintenance may not be performed when actually needed. Additionally, preventive maintenance periodicity is often defined by recommendations from the system designer and this practice is not applicable when stakeholder's primary objective is minimizing cost or maximizing performance.[13] This is not a new challenge; one study of machinery in an automobile factory found that overall system effectiveness can be as low as 55% due to maintenance cycles.[14] This demonstrates clear value in optimizing maintenance periodicity. A poorly balanced maintenance frequency results in both reduced availability[14] and affordability.[15]

With a TBM philosophy, devices are either overmaintained or undermaintained, potentially leading to inappropriate levels of downtime. Many less common failure modes are experienced with failure-driven models (FDMs) and components are operated until the point of failure—resulting in downtime due to unexpected failures.[16] In a risk-adverse community there can be a bias toward over maintenance, which is only made worse without strong data driving maintenance.[17] Today's rapid evolution in technology and increasing system complexities makes smarter maintenance a necessity. The net impact of under- or overperformed maintenance is a degradation of availability, cost, or both. This challenge has been observed for many years; in 1990 Wireman analyzed maintenance trends back to 1979 and found that maintenance duration trends have risen by 10% to 15% per year.[18]

To explore the interest in industry and defense[2] to transition from TBM to CBM, it is worthwhile to look at the benefits of CBM and weaknesses in a TBM strategy. For industry, there are profits to make; for defense, arguments can be made for either economic or operational capability. The following factors demonstrate how maintenance performed before or after the required maintenance action result in inefficiency.

1. If maintenance is performed prior to an ideal point in time, maintenance is overperformed and there is a resulting net waste in the total labor and consumables. In a reduced manning environment, this puts a tax on the maintenance crews. In an autonomous environment, the device may be pulled offline prior to a critical mission or at an unnecessarily high frequency for service, which in effect, either reduces the number of operational days for each unit, or increases the number of spare units required to support a task.
2. If maintenance is performed after the optimal point, maintenance is underperformed and components can degrade at a higher rate, the number of unexpected failures naturally rises due to fewer inspection periods. Unexpected failures may bring the system offline in a time-sensitive period, and in the case of autonomous operations it may lead to complete loss of a system.
3. If maintenance is driven by embedded sensors passing data to stakeholders, maintenance can be performed precisely when needed—minimizing downtime, excess consumable usage, and minimized component wear.

An additional challenge that exists with a TBM program is if maintenance is not performed, there may not be objective quality evidence reporting maintenance was not performed. One notable and significant example of this was Alaska Airlines Flight 261, in which it was found that insufficient lubrication led to the crash, after an investigation found a wide range of human, technical, and organizational factors contributed to the event.[19,20] Under a CBM philosophy, embedded sensors can mitigate risk due to human error since sensors monitor system health and provide additional confidence that the system is well equipped to support the mission.

One final challenge with TBM for consideration is there are strong motivations to leverage autonomous vehicles both to reduce operational costs[21] and improve operational flexibility and agility.[22] The operations and scheduling of these assets is complex, as is their likelihood of failure or loss[23] so having a strong understanding of readiness and maintenance required is even higher for these types of assets.

The discussion of TBM versus CBM is very well aligned with the discussion surrounding DT within this article, in alignment with the previous generalized definition for DTs from Section 1.3. The existence of a readily available rapidly testable digital analog to the system of interest provides infrastructure for the analysis of various data for decision making. In this case, maintenance data can be monitored and correlated to a desired outcome, and the aggregation and output of this analysis provides objective, quality evidence that status is understood and operations are proceeding as expected and intended. In effect, the DT collecting the necessary data provides confidence that the system will support the mission in question.

1.5 | Barriers to DT adoption

In some fields, notably the manufacturing sector, there is a significant amount of research covering use cases and return on investment of DT for remote diagnostics employment.[24,25] Unfortunately as with the adoption of a new and novel concept, the development time and costs associated with building a DT make it a difficult undertaking for many organizations. Often publications ignore the cost of DT development as a barrier. Implementation of a DT may be difficult; the cost of a DT may be extremely high or cost prohibitive.[26] In a large program such as the F35 Lightning, the relative investment cost in the DT may have positive return on investment due to a widely fielded population of systems, or a significant cost of operations and maintenance.[5] In the experience of the authors, many programs with low populations of fielded assets such as the Navy, the DT development cost barrier may seem insurmountable. Furthermore, there are only a handful of instances where DTs have successfully been incorporated into the fielding strategy,[24] and the prospective confidence in positive return on investment is hard to quantify.

One major barrier to the employment of DTs is the process for building or implementing them is a very use-case–specific endeavor, so exploration of the academic literature yields very few resources that provide interested stakeholders with a repeatable and generalizable process or strategy for employment. DTs in the literature often cover systems that are already in their operations and maintenance phase, so the development is entirely an after-deployment consideration.[27] This ad hoc nature presents engineers and data scientists with challenges in the lack of a common process for defining requirements for the DT, an unclear path for development, and a steep learning curve for the early stages of implementation. The result of the previous factors is a high DT development cost, and risk that the DT will not have the appropriate functionality to maximize utility to its stakeholders. This results in an overall cost/risk pair that will dissuade many sponsors—especially for programs such as accelerated acquisition or developmental programs.

1.6 | The case for developing a DT during system architecture

Currently many Fleet systems follow a RCM model in which many maintenance actions, notably for hidden failures in which there is no noticeable symptom, are planned and scheduled based on the reliability of components within the system.[28] Given the randomness of many failure modes, TBM is inherently inefficient;[16] many maintenance actions are performed before they are truly required—notably in risk adverse communities[17] such as the DoD, resulting in more maintenance labor than required and increased consumable use. Furthermore, when failures are experienced, corrective action time initiates after the incident resulting in unplanned downtime that can have a significant detrimental effect on business or operations.[5,29]

Often when dealing with internationally distributed systems, the logistics delay times of getting parts to the end-user can take days or weeks. In this environment, PHM tools that can predict such failures, then schedule and prioritize maintenance when it does not impact operation of the system is enormously beneficial to stakeholders. Human capital often ends up being one of the most expensive parts of a business and as a result, many communities are trying to minimize the number of people in the loop,[30] and increase the use of data, analytics, and planning in support models. In the Navy, this is reflected in the Littoral Combat Ship (LCS) community, which has dramatically fewer sailors onboard than would normally be the case.[31,32] In this environment, unnecessary or inefficient preventive maintenance puts a toll on system maintainers, creating even more demand for analytics aiding in maintenance analysis and scheduling.

A DT focused on supporting maintenance, failure predictions, and monitoring system health is effectively a model with integration to system sensors that provide stakeholders with automatic collection and analysis of data to provide PHM insights. “The goal of PHM is to allow systems operators to catch incipient failures early enough to be able to prevent or correct them.”.[33] Employment of PHM sensors early in a system’s design can effectively reduce the likelihood of failure of a component,[33] so by initiating the scoping efforts of the DT during early system requirements decomposition has the highest return on investment:

1. DT development is efficient because many of the questions that drive system synthesis as part of an MBSE approach also establish objectives or requirements for the DT.
2. DT development can play an early role in identifying failure modes, symptoms, and resulting impacts, reducing long-term reliability concerns.
3. DT development early in a program’s design arms PHM teams with early recommendations of the types, quantities, and locations of sensors that will aid the DT’s health monitoring of the physical system For the use case of this article, the authors will explore the operational impacts of deploying a DT for an unmanned system. In the world of autonomous systems, there are not onboard users that can assist with overcoming issues once a casualty is experienced. Deployed autonomous systems may even be completely lost under certain circumstances, resulting in an extremely high cost associated with the failure. Failure tolerance is lowest due to the impact. Due to these factors, it is even more critical to perform necessary actions before failures, which then drives up the preventive maintenance frequency, further driving increased inefficiency.

In addition to development cost and timeline, there are other strong reasons to begin DT development during system design. In addition to the DT, infrastructure and tools to analyze the data are also required. Within the physical asset, implementation of a DT may necessitate additional data storage for data logging, additional processing to perform any edge analysis that is required, a data transport mechanism to get the data to end users, and the end-user processing hardware, software, and tools necessary to interpret the results.

DT-driven requirements within the physical asset are very important considerations, which highlights the efficiency gained by architecting and designing the DT in parallel. In the DT literature, DTs are either built off of the current capabilities that exist in the fielded system, or additional sources of data (sensors) are added to the system. In the first case, the DT is limited in capability to the analysis of data sources that were predicted as a required or valuable data source during design. Accordingly the full capability of a DT may not be realized due to design constraints. In the second case sensors are added to the device after the system is fielded. This results in inefficiencies due to the added steps of installing and integrating those sensors, and in many cases the postfielding sensors are not as well integrated as those in the original design. These reasons are part of our motivations to develop a process that is intuitive that will aid in systems engineers in the architecting of the twin as the physical asset is designed. Finally, in government organizations, the costs associated with engineering changes postfielding can be significant, so there is a strong motivation within the navy to build and integrate the DT concurrently with the system of interest.

1.7 | Specific contributions

One challenge in the field of DTs is there is no standard process for implementing a DT. This article contributes to the definition and development processes for DTs by proposing a DT development model and path. This article specifically proposes a solution for scoping and defining the requirements for a DT, as well as guiding system experts through the process of architecting the DT by leveraging the traditional systems engineering efforts already integral to developmental and acquisition programs. The result of this method is a DT development process that is intuitive to systems engineers and requires

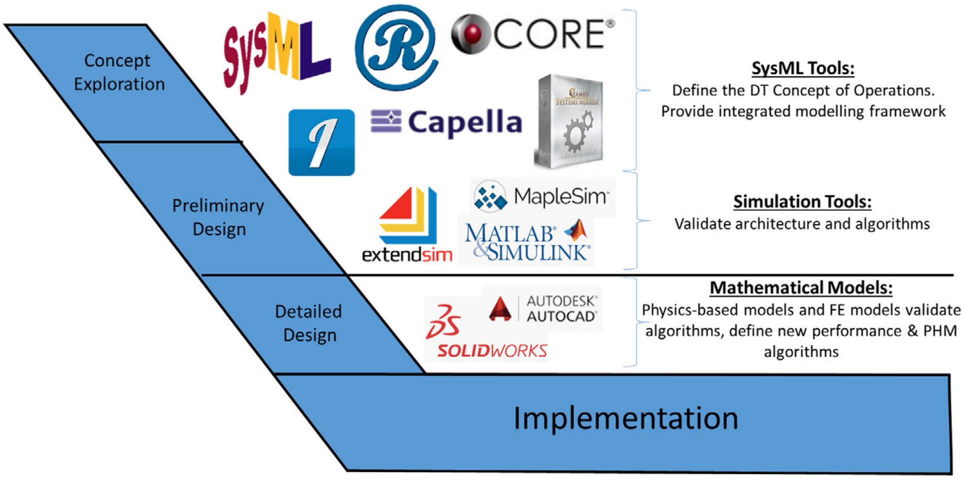

FIGURE 3 Relationship of MBSE, FE, and physics-based models to DT development

lower systems engineering or developer time investment than if a DT is developed as a separate activity postfielding. Specifically, this process leverages the requirements development and verification processes to guide the development of a DT, which is then employed to aid throughout the maintenance phase. Finally, this article explores how the notion of DTs fits in with the field of systems engineering, and describes how a systems engineering approach to defining and fielding a system can also aid in the development of the DT.

2 | BACKGROUND AND RELATED RESEARCH

There are five primary related research areas that are necessary to be understood for the purpose of this article. These research areas include: systems engineering, MBSE, DTs, PHM, and computer-based modeling including finite element (FE) modeling and physics-based modeling. MBSE provides a natural framework for developing a DT. The developed DT is the foundation for implementing PHM algorithms that will enable performing CBM.

2.1 | Systems engineering

The systems engineering process leveraged throughout system design is a very well understood process with decades of research and methodology developed.[34] While this article will not speak directly to a specific systems engineering methodology beyond MBSE, it is important to note that the majority of systems engineering processes have the same fundamental stages for system design: requirements analysis, system specification development, system design, implementation, test, and operations/maintenance. This article emphasizes opportunities to align the development of a DT with the systems engineering process up-front in a programs lifecycle.

Integration of modeling and simulation to answer questions throughout the design process is commonplace. Figure 3 outlines the generic systems engineering process, various tools available to practitioners, and the relationship with DT development. There are two notable considerations of the systems engineering process that will be covered in more depth due to their significant contributions to the DT concept: system architecture definition and stakeholder requirement decomposition.

2.2 | MBSE

MBSE is a field of study within systems engineering focused on the execution of the generic process outlined earlier (requirements development, system design, implementation, test, and operations) within a model-based environment. MBSE is generally described as a methodology used by system architects and technical leadership to aid them in the requirements generation and validation process, system synthesis, and system verification. The International Council on Systems Engineering (INCOSE) defines MBSE as “the formalized application of modelling 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.”

The use of modeling and simulations to aid in system design is a very well-understood concept with numerous publications and instances of use in industry. In 1990 INCOSE was founded and has the vision of “a better world through a systems approach.”.[35] Today in the DoD, the majority of programs undergo some form of systems engineering, and MBSE is becoming increasingly common.

One critical aspect of MBSE ideology is the transition from a document-based acquisition to coherent modeling of a system to describe and communicate among stakeholders. This approach “enhances specification and design quality, reuse of system specifications and design artifacts, and communications among the development team.”.[36] The idea of model reuse is the fundamental goal in the vision for fielding low-cost DTs to aid decision making, something that is consistent with the goals and objectives of modern DoD acquisition and engineering policies.

In practice today, MBSE is most commonly found in the first application, notably after 2003 with DoD Directive 5000.01, and 5000.02 establishes DoD policy that includes systems engineering. The 2003 version of DODD 5000.01 states "[a]cquisition programs shall be managed through the application of a systems engineering approach that optimizes total system performance and minimizes total ownership costs.".[37] Due to this instruction, the use of MBSE is commonly used as the formal process used to decompose stakeholder top-level requirements to subsystem requirements for defense acquisition systems.

One MBSE survey[38] shows that the majority of MBSE processes discussed are specific to the system synthesis process—notable is the use through requirements analysis and decomposition. While DODD 5000.01, INCOSE, and many other sources state MBSE is applicable to the full lifecycle of a system, there are very few publications on how MBSE can be used for sustainment. Given that one of the primary objectives of MBSE is to analyze performance and reliability, one can safely conclude that the use of integrated models that aid decision makers in the analysis of a system of interest's health and performance is an MBSE application. For the sake of this article our MBSE application is the use of this DT to analyze a live system's performance, reliability, suitability, remaining usable life, or other factors that stakeholders would deem necessary during initial system fielding.

MBSE is defined by INCOSE as "the formalized application of modelling to support systems engineering beginning in the conceptual design phase and continuing throughout development and later life cycle phases.".[39] In 2007, INCOSE expanded on this definition in their vision for 2020 by describing specific applicable systems engineering disciplines, stating MBSE is "the formalized application of modelling 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.".[40,41]

In line with these definition, there are three applications of MBSE that align strongly with the vision of building a DT in parallel to the physical system:

1. The use of modeling to aid in system requirements definition and decomposition.
2. The use of models to assist with analysis to demonstrate a chosen conceptual design will meet the necessary requirements.
3. The use of system models throughout a product's lifecycle, notably to assess system health, reliability, maintainability, supportability, and fielded performance.

There are many different methodologies and tools currently in use to implement MBSE.[38,42–45] In the survey produced by Lu, he states SysML is one of the most common MBSE languages. From an architectural perspective, the different system modeling languages (SysML, UML, LML, and others) are general modeling languages. Huynh states that "a general-purpose modelling language for systems engineering, SysML is effective in specifying requirements, system structure, functional behavior, and allocations during specification and design phases of systems engineering.".[45] With respect to DT, all of the objectives and outputs from the different MBSE languages offer insights that will drive the definition and architecture of a DT. Given the fact that these languages all support the objectives for driving DT development, this article intentionally does not select or endorse one specific language, tool, ontology, or process because it is up to MBSE practitioners to select those tools that meet their specific requirements. Part of the value in this methodology is the broad applicability to diverse types of projects.

The critical element of MBSE with respect to a DT is the nature of a DT and is the merging of various models to answer specific questions. MBSE establishes a set of standards and an underlying ontology, which can be adapted to an appropriate architectural framework that guides the development of a DT. In some instances, early MBSE models can evolve and expand over time, increasing in fidelity to the point where they can become part of the DT. There have been several demonstrations in the literature that MBSE modeling efforts can evolve beyond traditional UML, SysML, or LML. System modeling languages have been demonstrated to integrate with MATLAB Simulink to perform CPU processor performance assessments of different architectures in support of chip design,[46] MATLAB for assessing performance of bio implants,[47] DEVSys for discrete event simulations,[48] as well as ExtendSim, SimPy, AnyLogic, NetLogo.[49] MBSE system modeling languages have also been successfully leveraged for use in agency modeling.[50] These examples demonstrate the initial descriptive high-level general models that traditionally would not integrate with future analysis tools, physics-based, or FE models now enable a future MBSE environment where UML, SysML, or LML software provides a framework for on-demand assessment or trade–space analysis. This opens up many new use cases, many of which align directly with current interests for future DTs.

From these points, it becomes clear that MBSE and the vision for DTs are very closely aligned; if developers are able to integrate those system models in the operations and sustainment phase of a program, they together in essence become a DT. In summary, MBSE is the study and application of system models throughout a system's lifecycle, and the authors propose a DT becomes the operational instance of those various models developed in the early stages of a program.

2.3 | FE and physics-based models

FE and physics-based modeling tools are incredibly valuable tools for DTs. FE modelling identifies potential algorithms or models of interest for inclusion within a DT. In effect, these advanced modeling techniques are one of the first insights into a systems performance or failure mode concerns and indicators.

Today many design or acquisition programs go through some level of FE modeling to analyze structural performance and reliability. Research describing the use of FE models date back to at least the 1940s,[51] and computer-aided FE models became popular in the early to mid-1990s. FE models are of particular interest to this article because they have been proven as a method for predicting the reliability of structural components.[52] Today FE models are commonplace during system design to identify critical parameters that influence specific design performance characteristics, and apply mathematics to gain system-specific insights on how requirements are met. Today many computer-aided design (CAD) modeling programs contain native FE analysis tools.

Physics-based modeling is often used for performance-specific applications relevant to the system under consideration. Physics-based or analytical models exist for a wide range of design areas including circuit design,[53] electromagnetics,[54] gas turbine engines,[55] laser atmospheric propagation,[56] projectile impact,[57] explosions,[58] and a wide array of other performance indicating parameters. Often these models are used throughout system development and test and evaluation (T&E).

Since physics-based and FE modeling is used to verify that a system design can meet specific performance characteristics, the insights from FE modeling can be directly implemented in a DT. The multiphysics foundation enables DTs to edge closer and closer to a true virtual representation of a system, and not just a series of models with extreme levels of abstractions. If integrating a physics-based model directly into the DT is not practical, designers may be able to characterize performance of the system based on operational or environmental conditions, and embed sensors that capture data that inform operators if the system is within or out of tolerances determined by models.

To provide an example to this concept—if a gimbal tracking system needs to maintain a certain tracking accuracy and that accuracy is dependant on jitter or vibration observed on the yoke arms, then FE or physics-based modeling may be performed to determine the vibration modes at the pedestal that results in performance degrading harmonics. DT designers can then in turn incorporate the necessary vibration sensors into the pedestal and yoke arms to measure data that predict performance. The DT integrated with the system can either run the physics-based model in parallel to the system, or perform analysis based on the range of normal parameters identified by the system. The resulting insights are then fed to operators in real time for operational decision making, or leveraged for event reconstruction to inform future operations, training, or maintenance decisions.

The final important aspect to FE or physics-based models is they provide knowledge on the operational modes of a system being designed. When compared with operational characteristics of similar systems in the literature, designers may find examples of other successful performance or health characteristics in academic literature that can be leveraged. These modeling tools also provide the opportunity to leverage commercial off the shelf (COTS) tools—essentially providing PHM off the shelf.

2.4 | PHM overview

PHM was introduced in the 1990s by NASA and describes the study of past failure data to devise ways to assess a system's health based on current monitoring data.[33,59] In recent years, PHM has been studied as an approach for assessing system health with the objective of introducing CBM to a system.[60–62] Critically for the employment of CBM, PHM provides predicted system health metrics that can be studied to aid in decision making. In the DoD the primary interest in PHM is in predicting failures to minimize downtime or maximizing operational capability. While these motivations are applicable to a wide range of operational systems, there is particular interest in applications for unmanned systems since there is not a “man in the loop” that can overcome technical challenges during operations. In these cases, PHM and notably PHM for autonomous decision making, something that has also been explored in recent years,[63] is of very high value.

L'Her et al. state “[t]he goal of PHM is to allow systems operators to catch incipient failures early enough to be able to prevent or correct them. The consideration of PHM hardware in the early phase of engineering design can optimize the system design toward this goal.”.[33] From this perspective, PHM strongly aligns with the objective of a DT and provides the conceptual framework for capturing sensor element data to assess potential failures and provide an overall healthy state. For this case study, PHM is our primary means for enabling the desired CBM philosophy.

To implement CBM in a Fleet, system stakeholders need to leverage the application of sensors and predictive analytics/prognostics to schedule maintenance based on when it is needed, versus the traditional TBM schedule or periodicity used in the past. CBM is an opportunity to improve system availability, improve maintenance, and reduce maintenance costs by resolving small issues before major issues arise. On the other hand, preventive maintenance is based on symptoms observed or predicted to mitigate failures once they occur. In order to successfully implement CBM, there are a number of critical elements that must be captured. The operational team needs to understand remaining useful life of components, subsystems, and systems, and maintenance activities must be scheduled based on PHM data.

PHM has a number of similar challenges to DT fielding, notably that PHM is often a consideration after the initial fielding of a system.[33] This means a program does not benefit from PHM until some period after fielding. Additionally, PHM is a relatively new field, especially within the Navy; therefore many design teams may not have expertise in remote monitoring or prognostics. To further complicate this, many algorithms developed to understand health of components are use-case or technology specific. Many approaches exist for implementing PHM,[13] and a variety of different types of algorithms exist for components such as batteries,[64] gearboxes,[65] bearings,[66] hydroturbine blades,[67,68] and others.

Due to the natural alignment between DT and PHM objectives, it can be concluded that leveraging an MBSE methodology throughout system design is a useful strategy and the framework for DT development outlined in this article successfully aids stakeholders in PHM employment, but has broader objectives of identifying and implementing other analytic techniques that might be of interest.

While some of the objectives of DT fielding align well with PHM, it is important to note there are distinct differences, which will become clear in the examples of different types of DTs. A PHM system or algorithm is a component within a system, and rarely exists and provides value without the parent system. A DT can live as a separate entity that provides an example of what a healthy system will look like.

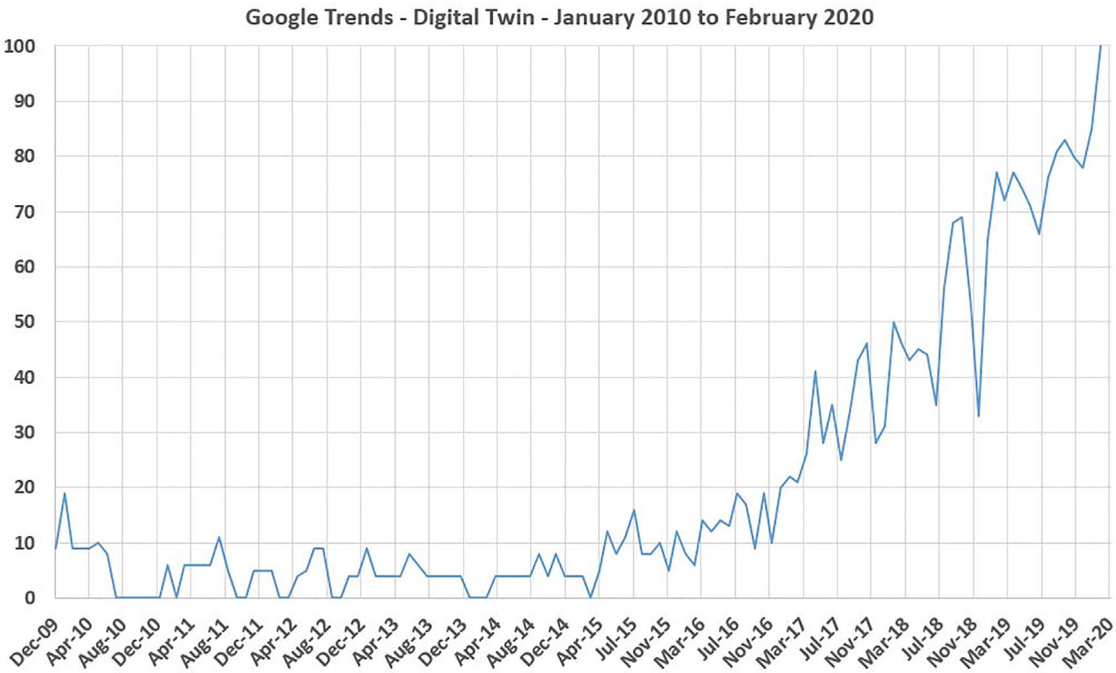

FIGURE 4 Google search trends—January 2010 through January 2020 Data source: Google Trends.[69]

Further, a high fidelity and well-integrated DT can assess the impacts of component degradation on mission effectiveness, something traditional PHM systems often do not include.

In essence, PHM is one critical component in the evolving and expanding objectives for DTs, but it is only one component that is combined with other capabilities to deliver new and unique operational utility. This also exposes DT development to the concept that the DT is itself a separate system to be architected and integrated with the physical asset.

2.5 | DT

DT is a concept that has been described for a number of topics prior to 2004, but has seen a significant rise in the last 10 years as shown in Figure 4. The term DT essentially describes the development and fielding of a virtual representation of a system.[70] There are a wide range of different applications for DTs. DTs are characterized by the seamless integration between the cyber and physical spaces, and have been successfully implemented in product design, production, PHM, and other fields.[71] To highlight the diverse functionality of DTs, several research areas and applications are described below.

In 2012, the NASA defined a DT as the multiphysics, multiscale, probabilistic, ultrafidelity simulation that reflects, in a timely manner, the state of a corresponding DT based on the historical data, real-time sensor data, and physical model.[11] This commonly cited definition helps clearly couple the relationship between a DT and objectives for MBSE.

2.5.1 | Visual aids

For configuration management for infrastructure modernization, the DT may provide a user friendly, authoritative source of a digital view of a physical system that aids users in quickly assessing the as-is state.[72] One example of this type of DT demonstrated in practice includes LiDAR scan point clouds of a power substation that display the spatial locations and visual condition of equipment that allows planners to quickly scan and assess physical assets and infrastructure requirements. In this example, the DT is the dimensional data of how the system of system relates to other elements within or external to the system. In line with the authors' summary of the objective of a DT in Section 1.3, this dimensional DT improves decision making, operations, and maintenance by answering questions on the physical layout of the as-built system. Those questions may be driven by needs to expand capacity, remove and replace obsolete equipment, or even translation into a CAD file type for analysis with other simulation tools as mentioned in Section 2.3.[73]

2.5.2 | PHM

DTs in many instances provide the infrastructure to analyze and report PHM data to stakeholders to better plan and execute maintenance, assist with troubleshooting, determine remaining usable system life, or other health data as required by stakeholders. A NASA team,[11] along with many others in a variety of fields demonstrate the value of integrated robust modeling to answer specific and complicated questions.

DTs have also been proven for airframe health monitoring;[74] in applications such as the NASA use case, the DT is responsible for monitoring crack formation in NASA and Air Force aircraft. These types of applications can be invaluable for stakeholders managing a fleet of fielded systems. As mentioned in Section 2.3, one place to look for insights for implementing PHM focused DTs is early FE modeling, were there may be significant reuse. Further background information on PHM is provided in a subsequent subsection.

2.5.3 | Lifecycle sustainment models

For the logistics community, MBPS, or product lifecycle management (PLM) has emerged in recent years and comprises of a family of integrated models that can increase the efficiency of the operations and sustainment phase of a system.[75–79] PLM provides a capability that is part DT of an asset, plus an analytics model of the supply system applied to sustainment and the logistics tail. Integrated DT models are effectively a DT of the asset, while MBPS delivers a DT of the supply system among other capabilities. Combined they allow modeling and simulation of various use cases to optimize support including maintenance overhauls, adaptive training based on how users interact with a system, enabling dynamic sparing postures, and enabling data-driven decisions in a variety of other supportability considerations.

2.5.4 | Manufacturing

In manufacturing, a DT may be a tool that aids in implementing "Smart Manufacturing" or improving the manufacturability of new designs, notably in an IOT world where distributed stakeholders want to monitor physical equipment or manufacturing processes, analyze throughput, assess ability to manufacture a component with specific tolerances in a manufacturing process with varying tolerances, and many other applications.[5,80]

2.5.5 | DT takeaways

In the following methodology section, this article will demonstrate that the natural MBSE process performed throughout system acquisition helps stakeholders identify questions they want their DT to answer. One will notice there is a common theme across the use cases and applications mentioned above. The application of the DT is focused on delivering insights on a physical asset's condition to stakeholders to drive data-driven decisions. Given the variety of possible DT applications, the authors of this article propose an underlying general concept of a DT: the purpose of a DT is to answer some specific question about the system under consideration.

The key takeaway, and most general definition of a DT the authors will propose, is that a DT is a form of virtual model that answers specific questions. This is an important definition for the sake of this article, as the designer of a DT needs to start with top-level requirements for the DT. What specific questions do end-users need to answer? Examples of the types of questions a stakeholder may want insights on include: "How should this device be serviced based on it's materiel condition?" "What additional training should be incorporated based on user error in the past?" or "How much remaining life exists within this physical structure?"

For the use cases described in the following case study, the proposed concept of a DT will be a packaged multidisciplinary solution that delivers prognostics and heath management, with the ultimate objective of driving CBM and informing logistics systems that leverage MBPS/PLM.

Many DTs aim to provide performance indicators for decision making to stakeholders, mission planners, or operational units, creating a demand for the reuse of performance models throughout the system lifecycle. When considering DT architecture and software, FE and physics-based models may be valuable for the rapid development of the DT due to the potential for reuse of modeling from the development phase of system acquisition. In the author's experience it is not common for their continued use throughout the lifecycle.

3 | METHODOLOGY

While the following methodology is applicable to all of the DT concepts identified in Section 2.5, utility for driving PHM will be the emphasis. A description of such a DT is closely aligned to that of the NASA definition discussed in Section 1.3. Designers are interested in leveraging embedded sensors and the data elements they produce as inputs into modeling and simulation tools to support PHM, and prompt action by operational and sustainment teams. While this is similar to the objectives of PHM, DTs offer a much broader opportunity for real-time monitoring to aid in operations, and an ability to reconstruct a sequence of events based on sensor data. The end goal is to create an integrated framework that provides near real-time visualization of overall system health and streamlines the delivery of data to analysts and operators allowing them to more easily incorporate data-driven insights into their decision-making processes.

One common theme across the current literature and case studies of fielded DTs, is demand for their development arises out of response to some emergent need. In the NASA example,[11] maintenance and sustainment teams needed an integrated model to monitor crack development and structure health impact on aircraft lifespan. In other cases, practitioners will find similar drivers during the operations and sustainment phase. It has been shown in the literature that the inclusion of PHM sensors into a design can have a significant improvement on overall system availability.[33] Since a DT provides the framework for PHM implementation, this conclusion can be made here as well, when considering the use case of unmanned systems where the long-term value in a DT is high due to a significant need to understand and monitor actual system health. As a result there can be great benefit in a systems engineering approach to DT development throughout system development.

In this article, the authors propose a process that aids stakeholders and decision makers in the initial conceptualization and architecture of a DT, as well as address the value added for DoD stakeholders.

TABLE 1 Systems engineering and MBSE efforts

Lifecycle phase	Systems engineering processes	MBSE efforts
Concept exploration	Concept exploration	Capability views
	CONOPS development	Operational views
	System-level requirements (Reqs)	System services models
Preliminary design	Subsystem-level requirements	Activity diagrams
	High-level design	System views
		Interface diagrams
Detailed design	Component-level requirements	System models
	Detailed design	Performance models
		CAD models
		Logistics models
Implementation (assembly)	Hardware and software development	CAD model iterations
	System assembly	Performance model iteration
		Product support model iterations
Test and evaluation	Component requirement verification	Use of system models
	Subsystem req verification	Performance and
	System verification	product support models
	Performance testing	to verify system operability
	Suitability testing	and performance
Operations and maintenance	Lifecycle sustainment	Use of various models to maximize
	Reliability analysis	reliability, availability,
	Performance analysis	and performance
	Modernization	

The authors' vision of the concept of a DT is an integrated composite of different algorithms and tools that help analysts and operators incorporate data into their decision-making process. In the context of this article, the authors are focusing on the operations and performance assessments application of a DT. Those in the operations and sustainment communities will glean insights for their respective industries.

One persistent challenge with the employment of DTs is in practice, they are often undertaken as a capability applied to a system post its initial fielding. As a result, the development of this DT is a new additional activity the sponsor and stakeholders must fund. This limits the fielding of DTs to large programs in which the development cost is low relative to the program's budget, or programs with high numbers of deployed assets that raises the number of systems benefiting from the DT, spreading out the development cost over multiple applications. This is something that the Navy cannot rely on—especially in communities with low-yield high-mix configurations due to rapidly evolving technology and capability. Given the current state of rapid technological evolution, unmanned systems and directed energy are good examples of these types of programs; there is no strong appetite to build robust system-specific analytic tools when the system under consideration will field in a small number, and will be obsolete in a few years.

In order to overcome this inherent challenge with DTs, the authors propose the following methodology that can leverage a significant amount of the work and thought processes followed by the majority of DoD customers. The following methodology is applicable to programs both in-development, or currently fielding, and may lend insight to DT development for fielded systems.

3.1 | Systems engineering process

The following methodology is applicable and tailorable to a number of different systems development and fielding processes. For illustration of the following methodology outline and case study, the authors describe the following lifecycle phases and the accompanying systems engineering processes, and MBSE Efforts of high importance to DT development (Table 1).

Through this system development framework, outlined in Table 1, it is possible to break down the specific questions and data elements that will define the scope, objectives, and drive the implementation of the DT. By doing so, subject matter experts are not duplicating previous work that was performed by previous systems engineers. The following outline in Figure 5 provides the decision process of architecting the DT throughout the traditional MBSE process. It is important to note that while a DT is codeveloped with the physical asset, the DT's development can actually precede the development of the system itself, and in the right circumstances can in fact aid in the development of the physical system by providing a modeling and simulation framework. Further,

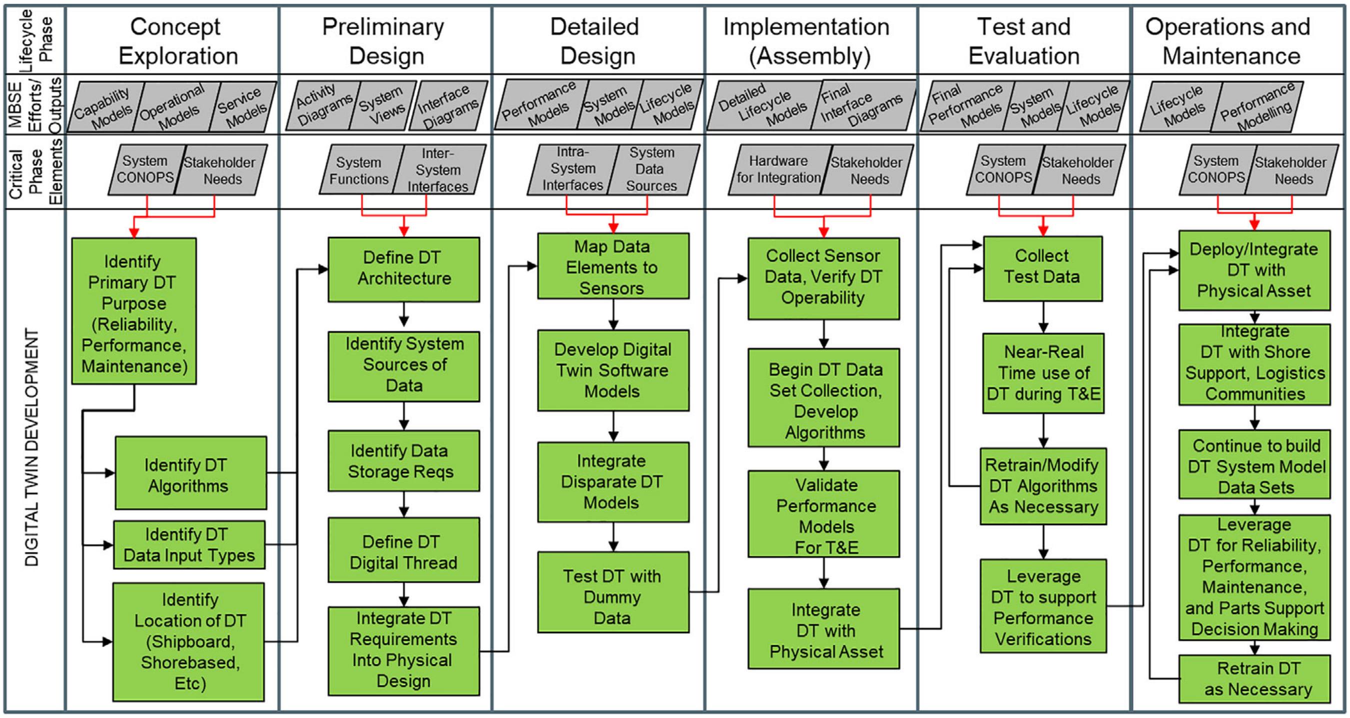

FIGURE 5 Digital twin development through MBSE process

these early DT discussions should also drive component-level requirements for the physical asset to maximize PHM opportunities.

3.2 | Step 1: Concept exploration

Throughout the concept exploration phase, stakeholders analyze the system of systems involved in the intended mission to identify how the new system works within this operational context. Concept exploration includes the development of the system CONOPS, and the derivation of system top-level requirements. This phase is critical for assessing both the intended use cases and mission threads of the system, but these questions also provide significant insights to what stakeholders will desire from the DT; this is essentially the ideal time to identify the primary purpose of the DT.

3.2.1 | Step 1.1: CONOPS

During the CONOPS development phase, systems engineers leverage MBSE to identify external system interfaces, and define the mission context and mission threads. The authors propose that this stage also helps define the scope of the DT, and its CONOPS for use. The CONOPS development for the system also helps identify the various external interfaces that exist to support the mission. Those external interfaces may be valuable sources of data in support of mission performance analysis, reliability assessments, or logistics implications of the current state of operations. From a technical perspective, this is a good time to identify local and remote consumers of DT data. DT designers can identify the ideal location for the DT to reside; if the primary consumer of data is an operator of the system, it may make sense for the DT to reside collocated with the device—especially in circumstances with constrained communications or bandwidth limitations. If the primary user of the DT data is a remote or shore support team, the DT may make sense to reside at their site, or in a cloud linked to the internet or government networks.

3.2.2 | Step 1.2: Top-level requirements analysis

During this phase of system development, the acquisition team takes the system CONOPS and stakeholder top-level requirements, and explores the set of possible solutions. At this point in system development, the authors propose that the systems top-level requirements be used to identify what types of high-level decision making aids may be valuable DT outputs. These top-level requirements are also a valuable source of information regarding the specific mission parameters and performance indicators the DT can provide answers for. For improving operations and sustainment, the primary applications for DTs include reliability, maintainability and maintenance planning, health monitoring, and performance assessments. This is the appropriate time to identify what specific functions this DT needs to perform.

If the consequence of an unexpected failure is catastrophic or the cost of a missed mission due to down equipment is high, stakeholders may desire a DT that aids in the assessment of system reliability, maintains system-specific reliability parameters, and can predict failures and remaining system life. This may be the case for systems like unmanned vehicles that may be difficult to recover if there is a failure during operations and therefore the financial and operational cost of unexpected failures is high. If a fleet of systems are sustained with limited maintenance throughput, the duration of maintenance becomes an operations planning driver, or other maintenance challenges that result in high value in maintenance scheduling and prioritization, then a DT that tracks system health and correlates maintenance actions to extended system longevity is high priority. If mission performance or mission success is of high criticality such as a self-defense system or surveillance system, then a DT that supports performance analysis to provide insights on system performance based on materiel condition may be desirable. The ability to provide rapid decision aiding tools based on environmental or health assessments can be invaluable to operations planners.

Stakeholders must ask where concern areas are, or where data-informed decisions have high return on investment; this will inform the engineering community of priority analytics functions within the DT. Notable DT goals may be to maximize availability, minimize required resources, or drive better use of the system based on performance analysis. Potential high return on investment capabilities include performing predictive analytics to enable CBM, improve maintenance scheduling and priority, maximizing system availability, predictive part failures analysis, or other factors. Notable insights include concern areas that can be tracked or identified by the DT, impacts and value of those early indications, and the necessary external interfaces that will exist for the DT.

3.3 | Step 2: Preliminary design

During the preliminary design phase, systems engineers take the top-level requirements, a mission thread, and the CONOPS, and decompose those requirements into the critical functions that the system must perform. The authors propose that this is the appropriate time to take the previously identified objective and functions of the DT and develop the support DT architecture, and the CONOPS of the DT's employment. If the program is using a rigorous MBSE process, the analysis performed through MBSE is directly applicable and may be leverageable for the DT development. Any mission modeling that is performed to drive requirements can also be leveraged to analyze mission degrading impacts due to physical, materiel, or environmental conditions. These insights identify system sources of data to meet defined DT objectives.

In later stages of the preliminary design phase, systems engineers leveraging MBSE increase the fidelity of system models through the modeling of activity diagrams, various system views, interface diagrams, and resource diagrams to help derive subsystem-level requirements. During this phase, subsystem-level requirements and a high-level design begin to come together. The developer of the DT can start to assess what generic data element types inform stakeholders of subsystem-level health and performance characteristics in support of the previously mentioned DT objectives. If physics-based modeling is included in the MBSE work performed by the systems engineering team, then these subsystem data elements, algorithms, and integration requirements should be leveraged within the DT—either by the reuse of MBSE models becoming the foundation of the DT, or by the replication of the MBSE process and framework within the DT leveraging other analysis or modeling and simulation tools.

This is the appropriate time to revisit the DT objectives to conceptualize the data requirements to support the DT. One general DT data element of high interest for a broad array of DT applications is operational sensor data. If embedded sensors are expected to exist within subcomponents of interest, those data outputs may be useful for trend analysis and correlation to specific casualties, may indicate or trigger specific maintenance actions, and may provide insights to system-level performance impacts based on subcomponent performance indicators.

For a reliability, failure prediction, and remaining system life DT, it may be beneficial to begin to build a detailed system tree or configuration document identifying all components within the systems, and the missions they support. Data should be associated with each entity within the system configuration documentation. Specific data types that will aid in the analysis include but are not limited to casualty tracking data, configuration data, component history and usage data, environmental data, and operational data.

For a DT with requirements to support maintenance scheduling and prioritization, the DT will likely need to consume maintenance data, sensor data that indicate degraded performance, and some level of remaining component life indicators to drive the replacement of components that are high risk.

For a DT that emphasizes performance analysis, the primary data source for analysis will be the previously mentioned subcomponent sensor feeds. DT developers and systems engineers should work with the component subject matter experts to identify how subcomponent performance is traceable to system-level performance so that system-level performance indicators can be created from component sensor data. One possible valuable architecture for this type of DT is the concept of risk-based decision making[81–83] to inform mission planners of the various probabilities of mission success.

At this point in a system's design process, PHM or performance assessment methods will come into play. DT developers should begin to work closely with component engineers to identify and verify the right data sources and data elements are being considered. It is critical to capture derived system requirements that are necessary to support the DT, and ensure those requirements result in the necessary hardware and software changes to support DT. It may be necessary to revise the design to include additional sensors to ensure the appropriate data will be available in the final product. By this point, the DT framework should be well established, and estimated data can be entered into the DT for test and validation that the DT supports mission requirements.

Once the DT architecture and data elements are defined, it is appropriate to begin to develop the digital thread, or the integration of systems and communication channels that transfer DT data from sources to consumers.[84,85]

As the system's conceptual design matures, so will the DT as specific data elements of interest can be inferred before final parts selection. If enough investments are made in the DT, it can now start to be used as a design aid by providing modeling and simulation capabilities for the analysis of alternatives. This may come in the form of a detailed requirements tree that assists with allocation of reliability requirements, jitter budgets for laser, radar, or electronic warfare systems, or other health or performance characteristic metrics of interest. When considering the development of the DT, this is a good time to finalize the DT's architecture, and identify what sensors are expected to exist within the system that data need to be collected from, what application programming interface (API) is required to collect and distribute that data, and what the resulting data collection and storage requirements are for the DT.

3.4 | Step 3: Detailed design

As the system design progresses into component-level requirements and a detailed design, sensor or component-specific data elements need to be mapped to the appropriate functions and algorithms within the DT. Many derived component requirements may need to be pulled into the DT. For example, a highly redundant phased array radar's effective transmit power scales with the low-level component powers. These types of component-level design trades drive a detailed system design that meets system-level requirements. For a performance-focused DT, this analysis is the foundation for the future DT's performance analysis algorithms. Modeling performed to confirm that component-level parameters support system-level requirements lend direct insight to how that data, when collected and monitored, will assist in PHM or performance analysis.

If these component design trades are not performed through the MBSE process, the opportunity still exists for design engineers to develop algorithms assessing component-level performance variations on the system-level performance or reliability capability, but the DT development will require more attention from the component SMEs.

Various disparate DT algorithms or models can now start to be integrated where possible. If risk-based decision making is being used to build a composite recommendation based on disparate PHM algorithms, this is the appropriate time to start determining weighting factors for the different models.

From a DT development perspective, by the end of the detailed design phase, DT designers should have enough information by this point to finish the preliminary design for the DT, ensure the included analytics techniques and algorithms perform correctly. If so, DT software can be written, artificial data used to verify interoperability, and validate recommendations.

3.5 | Step 4: Implementation (assembly)

During the software and hardware development phase, the system under consideration materializes as the system is assembled from its base components. This means sensors, hardware elements, and software that generate data that will be analyzed by the DT now become available to DT designers. As a result, a best practice would be to leverage the DT to feed performance insights back into the system's design as an analytics framework. During prior steps, DT designers take insights from the system's design to drive the development of the DT. By this point the DT's objectives, architecture, and design should be stable and the DT sensor requirements previously identified should be manifesting in the physical system.

3.6 | Step 5: T&E

When the system transitions into the T&E phase of the program, DT developers now have an opportunity to begin to use the DT, collect test data, and train DT algorithms. There also may be opportunities to use the DT and algorithms to support T&E, as outlined below.

3.6.1 | Step 5.1: Component-level testing and verification

At the component testing phase of system development, the design team begins to collect data on the performance of system components. This makes it a good time to start demonstrating the capability of the DT, and depending on level of design maturity of both the DT and physical system, the DT may be a valuable tool for many subcomponent tests and validations. As components start to transition into component-level testing, any data collected should be loaded into the DT to verify algorithms work as intended. This may be a reasonable time to begin collecting these sensor data to build the system's data library. In certain circumstances, the design team can use the DT to model actual component performance and the expected impact on system-level performance. This can assist with validation that the chosen parts do support the top-level design.

Finally, the logging and storing of component data throughout the system's lifecycle may be a desired function of the DT; if this is the case, the DT should be collecting and logging serial number specific data elements. These data elements will be valuable for comparing laboratory versus field conditions impact on performance, and over time will be the initial data elements for long-term reliability and performance trend analysis. Additionally, if there are performance differences between identical fielded units, these historic component data elements may provide valuable serialized data sets for analysis and engineering investigations.

3.6.2 | Step 5.2: Subsystem-level testing and verification

During subsystem testing the involvement of the DT is very similar to that as in component-level testing, but by testing higher level assemblies, designers may have better interfaces to work with. If DT development is advanced enough, the actual interface that passes data from the physical asset to the DT may be stable and can be used and verified as well.

3.6.3 | Step 5.3: System-level testing and verification

As the program enters system-level testing, the design and test teams should now be able to leverage most of the M&S capability within the DT and it can be a valuable asset for performance analysis. If the DT is focused on reliability modeling, maintenance scheduling and prioritization, or feeding a PLM tool or logistics chain, then the DT may not have large enough sample sizes to be high impact. In these circumstances T&E data should be collected to support the building and refining of algorithms—especially if machine learning is to be used.

3.7 | Step 6: Operations and maintenance

Once the system under development hits deployment, operations, and maintenance, the DT should now be employed with the physical asset. A rigorous data collection, storage, and analysis process must be established to build a strong data set with which the DT can draw insights from. Stakeholders should start addressing feedback or recommendations from the DT when making decisions about operations and sustainment of the system. If recommendations are good, confidence will grow in the DT. If recommendations are bad, the DT must be refined as necessary.

DT development does not end once the physical asset is deployed. As with any data science program, increasing volumes of data improve model accuracy and analytics capability. Data collected in the early stages of the program are essential to refining these models. Further, stakeholders such as fleet stakeholders may identify emergent requirements for the DT, or changes to the DT based on changes to the support infrastructure, depot locations, updated maintenance task analysis efforts, etc.

3.8 | Methodology summary

The methodology outlined in this section demonstrates that the process for defining, architecting, building, testing, and deploying a physical system naturally aligns with the process a systems engineer would take to design and build a DT. The methodology demonstrates how key MBSE processes that drive system architecture also drive DT architecture. Critically, the discussions around the development of these models support the development of the DT including:

1. Operational views provide insights to where the DT should integrate with the system and where data might be consumed.
2. Activity models show the system actions and interactions of interest for DT monitoring.
3. System hierarchy models show the system of systems, components, and subcomponents of interest for display or monitoring.
4. Scenario diagrams show mission threads of particular interest if there is motivation to model mission performance.

From a return on investment perspective, this methodology accomplishes two goals for stakeholders. First, the DT is available to support early phases of the program—possibly including T&E. The up-front investment in a DT model ties together all of the available analysis performed throughout the lifecycle, rather than a limited subset, maximizing total utility. Second, DT development is not an isolated delayed activity initiated postfielding after a systematic issue has been observed in the operations and sustainment. Given these concepts, it is fair to assume these two factors result in decreased overall cost of DT development and employment.

4 | CASE STUDY

This section presents a case study to illustrate and demonstrate the method proposed above. The case study presented here is not an exhaustive study of a specific system. Instead, the case study shows how the method can work in a simplified manner to highlight the benefits of the method.

4.1 | Unmanned systems background

In recent years there has been an explosion of unmanned systems entering the maritime environment. A wide range of both surface and subsurface unmanned systems are currently operational. Of note, Seagliders have been employed for academic and research purposes for many years.[86–90] In the surface community, unmanned surface vessels (USVs) have seen significant growth in recent years as well. In 2016 the U.S. Navy fielded a medium displacement USV named the Sea Hunter,[91] with an operational architecture defined by Casola et al.[92]

Use cases of these systems range from logistics transport vessels, environmental data collection and monitoring, surveillance and patrol, and a wide array of military applications.[93] For the case study of this article, the authors will build upon the conceptual USV (USV) mission sets described by Corfield and Young,[94] Ru-jian Yan et al.,[95] and Yaakob et al.[96] In these examples, the concept of unmanned systems are thoroughly explored as a cost effective, low risk, force multiplier—notably for littoral environments.[93] The specific use case under consideration is the use of a distributed fleet of USVs for the patrol of a remote island area. Of particular relevance to the topic of DTs, unmanned systems offer a new challenge when compared to manned vessels—unmanned vessels do not have a human in physical contact with the asset that can resolve or mitigate risk from unexpected failures. As a result of this challenge, there is lower tolerance for risk and increased need for fault diagnosis, fault tolerant controls, and redundancy.[97]

This case study will leverage an idealized unmanned surface vehicle (USV) to compare theoretical availability both with and without a DT developed in parallel to the system.

As shown in Figure 6, there are a number of commercially available unmanned systems that are inherently modular and can support a variety of hardware modules and missions. Notable examples include the Arctic Research Centre Autonomous Boat (ARCAB),[98] Aquarius

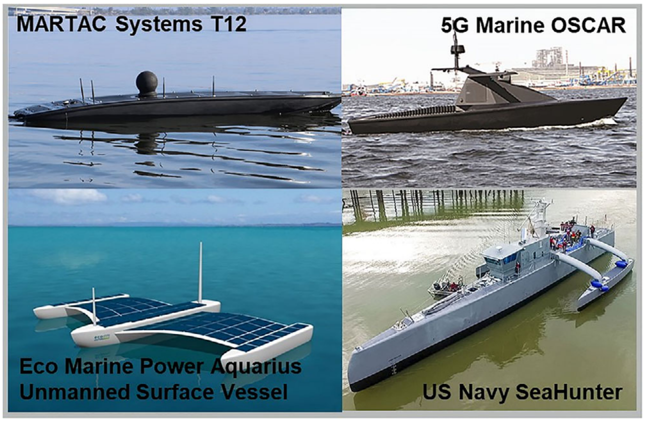

FIGURE 6 Currently available unmanned surface vessels of interest for this case study

USV Vessel under development by Eco Marine Power,[99] MANTAS Unmanned Surface Vessel developed by MARTAC Systems,[100] or several products produced by 5G International Inc.[101] These systems are shown and described to familiarize the reader with comparable real-world systems. The following case study will not assess any of these vehicles directly, and will leverage a generic USV architecture.

USVs are regularly cited as a natural platform for surveillance.[102] For this case study, an idealized fictitious operational scenario will be used. This case study is illustrative of the method and is representative of what might happen to the real system but is explicitly not used to make engineering decisions about any real specific system or ongoing project.

4.2 | USV mission context

A small fleet of USVs operate out of an unmanned or minimally manned forward USV base, as seen in Figure 8. These USVs autonomously patrol a coastline via fixed GPS coordinate waypoints. The specific coastline in consideration is of important strategic value and the cost of a missed or failed patrol is considered high to stakeholders. Due to the remote operation area, logistics delay times are significant and maintaining a large manned contingent becomes costly.

4.3 | USV scenario

The following system assumptions are made in the case study:

1. The unmanned vehicle's primary purpose is littoral patrol.
2. The unmanned vehicle is semiautonomous and can run missions based on GPS waypoints.
3. The unmanned vehicle is based out of a forward operating, unmanned or minimally manned port and has the ability to periodically replenish its fuel reserves.
4. There is a fleet of 10 unmanned systems.

The following stakeholder assumptions are made for the sake of this analysis:

1. Inability to perform a mission is of high consequence.
2. Loss of communications of the USV has a high likelihood of resulting in complete loss of a USV.
3. Due to the cost of sustaining the forward-operating base, assets in-theater are kept to a minimum, including maintenance crews, support personnel infrastructure, tools, and spare parts.

4.4 | Case study systems engineering process

For this case study, the high-level generic architecture consists of a battery-based energy storage module (ESM) that serves as the primary energy stores for the USV, an electric propulsion system, a satellite communication (SATCOM) system, surface electro-optical (EO) cameras for surveillance, water sampling systems, and an onboard computer that controls the USV. An example block diagram can be seen in Figure 7.

The following describes the systems engineering methodology, and the resulting DT insights gained at each step.

4.4.1 | Step 1: Concept exploration

Stakeholders require an USV that can operate in a remote forward operational area. Due to the high volume of searchable area that requires patrolling, and the significant burden of sustaining a large team at this remote site, USVs have been identified as the appropriate asset. USVs will execute continuous patrolling operations along a long and extensive coastline.

Due to the remote nature of this forward operating site, the port is minimally manned to reduce logistics requirements, which puts an increased priority on the ability to predict and plan maintenance, hardware remaining usable life, and potential hardware failures. The implementation of PHM to aid in the prediction and scheduling of maintenance is a key function of the DT.

Due to the high priority of this specific coastal area, inability to perform a mission due to unplanned maintenance or hardware failures is high consequence. Given the nature of autonomous operations, there is an always present risk of total system loss due to some critical failures. These factors drive requirements for the DT to monitor each USVs health, perform predictive failure analysis. For this case study, this drives a confidence in availability to 95%.

Due to the potentially long transit times of the USV, and loss of awareness if a unit is recalled and a replacement is redeployed—stakeholders will want the DT to answer questions regarding the system's ability to successfully perform a mission based on the performance metrics of its components. This decomposes to a requirement for the DT to perform analysis for sensor systems, propulsion systems, and communication systems. Algorithms that aid in the tracking of the health and performance of these components is of high value to avoid missed missions.

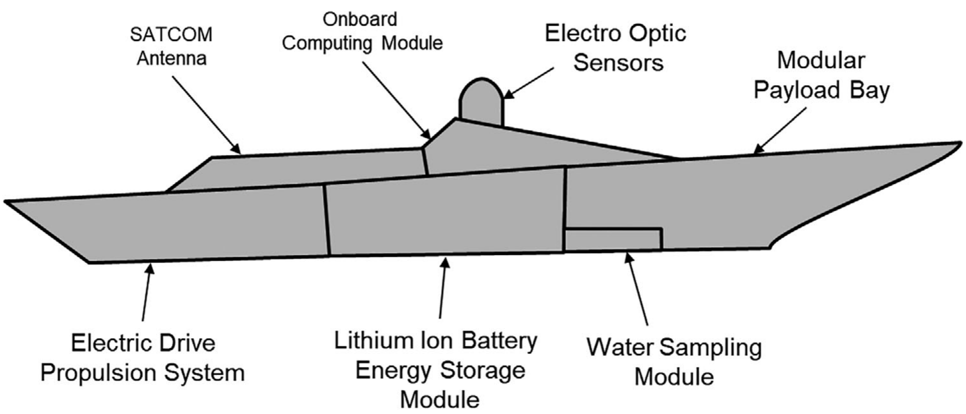

FIGURE 7 Block diagram for the notional USV

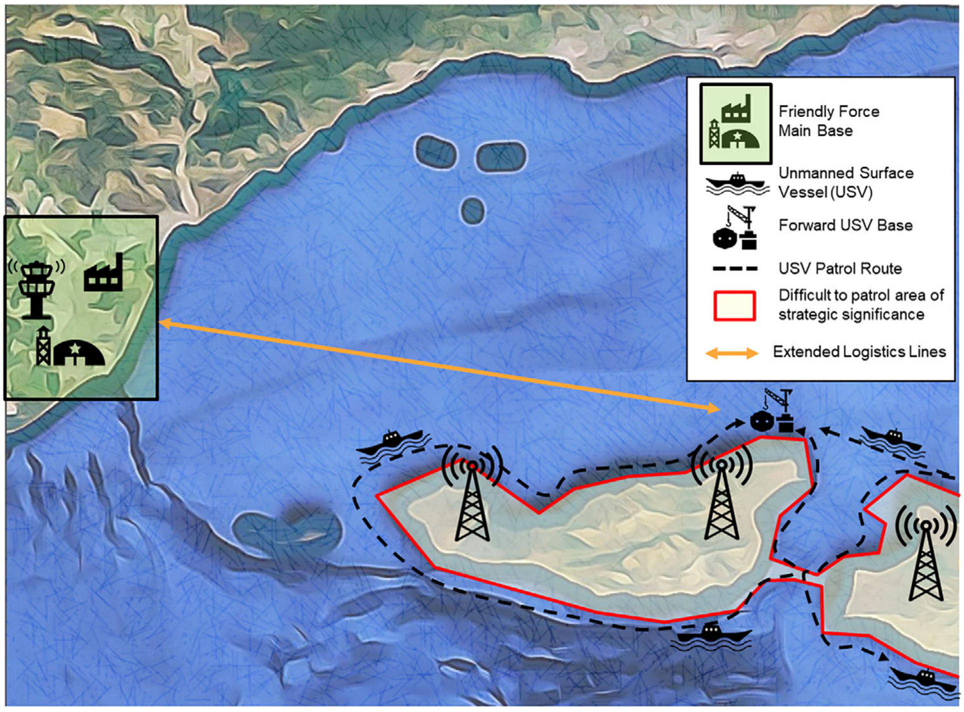

FIGURE 8 USV operational environment

Given the stakeholder requirement analysis performed throughout the concept exploration phase, the DTs CONOPS can now be formalized. There is concern with missed missions, and lost USVs due to unexpected system failures. It is important that at this point in the requirements analysis to assess stakeholder risk tolerances.

1. Predictive failure analysis: will identify components that are at high risk of near-term failures. Local stakeholders will leverage this information to plan near-term preventive maintenance and determine which assets should execute specific missions. Predictive failure analysis will also be used to prompt the ordering of repair parts when certain risk thresholds are met.
2. Health monitoring: will aid in mission planning to ensure vessels selected for specific missions have the ability to perform the necessary mission, and will help plan longer term maintenance actions such as major system overhauls that will take USVs offline for extended periods of time.
3. Physical location: given that the primary consumer of DT data will be the operations and maintenance teams so it is logical for the DT to reside at the forward USV base with some of the processing performed by the USV. General health monitoring data can be remotely transferred to additional stakeholders via an internet connection. Operators will want constant health and status of the USV and there is also value in emergency PHM reports directly from the

USV to the forward base to aid in recovery after an unexpected loss.

Taking the required functions and general CONOPS from the previous step, DT developers can now identify the general types of algorithms that will support these mission areas. For component failure predictions, algorithms and methodologies need to be gathered from application-specific literature and collaboration with the physical asset's design teams as the system's preliminary design solidifies and the types of components are identified.

4.4.2 | Step 2: Preliminary design

When an acquisition program gets to the preliminary design phase, DT developers know the general DT CONOPS and architecture and can outline the DTs architecture. Embedded sensors throughout the USV provide data to the USV onboard computer, which performs basic data reduction and sends status updates to the shore support community. Upon return to the Forward USV base, data are uploaded to a computing system. As the preliminary design progresses and the high-level USV design depicted in Figure 7 is selected, the DT developer can begin to look at the available PHM literature to identify the specific algorithms.

System models such as activity diagrams, interface diagrams, and service models inform stakeholders that shipboard infrastructure is required to collect PHM data. The onboard computing module within the USV already contains the necessary interfaces to support this analysis.

Once the general DT CONOPS is defined, it is valuable to assess current PHM and performance analysis techniques that are applicable to the system under consideration. This helps refine the DT architecture and identify system sources of data. For this case study example, PHM is widely studied for Lithium Ion batteries, and tools are available such as the Adaptive Recurrent Neural Network (ARNN) developed by He et al.[64] to conduct PHM analysis. For the application of PHM for the electric propulsion system, a process such as that developed by Ginart et al.[103] may be useful. Identifying these types of algorithms that exist help clearly identify system sources of data, or areas where senors might be of interest.

This process may not work for all subcomponents in the system. For example, SATCOM antennas come in a variety of architectures with a wide array of electronics. In these cases, working with the component's OEM to model or derive reliability parameters may be necessary.

Toward the end of the preliminary design phase of the USV's architecture, we now have a defined DT architecture, we have identified system sources of data and some types of general algorithms that will assist with the necessary analysis, data requirements can start to be defined, and a digital thread can be established. DT system requirements can now start to be integrated into the system's requirements documentation, and as hardware is selected, assessments can be made regarding whether or not included sensors are sufficient to meet DT requirements, and if not—additional sensors can be designed in during the detailed design phase.

4.4.3 | Step 3: Detailed design

As the system transitions into the detailed design, DT architects can now verify that the chosen design meets the necessary sensor requirements for the DT, and DT designers can now verify these parameters are available for the selected battery systems in the USV, and these data elements can be mapped to specific sensors of interest. At this point, a data/sensor traceability matrix may be of value to ensure all PHM data streams have the appropriately identified data source.

Any physics-based models or FE models generated for system assessments also come into play at this point. With a relatively simple system such as this USV, PBMs are likely to only be performed for the surface vessel's structure, and induced jitter on the sensor payload. It is assumed that this is the case, and these models are mentioned below.

4.4.3.1 PHM algorithms and considerations for the USV case study

For the lithium-ion batteries in the power storage module, the PHM algorithms use internal impedance, cycle numbers, and battery aging rate to determine remaining useful life. Cycle numbers and internal impedance is readily available for most lithium ion batteries so data collection is trivial. The battery-specific aging rates need to be characterized, so that data will need to be included in test plans for component testing so that they can be analyzed and the necessary PHM algorithm can be developed to support initial fielding.

For the propulsion system, Ginart[103] has shown PHM can be implemented by analyzing the inverter pulse-width modulation (PWM) waveform to analyze transistor degradation. PWM data need to be included in the DT plan, and the design team needs to ensure integration between the onboard computer and the necessary sensors to capture PWM.

Strain gauges and fiber optic sensors are one accepted way to monitor structural health and fatigue.[104–108] Grisso and Drazen have demonstrated the use of sensor data for DTs of ship structures.[105] Fiber optic sensors are inherently rugged, and instrumenting a relatively small USV with these fibers is a very achievable endeavor. This is an area where PBM may have played an important role in hull selection. Models used for the assessment and downselect should be assessed to determine if the new application of PHM sensors align with model inputs or outputs. If so, bounds or correlated values may be drawn for early versions of the model.

Employing PHM for complex electrical systems can be challenging. In the case of the SATCOM subsystem DT developers have options. First, they can rely on the built in test capabilities provided by the SATCOM system vendor. Second, DT developers can inspect the system and perform a failure modes effects and criticality analysis (FMECA)[109] to assess the various failure modes that will result in degraded mission performance, a failed mission, and total loss of an operational asset. For each of these failure modes, DT developers can analyze the various embedded sensors supporting each mission, and work with the design team to collect data sets that can be correlated to each failure mode. Prognostics failure mode/sensor data correlation and algorithm development can be a major undertaking so it may be best to defer to the OEM for a small program.

PHM for electro-optic systems (EO/IR) will likely be focused on degrading sensor performance and the EO/IR's ability to support mission requirements. Monitoring changes from baseline or the sensors ability to modify contrast, blur, noise, or dynamic range will provide indication of system performance. Stakeholders can analyze these performance indicating parameters to correlate outputs to performance in detecting and identifying targets at required ranges. There have been several studies and methodologies developed to apply PHM to complex electrical systems that may aid design engineers and DT developers in building capability within their systems.[110]

The DT data source and algorithm mapping is now driving embedded sensor requirements, the onboard computing system now has the additional requirements of hosting the DT models, and the SATCOM antenna has the additional requirements of providing data link to the forward USV base.

4.4.3.2: Develop DT software

For the implementation of the DT, developers have a number of different tools at their disposal. DT work can be done in LabView, Simulink, MATLAB, Python. In general, any tool that can support the required analytic processes can work. There has recently been the emergence of advanced software tools that have built in physics engines and models that can accelerate some development timelines. In our use case, the DT is intended to run continuously during operations and partially resides within the physical system therefore a human-in-the-loop excel based or other software tool that works optimally when controlled by a user is not desired.

For the architecture of the DT described, as previously mentioned embedded system sensors continuously collect data during normal operations. Block-specific algorithms analyze those sensor data streams and provide maintenance and performance insights to operations and maintenance teams.

The final remaining key component of the DT is something that translates individual component knowledge into actionable information. In this case, the DT is monitoring the individual health of SATCOM

4.4.4 | Step 4: Implementation

During the system implementation phase, the DT framework should be developed, algorithms should be notionally established, and where possible validated or tuned with real data captured during any component testing that was performed during the detailed design.

In this case study, we will keep the specifics general to remain hardware agnostic. During system implementation, the DT should be fully integrated with the physical asset: sensors identified in the previous step must be integrated into components, data interfaces must be established between sensors and the onboard computer to collect and analyze data, operations and maintenance recommendation tools must be established, and data collection/transfer software must be written to deliver data to stakeholders for postevent construction.

4.4.5 | Step 5: T&E

Given that the primary purpose of the USV DT is to predict failures, track reliability, aid in maintenance planning, and indicate probability of a future failed mission, the DT in this case study is not expected to have significant value to stakeholders during the T&E phase. Areas where this may be reconsidered include specific parameters stakeholders may have identified as critical key performance indicators such as EO/IR performance assessments, propulsion performance parameters, power storage voltage or amperage values under load, or SATCOM bandwidth.

4.4.6 | Step 6: Operations and maintenance

Once the system enters operations and maintenance, the DT becomes fully operational. For the analysis of the impact of implementation of the aforementioned DT on a USV, notional mean time to failure (MTTF) data has been identified for the blocks of the USV under consideration. The following table identifies these reliability parameters. Additionally, this DT monitors optical sensor performance, which will predict possible mission failure due to performance degradation.

The primary delivered function of this DT, as shown in Figure 9, provides health and performance characteristics on the SATCOM, onboard computer, EO/IR, hull, energy storage, and propulsion systems. While valuable, these insights have limited value to an entry-level USV operator or maintainer. A maintenance and mission planning recommendation system front-end is a necessary final component.

4.4.7 | DT development summary

The previous steps demonstrated that the various stages of MBSE usage during the system development process can clearly help scope and define the requirements for the DT. Specific to this case study, stakeholders see high value in a DT that aids in predictive analytics to minimize downtime. Throughout the DT methodology, specific PHM algorithms and methodologies were identified that will aid in the future PHM that will drive predictive analytics and enable CBM. It is important to note that there is a common theme in the PHM processes identified—they require the usage data, sensor data, and environmental data to perform their functions. The individual algorithms within the DT make system-specific recommendations to operations and maintenance crews for the upcoming maintenance and parts required for continued operations.

It is also important to note that there is also an opportunity to leverage the data coming out of the DT to aid in improved usage of the system. This would be done through monitoring usage of some of these

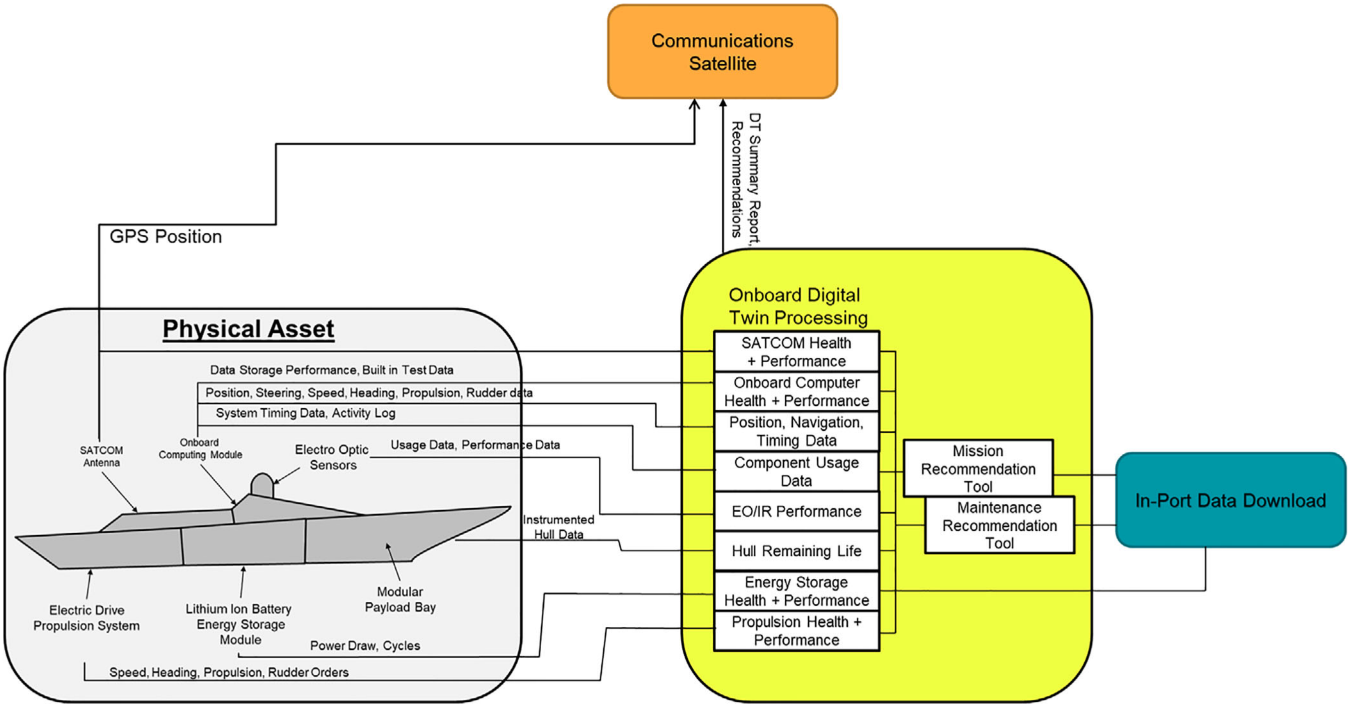

FIGURE 9 Final DT architecture

blocks, but the modeling of that impact on system operation is a use-case–specific application and is slightly out of scope of this article given the objective of the case study is demonstrating the ability to leverage the MBSE system development process to generate a DT. Further, the analysis in this case study demonstrates there is a high potential for very early return on investment from this development.

4.5 | Assessing DT availability improvements

Since the specific components, sensors, and operational context were generalized in this case study, actual performance analysis of the conceptual DT cannot be determined. Assessing the impact of a conceptual DT, however, is a great way of demonstrating applicability and value in the application of a DT. In this case, we can estimate the baseline theoretical availability of the USV system without a DT based on data found on vendor websites and within the literature. That baseline number can be compared to an estimated value based on a theoretical improvement by a DT that offers insights on required maintenance or potential failed missions.

For the reliability modeling of the deployed USV, the availability modeling process used for this case study is described by Ward et al.[111] Figure 10 shows the sequence of events within a Monte Carlo simulation. Reliability data, shown in Table 2 were gathered from a number of manufacturer specifications for representative hardware. Critical parameters for this model include MTTF, sometimes referred in other publications as mean time between failures (MTBF), mean logistics delay time (MLDT), and mean time to repair (MTTR). These terms are all defined in OPNAVINST3000.12a.[112]

TABLE 2 Notional failure rate data for the USV

System functional block	MTTF (hours)	MLDT (hours)	MTTR (hours)
SATCOM	10,000	336	3
Onboard computer (OBC)	25,000	168	4
Electro-optic sensors (EO/IR)	25,000	336	3
Energy storage module (ESM)	130,000	336	3
Electric drive (ED)	25,000	720	16

The reliability and availability numbers under assessment have been captured from a variety of manufacturer and academic sources. It is assumed that each major assembly has a normal distribution for its MTTF, MLDT, and MTTR. Delay times are estimated based on the experience and numbers observed by the authors in their professional experience given the operational scenario outlined in this case study.

4.5.1 | Monte Carlo simulation

To assess the theoretical system availability pre-DT incorporation, the data in Tables 2 and 3 were used. No variation was added to the mean times to repair as any deviation in material challenges are captured in the variance of MLDT. It was found that the system would experience an operational availability of approximately 0.93. If stakeholders determine they want a 95% confidence that no missions will be missed, that will drive the number of available USVs or spare parts to support the missions up significantly.

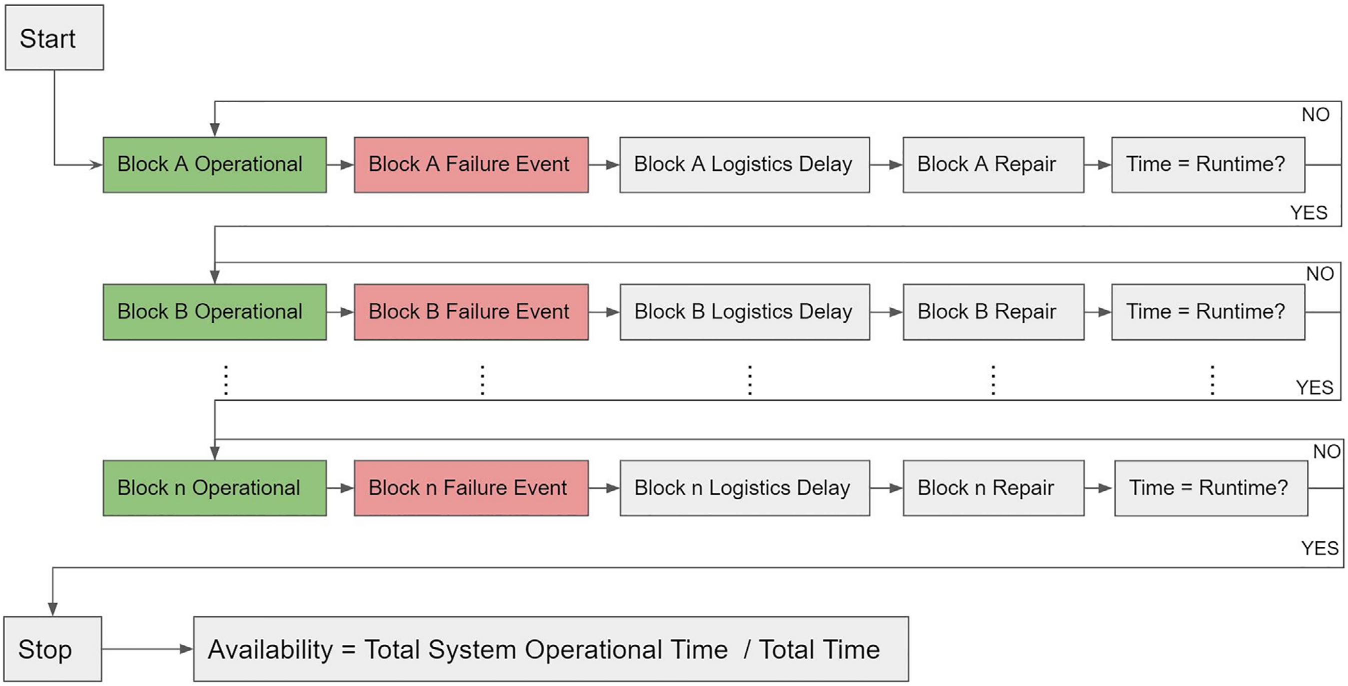

FIGURE 10 Monte Carlo simulation: Ward et al.

TABLE 3 Notional failure data standard deviations for the USV

System functional block	MTTF *SD* (hours)	MLDT *SD* (hours)
SATCOM	3,000	168
Onboard computer (OBC)	7,500	168
Electro-optic sensors (EO/IR)	7,500	168
Energy storage module (ESM)	39,000	168
Electric drive (ED)	7,500	168

The improved operational availability significantly reduces the concerns for maintaining an inventory of spares for the operational population. From the traditional operational availability (Ao) calculations defined in OPNAVINST3000.12a,[112] we can generate theoretical Ao values for each individual block within the USV. The equation for Ao is:

$$Ao = \frac{MTTF}{(MTTF + MDT)} \text{ where } MDT = MLDT + MTTR. \quad (1)$$

In the equation above, MTD is mean down time, an aggregate of any downtime factors including logistics delays, admin delays, outside assistance delays, or others.

From the values in Equation 2, an Ao of 0.917 can be calculated for the pre-DT condition.

This also provides the opportunity to field casualty or failure-specific training when needed along with the component, something of interest to the operations research community that will not be discussed at length in this article.

To analyze the potential impact of a DT, the Monte Carlo was rerun with a new set of input parameters that reflect a DT that predicts 70% of failures. From available data sources, an estimated PHM system that predicts 70-percent of failures seems very reasonable given the maturity of PHM algorithms for the components under consideration. MLDTs were decreased by 70% to estimate the reduced wait times due to predicted failure events. Mean times to repair were kept the same.

To analyze the sparing requirements for the forward operating base based on failure rates, we can leverage a Poisson distribution[113,114] to analyze sparing requirements at a specific confidence requirement. To do so, the following equation can be used:

$$Spare\ Requirement = (T \times n)/\lambda + q95\sqrt{(T \times n)/\lambda}, \quad (2)$$

where:

- T is mission duration or period between sparing
- n is the number of operational systems
- λ is the failure rate of the component
- q95 is a constant corresponding to the confidence level desired, and for a 95% confidence is 1.645

In this instance, a mission duration of 4 weeks is reasonable since the logistics delays assumed are equal to 2 weeks. The number of operational systems is 10 from the case study assumptions.

From the spare parts requirements analysis, Table 4 shows the theoretical operational availability value outputs from the Monte Carlo simulation, and Table 5 covers the corresponding estimated number of spares for each major assembly with and without the fielding of a DT based on the previously mentioned availability figures.

The resulting availability of the remodeled data resulted in a new system-level operational availability of 0.973, a significant increase

TABLE 4 Monte Carlo simulation results

System functional block	Theoretical Ao without DT	Theoretical Ao with DT
SATCOM	0.967	0.990
Onboard computer (OBC)	0.993	0.998
Electro-optic sensors (EO/IR)	0.987	0.996
Energy storage module (ESM)	0.997	0.999
Electric drive (ED)	0.971	0.991

TABLE 5 Sparing requirement comparison—DT deployment results in a significant reduction in required spare

System functional block	Deployed spares without DT	Deployed spares with DT
SATCOM	3	1
Onboard computer (OBC)	2	1
Electro-optic sensors (EO/IR)	2	1
Energy storage module (ESM)	1	1
Electric drive (ED)	2	1

from the previous value of 0.917. At 70% failure prediction, rather than sparing each of these components and maintaining a large inventory, components can be purchased prior to failure and installed when needed. This represents an approximately 5% improvement in availability compared to the pre-DT configuration. At this availability rate, such a small fraction of missions will be missed due to unexpected failures that many stakeholders may be willing to accept sparing only when needed. Given the risk-adverse perspective of the fictitious stakeholders in this case study, fielding one of each spare to the forward base is a reasonable compromise between cost and risk, and is shown in Table 5.

From these results, the number of required deployed spares prior to DT fielding is almost two complete USVs. Every major functional block requires multiple forward deployed spares, significantly driving up the procurement and sustainment costs. Further, some of these components may run past initial warranties offered by vendors due to extended periods sitting on the shelf waiting to be installed. With a DT, less than 1 of each spare is required. The net impact of this change is significant procurement and sustainment cost savings, reduced inventory and logistics footprint, plus other downstream improvements provided by the integrated DT. When comparing these sparing requirements to the post-DT fielded solution, it quickly becomes clear that there is high utility in scenarios like this for the fielding of DTs.

5 | DISCUSSION

This article develops a methodology that walks systems engineers through the development of a PHM-centric DT system in parallel to the physical asset being developed. By leveraging the various MBSE requirement decomposition and view development processes, a DT based on system operational requirements, system functions, and both inter and intrasystem interfaces can be conveniently architected and fielded alongside the low rate initial production assets. Additionally, through modeling the case study demonstrates how the application of various PHM algorithms can increase operational availability, while reducing deployed spare parts required on-hand to maintain fleet readiness.

Within the case study, considering the theoretical availability percentages in Table 4, sustainment teams have an interesting predicament. The overall availability of the components in the USV is quite high, meaning there is low demand for these components. Due to the low demand of these components, contracts with suppliers may not be maintained, inventories within the Naval Supply or Defense Logistics Agency (DLA) systems may not be maintained, and logistics delay times when parts are needed may periodically spike. In the authors' experience, programs maintaining systems such as these may occasionally have part lead times lasting several months, resulting in exceptionally poor operational availability, missed missions, and potential threats to national security. As a result, the MDTs identified in this case study are naturally extremely conservative, and the true benefit of the deployed DT may be significantly higher than that demonstrated in this case study. In effect, the case study has demonstrated a return on investment due to the implementation of PHM in agreement with the resulting takeaway from the PHM article described by L'Her et al.,[33] "a system can be designed with PHM hardware instead of expensive redundancies while maintaining a similar system reliability." While this article did not directly dive into the performance analysis decision aid value of a DT, it is clear that the fielding of the capability will offer high utility to operational teams aligning operational assets to a set of missions of different levels of criticality, risk tolerance, or performance requirements.

The inherent benefits of the approach proposed in this article is that it provides a natural and intuitive framework acquisition Systems Engineers can follow to deploy DTs for their systems. It also reduces the cost of deploying the DT because it leverages the processes already followed by system developers, ensures DT and PHM components are integrated into the system by pushing PHM discussions earlier in the system architecting process, eliminating an additional tasking and efforts postdelivery. The implementation of the DT also has a significant impact on operational availability at levels comparable to improving built in redundancy. Finally, the DT offers an architecture for the capturing, storing, and analysis of component performance and reliability data—a critical and invaluable element on an infant system as stakeholders resolve reliability and performance issues.

The one significant drawback that exists with the approach provided by this article is it relies on systems engineers to develop the architecture and framework for an integrated PHM system. Not all systems engineers are PHM subject matter experts, and will therefore rely on existing PHM analysis and research that is directly applicable to the components included in their system design. In emerging fields, notably ones with dramatically new or different architectures from previous system designs, there may not be publications and research into PHM applications. In these cases, the development of a PHM strategy will increasingly fall upon the hardware and software subject matter experts, effectively eliminating the efficiency of developing the DT in parallel to the system.

Another drawback that exists is DT developers need mature stakeholder requirements, objectives, and possibly assessment of risk. If these areas are not mature enough, DT development efforts may put the program down a path of investing engineering time, sensor implementation, or algorithms that do not answer the specific questions stakeholders will require. This will result in a suboptimal DT, and possible rework or redesign of the PHM architecture.

6 | FUTURE WORK

This article has demonstrated the alignment between DT, MBSE, PHM, and FE modeling but there are a variety of other research areas of direct applicability to DT development and fielding. The fields of mission engineering, PLM, and T&E enable new expansion of the integrated model concept as well as open DT data consumers. Additionally, risk-based decision making and aggregate risk provide new ways to interpret DT data—notably as diverse DT applications such as configuration management, sparing, reliability, and environmental data are brought together to aid in operational decision making.

6.1 | Mission engineering

One notable area that deserves significant exploration is the application of DTs to the emerging field of mission engineering. Mission engineering is effectively the analysis and design of a mission as one would a system. Mission engineering has been defined by Wertz as "the definition of mission parameters and refinement of mission parameters and requirements so as to meet the broad, often poorly defined, objective of a space mission in a timely manner at minimum time and risk.".[115] Dahmann and Gold define mission engineering as "deliberate planning, analyzing, organizing, and integrating of current and emerging operational and system capabilities to achieve desired warfighting mission effects.".[116–119] Considering the objectives and approach to mission engineering, the insights to actual system health and performance promises to be extremely fruitful, notably in systems with high levels of redundancy that results in scalable performance characteristics such as phased arrays or fiber laser weapon systems.

6.2 | PLM

The use of MBPS or PLM are growing rapidly in the DoD as stakeholders look for new ways to transform traditional logistics analytics and processes, and use integrated models and analytics to drive better decision making. Many traditional logistics planning processes are limited to their use of antiquated processes based on transaction data. PLM is an integrated system of tools that allow the modeling of a system's reliability, perform design trades, and model/adjust the sustainment tail. DTs are a transformational data source for the implementation of PLM capability and make sustainment decisions based on the materiel condition of deployed hardware—notably with prepositioning of parts, training, and remote assistance as well as supporting variable and dynamic sparing. The net effect will be the empowerment of stakeholders to model the operational environment and adjust the logistics posture and strategy quickly as the CONOPS evolves.

6.3 | DTs for T&E

DTs offer significant value for the T&E of complex systems. Traditional programs undergo rigorous T&E during acquisition but testing is executed in discrete scheduled events. Performance characteristics are rarely captured and analyzed on operational assets and operators are not informed of a systems actual capability based on materiel condition. There is an enormous opportunity to deploy real-time T&E with modern system DTs that track and monitor performance and deviation from program requirements. This can enable a next-generation operational decision-making aid that informs operators of system ability to support specific missions throughout an evolving conflict.

6.4 | Risk-based decision making

Risk-based decision-making is an area of particular interest for future DT work. As described in Section 2.5, DTs have a wide range of applications and use cases. Some programs may want the inclusion of multiple types of DT algorithms to make stronger decision making. Each DT application may provide its own insights or recommendations to system operators but unless they are somehow weighted and aggregated, DT outputs will not be intuitive. The concept of risk-based decision making and risk aggregation is one area that will be valuable for future DT work, as the topic provides insights on how to make decisions based on incomparable or incommensurable data types.

7 | CONCLUSION

In conclusion, DTs offer an opportunity to revolutionize the operations, support, and sustainment of deployed systems. Use cases of leveraging the DT to indicate performance and health characteristics of a physical asset have been demonstrated in both industry and academia, and there are enormous opportunities to develop stronger methodologies for conceptualizing, designing, and building DTs. This article has demonstrated that the objectives and fundamental concepts of MBSE and DTs are in agreement. Both intend to leverage integrated models to support a system's lifecycle.

Further this article has demonstrated that the nominal MBSE approach followed by many development programs, notably for DoD systems, assist with the architecture and framing of a PHM-centric DT as well. By following this approach, DT fielding on initial deployment results in higher operational availability, reduced requirements for fielding spare parts, as well as performance indicating decision aids.

Finally, this article has demonstrated even on program onset, there is significant value in developing a DT, as the academic community has well-established off-the-shelf prognostics tools that can be integrated into new designs to maximize system availability. The combination of these three positions makes it clear that sponsors and stakeholders should be motivated to consider the employment of DTs within their programs and this methodology is a natural approach for implementation.

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