On the Application of Structural Digital Twins for Surface Ships for Operational Guidance Support

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ABSTRACT

Digital Twin for surface ship structures is developing research field for marine vessels. The twin, as an integrated multi-physics, multi-scale, probabilistic simulation of the as-built vessel that uses the best available physical models, data, sensor information, use history, etc., to mirror and predict the life of its corresponding physical vessel, is a concept so extensive, that, to enable practical development and usage, scoping the twin is essential. This paper identifies critical features associated with the structural digital twin for use for shipboard operational guidance. A clear definition of the objectives, the resources available, and the model parameters is presented along with how structural digital twins (SDTs) incorporate uncertainty and performance-based approaches. A case study is presented testing a developed method for probabilistic assessments and forecasting for a marine vessel.

1.0 BACKGROUND

Since the early 2000's, the concept of the digital twin has emerged as a critical technology for use in industries ranging from structural engineering to biomedical engineering and on. For naval and marine structures, digital twins are discussed in their potentials for use in safe and efficient operations of ships, optimal maintenance for ships and fleets, optimal route planning for vessels (VanDerHorn and Mahadevan, 2021; Drazen et al 2019; Glaessgen 2012). The concept had been discussed during recent study performed by the Technical Cooperation Program (TTCP) Digital Twin Community of Interest (CoI) in an effort to understand the use cases for digital twins for operational support, optimizing and prioritizing fleet maintenance, long-term route planing planning based on platform health, and prognostic and predictive health monitoring. In the CoI effort, the capability, the benefits, and the concerns and risks associated with Digital Twins were reviewed and summarized (Woolley et al 2023). One of the uses discussed was the (near-) real time operational support and structural digital twins (SDTs). This paper will dig further into the design of the SDT to for (near-) real time support.

Like in research, there is high interest in the class societies to expand into the digital domain via digital twins (through "smart ships", "intelligent ships", and "condition monitoring"). A literature review of class guidances was performed (ABS, 2020; ABS, 2022; BV, 2021; BV, 2022; CCS, 2020; Class NK, 2020; DNV GL, 2020; DNV GL, 2017; Llyods Register, 2021). The value added is apparent by comparing the guidances and rules across the different agencies: the increased awareness of what has actually happened to the structure, and a clearer understanding of what may happen, can reduce risk. There is, however, a varying degree of specificity included in said documents. This lack of specificity can be because of the general state of readiness of the technology, the broad applicability of the technology, or both. This paper discusses the approach to designing a digital twin by posing the problem in terms of the objectives, constraints (or resources), and model parameters.

Operational guidance based on structural awareness naturally requires an assessment of structural performance. In order for an SDT to provide guidance that capitalizes on the data set available and the reduction in uncertainty that it offers, this paper proposes the use of a performance based engineering approach. Performance-based design would allow the engineers and designers to detail what failure looks like (Dusenberry, 2019). It allows for criteria to account for the knowledge around the loads (demand), the state of the structure and relevant failure mechanisms (capacity), the consequences of failure, and the requirement to comply with a required performance. This style of design has been shown to result in better performing, efficient, reliable, and cost-effective marine and naval structures (Hughes & Paik, 2010). The application to SDT for operational guidance and condition based management is logical and presented in this paper.

Structural Digital Twins are at the forefront of development for naval and marine applications. This paper outlines the critical features associated with the design of structural digital twin for use for shipboard operational guidance. The design of the SDT is proposed to include a clear definition of the objectives, the resources available, and the model parameters. For operational guidance, the design of the SDT is further so as to incorporate probabilistic and predictive capabilities. A case study is presented in to demonstrate some of the current needs for SDTs when it comes to integrating probabilistic and predictive quantities. The integration of performance based design concepts is then discussed as it pertains to the design of an SDT.

This paper also provided a case study on the use of digital twins that has a probabilistic-predictive solution to supporting operational guidance. This paper is intended to enhance the understanding of how SDTs can be designed and implemented in a way that supports the objectives, by using the resources and data sources (model parameters), to support risk-based decisions.

2.0 OBJECTIVES

Researchers have put forth objectives for structural digital twins, or “why”. This includes reducing maintenance costs, reducing risk in maintenance and operations, improving efficiency of operations of the vessel or of the fleet, increasing availability, reliability, and resilience (VanDerHorn and Mahadevan, 2021). It also includes optimizing for elements of re-usability, interoperability, interchangeability, maintainability, extensibility, and autonomy across the entire lifecycle (Moyne et. al, 2020). Alternatively, objectives like decision-making support, cost reduction, remote control and monitoring, maintenance, and condition monitoring, testing and simulation, and training personnel have been included (Assani et. al, 2022). Optimal route planning has also been posed as an objective for a digital twin (Lee et. al, 2022). In other discussions on digital twins, value creation is identified as being based on the actor-to-actor interactions for a particular solution, making it more complex to identify the objectives (or requirements) (West et. al, 2021). The review of the above literature highlighted a key concept: clarity in the definition of the objective for a SDT is essential. That is to say “operational guidance support” was used often, but without specificity (in terms of: essential information, accuracy, timeliness, and resources, amongst others), there was an inconsistency the discussions. Example being in the use of gps data to provide performance related indicators. A potential solution of pair with environmental data as a low-cost, low-footprint solution a useful example for some cases (Thompson, 2020), but, if the digital twin does not have ready access to that or the computational resources available, then then the solution is not valid for the application.

A review of the class guidance products relevant to digital twins (e.g., rules and guidances for monitoring systems, rules and guidances for smart structures, etc) was also preformed to understand the objectives and requirements for digital twins (and related products). The classes have tended to break out guidances for Hull Monitoring (or similar title) and Smart Vessels (or similar title) when discussing concepts related to structural digital twin. The objectives and description are summarized in Table 1, and are brief descriptions and/or excerpts from the referenced document. The Hull Monitoring documents tend to focus on ‘how’ the objective can be supported, with minimal discussion on the overarching objective. The Smart vessel documents tend to focus on the overarching objectives, sometimes tying more detail.

Table 1: Class standards for condition monitoring and "smart" vessels.

Class Standard	Objective/Description
ABS Hull Condition Monitoring (ABS, 2020)	Hull Condition Monitoring (HCM) is to monitor, visualize, and trend parameters relevant to environment, structural loads, and responses through sensor-based measurements. HCM typically involves onboard and/or onshore reporting and threshold-based alarms for operational guidance and post-voyage analysis.
ABS SMART (ABS, 2022)	Provide the crew and support personnel with key information to aid in decision making. Use common smart functions that include structural and machinery health monitoring, asset efficiency monitoring, operational performance management, and crew assistance and augmentation to support vessel operations. SHM provides structural health diagnostics and prognostics through correlation of various parameters and integration with analysis and simulation; HCM handles parameter-based monitoring and covers the loads, responses, and identifiable damages from direct sensor measurements at certain sensor installed locations"
Rules for the Classification of Steel Ships, NR467 - JULY 2022, Part F, Additional Class Notations (BV, 2022)	Hull Monitoring System is a system which: Provides real-time data to the Master and officers of the ship on hull girder longitudinal stresses and vertical accelerations the ship experiences while navigating and during loading and unloading operations in harbor Allows the real-time data to be condensed into a set of essential statistical results. The set is to be periodically updated, displayed, and stored on a removable medium.
BV NR675 Additional Service Feature SMART (BV, 2021)	A smart system is defined as a computer based system that incorporate functions for the collection, transmission, analysis, and visualization of data. A function is a defined objective or characteristic action of a system or component. Smart functions may include operational information such as monitoring, decision making support, remote monitoring, as well as maintenance
DNVGL-RU-SHIP Pt.6 Ch.9 (DNV GL, 2017)	The system shall give warning when stress levels and the frequency and magnitude of ship accelerations approach levels that require corrective action. The owner shall decide how the hull monitoring system should be configured, i.e., which features to be included and how the measured and processed data shall be use intended as an aid to the Master's judgement and not as a substitute.
DNV GL Smart Vessel (DNV GL, 2020)	Use data and information to further optimize vessels' operations and reduce the environmental footprint. Operation and maintenance – hull and structure (OPH) enhancements include solutions that use data as an important element and provide options related to structural integrity management
Lloyds Register, ShipRight, Ship Event Analysis (Llyods Register, 2021)	Provide warning the ship's personnel that stress levels or the frequency and magnitude of slamming motions are approaching a level where corrective action is advisable

Class Standard	Objective/Description
CCS, Rules for Intelligent Ships (CCS, 2020)	To provide assistant decision-making for hull and deck machinery maintenance and structural renewal during in-service period of the ship based on the establishment and maintenance of hull database system and three-dimensional hull structural models.
Class NK (Class NK, 2020)	To monitor the behaviour of hull girders during navigation, loading and unloading, and to provide real-time information on stress levels due to longitudinal bending moments and acceleration levels due to ship motion. Information is to be intended to aid the judgment of Shipmasters and crew members during navigational operations, it is not intended to be a substitute for the judgment and the responsibility of Shipmasters.

In order to form clear and coherent objectives for SDTs, the complexity of the objective, the actor-to-actor interactions, and the broader context of decision making is critical. Thus, this paper puts forth that the objective for a structural digital twin is, in fact, defined with a hierarchy of objectives as shown in Figure 1; the hierarchy is grouped into different levels:

- **Vision**: this is the highest level that expresses what the twin wants to be, it is the high level purpose. For structural digital twins, this includes increasing the availability of the fleet, reducing costs for operations and maintenance, and optimizing performance
- **Strategic**: this is the middle level that includes a targeted mechanism for meeting the vision. For structural digital twin, examples of this include supporting the operator via operator guidance and route planning, supporting the maintainer and planner for condition based maintenance and fleet asset planning, and supporting designers to optimize the design.
- **Operational**: this is the lowest level, where the objectives are scoped to support the development of a practical instantiation of a structural digital twin. This is where the objective is scoped out for basic requirements and constraints including the complexity of the analysis needed, the planning time-horizon, the resources available, the flexibility of the vessel to stay/change course due to mission criticality, the level of integration with the decision making process, among others.

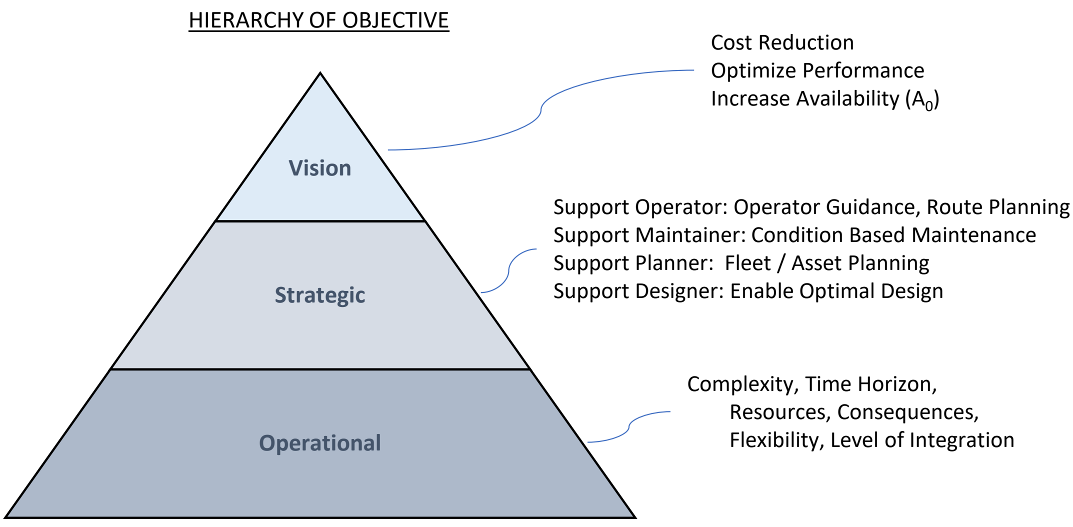

Figure 1: Hierarchy of objectives as applicable to structural digital twins.

The operational objective refines the scope of the strategic objective. For structural digital twin, this essential for the tractable development of a functional product. This includes:

- Timeliness (Real Time, Near-Real Time, Time-Delayed): when is the decision support needed. If information and decision support is needed in real time, the complexity of the digital twin must be designed to support that objective. If it is near-real time, a different complexity of twin may be warranted given the trade-off between time and accuracy. If time-delayed decision support is warranted (as may be the case for condition-based maintenance recommendations that may be given after a deployment), the twin can take a different form.
- Use (Operational Guidance, Condition Based Maintenance, Route Planning, Fleet Planning): what is the decision that the information is intended to support.
- Time Horizon (Instantaneous, Near Future, Transit, Deployment): what is the required window of time that the data must account for.
- Consequences: Is the vessel manned, unmanned, autonomous but operating as a part of a group?
- Operations: Is the vessel operating in routine conditions or critical conditions? Critical conditions may be storm operations for marine vessels, or critical missions or wartime for naval vessels. The twin may need to be flexible to support both.
- Level of Integration (Support Operator, Human-in-the-loop, full autonomy): How redundant, aware, capable of handling uncertainty, does the twin have to be?

An example between a strategic objective and an operational objective that both support vision objective of increasing operability is shown in Figure 2.

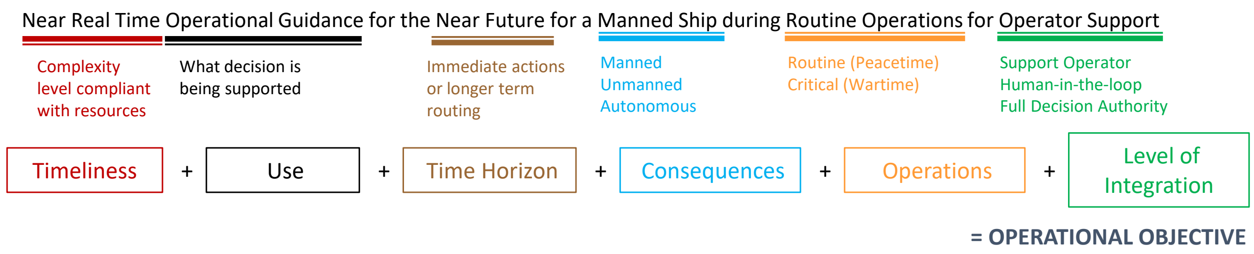

Figure 2: Operational objective decomposed.

3.0 RESOURCES

Digital twins are often discussed with in the hypothetical: "what could a digital twin do". But, when pivoting to the practical development of a functional SDT, the design of the SDT also has to consider the constraints of the practical problem. If we were to think about the design of the SDT as an optimization problem, there is the objective function, the constraints, and the design variables. Resources can be looked at as the constraints. In the review of technical papers and class guidances, the following groupings have been made so as to broadly speak about the resources for SDTs:

1) Access to Data
2) Computational Resources
3) Digital Infrastructure
4) Timeliness

Access to Data refers to accessibility of data to the digital twin:

- Inspection information such as the as-built configuration of the structure, existing cracks, deformations, and out-of-planeness are ‘quasi-static’ data types. They are collected at the initial inspection, and updated over time, but are typically not updated during an underway. This information can be readily available to SDTs that are located on the ship or land-based.
- Sensors on the ship provide time history data of the measured quantity. The sensors are intentionally added to support the SDT. These could be strain gages, accelerometers, etc. The time-history data is available on ship. If communication with the land is unavailable or bandwidth-limited, may not be available to the ship.
- Outputs derived from processing the time-data could include basic statistics (min, mean, max, std), advanced statistics, performance assessment metrics. The outputs can be summarized or compressed for usage. This data would be accessible on ship, and if communication with the land is available, then accessible there too.
- Personnel on the ship have more information coming to them than just the measured quantities. They can see the ocean, feel the ships response, hear what sounds the vessel is making, and have previous operational experience. As such, they are a source of qualitative data. A shipboard SDT would have ready access to shipboard personnel. A land-based SDT could also have access to the qualitative data that shipboard personnel can provide but may be hindered by bandwidth and digital infrastructure.
- Streaming data from other systems on board the ship (such as the GPS, or the ships’ gyroscope) may be accessible to Shipboard SDTs. Similar to the dedicated measurements, the time histories of the other ship system data may not be accessible to a land-based SDT.
- External data sets such as weather forecasts, climatology data, etc are not ship-specific data, but are amongst the useful parameters for an SDT. Land-based SDTs will be able to access this data more readily. Shipboard systems may not, or they may be limited in their access.

Computational resources also constrain the design of the SDT. If there are unlimited computational resources, then the problem is unbounded. But, in reality, there are computational limits for both shipboard and land based SDTs. The computational time may be too long to affectively support the objective. Or the computational power may not be available; as would be the case for a self-contained, shipboard SDT that only has access to the shipboard compute capabilities (and must share them with the other shipboard systems).

The Digital Infrastructure that exists is also a constraint. The digital communication systems on and off ships vary significantly between commercial vessels and navy vessel. There may be wired systems that allow for communication throughout the ship, there may be wireless systems. The vessel may have access to of-ship systems (“the cloud”, etc). The US Navy, as many other navies and commercial entities, are shifting towards digital engineering strategies that enable a digital transformation (US Department of Defense, 2018). There is much more to the digital infrastructure conversation beyond what is discussed above which will not be addressed in this paper. It often poses a “chicken or the egg” paradox when it comes to the design problem for SDTs: It can be both a constraint to the design of the system or a requirement of the system that then gets built.

Table 2 presents the summary of location, data, computational resources, infrastructure, and time-delay considerations.

Table 2: Resources and location of SDT.

Location		*Shipboard*	*Land-Based*
Resources: Access to Data	Quasi-Static Information	Available	Available
	Monitoring Measurements	Available	Possible
	Summary Data from Digital Twin	Available	Available
	Qualitative Information	Ready Access	Remote Access
	Data from Other Ship Systems	Available	Possible
	External Data Sets (Environmental Forecasts, History, etc)	Possible	Available
Resources: Computational		Limited	Advanced / Unlimited
Resources: Infrastructure		Wired/Wireless	Digital Communication System
Timeliness		Minimal Delay	Minimal to Substantial Delays

4.0 MODEL PARAMETERS

In the functional design of the SDT, the model parameters are the variables that will be ingested, analysed, fused with, and post-processed by the digital twin. These, like the Resources, are also a "chicken or the egg" situation. The input parameters can be set first, then a SDT (or model) can be designed around them. Or, the SDT can be designed, and the input parameters dictated.

Path 1 – Defining the Parameters, Designing the SDT: This path is useful if there is a relatively clear idea of what data set is available. This may be the case where a ship has GPS and a gyroscope, the desire/need for a SDT, and limited funding. The design of the SDT may then need to heavily rely on fusion with finite element models, analytical seakeeping models, existing experimental derived databases (i.e., model test data, dedicated trials data, to name a few), climatological models, amongst others. The resultant SDT carries the compounded uncertainties from each step in the process, leading to (potentially) high uncertainty bands around the output product of the SDT.

Path 2 – Defining the SDT and Setting the Parameters: This path is useful if there is a clear understanding of the uncertainty bounds that a required for the output products of the SDT. This may be the case in the example of operational guidance with personnel on board where there is a required probability of failure that must be met. Then the SDT can be designed such that this requirement is met, exploring the use of alternative input parameters, finally to converge to the required set.

While SDTs still exist in the state where they can be a very wide range of models (i.e., not one exact and specific product), there will be a trade-space for the cost associated with model parameters, and the uncertainty bounds associated with the SDT output product. As such, the convergence to the model parameters for the specific platforms will be a negotiation of the two metrics. Figure 3 qualitatively depicts the multi-objective optimization solution space and pareto optimal solutions. There are solutions that may exists that are above the available budget or have too high of uncertainty bounds to be useful; these are outside the bounds of the constrained multi-objective optimization problem. There are also solutions that are feasible from the perspective of budget and certainty, but are suboptimal, as there are solutions that exists with higher certainty for the same price or lower price for the same certainty. The optimal set of solutions lie along the pareto front. The final choice along the pareto optimal set, is dictated by external factors (which may include time it takes to install, feasibility of installation of sensors, among others).

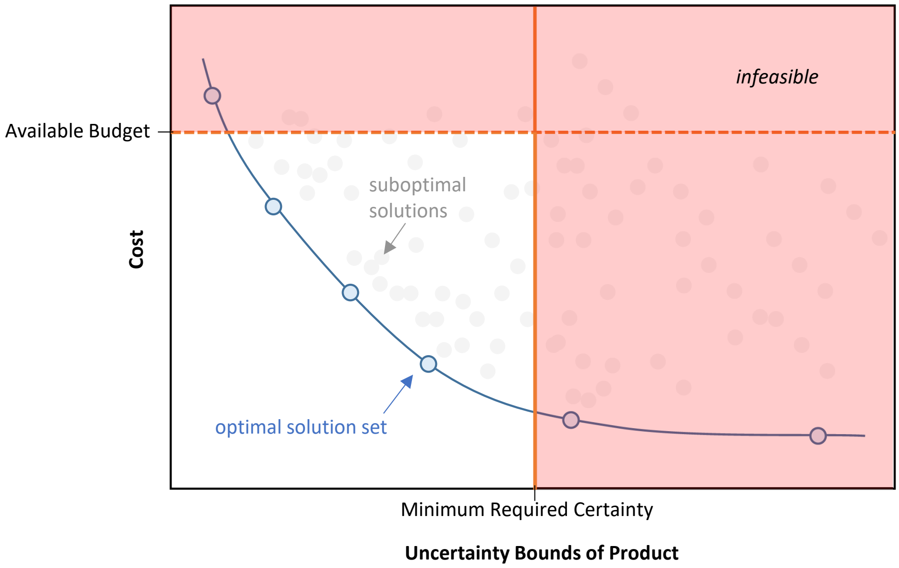

Figure 3: Multi-objective optimization for design of SDTs.

The potential input parameters for structural digital twins are extensive and includes all the parameters that affect ship's response and all of the ships' response parameters. The former will be referred to as operational information in this paper. This includes wind and air temperature, ocean waves and temperature, both current and future, as well as ship ballast, draft, heading, and velocity. The extent and availability of these parameters for integration into the digital twin will be affected by the location and resources available for the twin.

The second set of parameters for SDTs are referred to as structures-intentional data. This refers to data collected for the specific intention of quantifying the state of the structure, monitoring the structural loads and/or response. The sampling rate for this data may differ significantly across the types of data. For example, structural inspection data may only be collected every year (if that), while, if there are sensors on the ship (such as strain gages, pressure transducers, accelerometers, etc), real time shipboard data may be sampled at 100 to 1000 Hz.

The two groups, operational information and structures-intentional data, are summarized in Figure 4. There are many more parameters that affect ship's response (operational information) and parameters that can be used to define the structural response (structures-intentional data), that are not listed here. Additionally, there are other uses that the same measurements may have (e.g., seakeeping performance awareness). This is intended to provide a basis of the parameter set, which could be expanded when developing a specific SDT.

The difference in the sample rates between inspection data and real time ship data fundamentally does not affect the design of the model, but it does affect that way that humans talk about the twin. It may be discussed in as 'a model that can ingest the inspection data', or 'a model that is updated by the inspection data', or "a model that will be revised when inspection data indicates a significant change in structure (or there is a new objective the model needs to support)".

To add to the complexity of the SDT design problem, there is also the potential for nested digital twins to be the SDT solution. The following is an example of a nested SDT. At the start of the life, there may be a complex, land-based model, and a surrogate (or simplified), ship-board model. The complex model may rely on a more complete representation of the vessel, advanced physics based models, and external data sources (like wave databases). The complex model may also have inputs parameters that are output parameters of the surrogate shipboard model, and/or the input data from the surrogate shipboard model (depending on the digital infrastructure and communication bandwidth). Meanwhile, the surrogate shipboard model may include the monitoring parameters as inputs and rely on simplified or representative response models. The nested twin approach is a useful way to capitalize on the breadth of available data sources and on the different computational power in each location. It does, however, have a heavy reliance on digital infrastructure. And it may require human-provided input, and engineer-directed revisions. Consequently, the digital twin involves non digital components, which (a) requires a clear enumeration of what is automated versus manual and (b) affects cost.

	Operational Information	*Structures-Intentional Data*
Recurring		• Structural Inspection Data (materials, cracking, deformation, configuration, etc)
Real Time	• True & Relative Wind Data • Air Pressure, Temperature and Humidity • Wave Height, Frequency, Directional Content • Sea Temperature Data • Weather and Wave Forecast • Ballast & Draft • Ship's Position, Attitude, Heading and Velocity	• Accelerations • Strains • Pressure Transducers
After Data Collection	• Hindcast Data (Wave Height, Frequency, Directional Content, relative headings, speed over ground)	

Figure 4: Example model parameters for SDTs.

5.0 PROBABILISTIC AND PREDICTIVE ASSESSMENTS

Probabilistic and predictive methods for support SDT have been the topic of continued research and integration into class guidance and standards. One of the major challenges associated with statistical support for guidance is the different sources of variability in the problem. This paper classifies the types of uncertainty for operation guidance into three main categories:

1) **Natural Variability:** the seaway is a random field in which the ship operations. Thus, if the seaway remains stationary (in mathematical sense), the ships response can be defined as a random process and/or random variable. The ship's response is a steady state response (where if the ship is linear operator, its response is also stationary in the mathematical sense).

2) **Evolution of Environment:** the climatology of the ocean leads to the development and dissipation of storms. This is a continuous process that can lead to a ship's response also evolving with the environment. This is a gradual change in the ship's statistical response characteristics.

3) **Abrupt Changes:** Changes in the ships' course or speed represent abrupt changes in states. The passage out of or into sheltered areas lead to relatively abrupt changes in the seaway.

Given these sources, there is almost a need for the SDT tree to be piece-wise defined by state. Where the twin can identify if the ship is in a steady state, a state of gradual change, or undergoing an abrupt change. This is shown visually in the logic tree in Figure 5.

A literature search of the class guidances and related products was conducted and summarized in Table 3. The review indicated that the classes recognize that there is randomness in a ship's response to a seaway; their methods for setting requirements differ. Some indicated that the probabilistic models should be based on data from the most recent data. The window time that defines most recent differs from 20 minutes up to 4 hours across the different documents. Some recognize that the ship matters; for example, DNV sets different windows for displacement vessels and high speed vessel (DNV GL, 2017). In the Rules for the Classification of Steel Ships, NR467, Part F (BV, 2022), there is language that calls out "steady navigation" as a specific state the ship may be in and provides an expectation of performance for a model. But the clarity as to how to address the other states (gradually changing environments, or abrupt changes) was not identified by the authors of this paper. Others still provided requirements that the window should be configurable. While this solution provides flexibility, clarity that it should be implemented to account for the different potential states was not found.

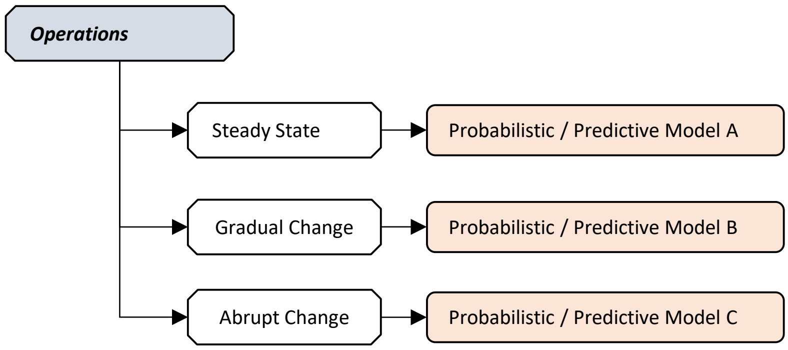

Figure 5: Logic Tree for state-based SDT for operational guidance.

Table 3: Integration of probability into class guidances and related products.

Class Standard	Calculation Period
ABS Hull Condition Monitoring (ABS, 2020)	20-30 min; Rolling basis is accepted
ABS SMART (ABS, 2022)	Not identified
Rules for the Classification of Steel Ships, NR467, Part F (BV, 2022)	Not less than 10 minutes (the recording duration per cycle is to be adapted to produce results that are not to deviate by more than 10% from one wave encounter to the next in steady navigation conditions.)
BV NR675 Additional Service Feature SMART (BV, 2021)	Invokes NR467 - JULY 2022, Part F
DNVGL - Rules for classification: Ships — DNVGL-RU-SHIP Pt.6 Ch.9 (DNV GL, 2017)	Time period for statistics shall be configurable; For predictive assessments, past 4 hours for displacement ships and 30 minutes for high speed vessels.
DNV GL Smart Vessel (DNV GL, 2020)	Invokes DNVGL-RU-SHIP Pt.6 Ch.9 Sec.3,

Class Standard	Calculation Period
Lloyds Register, ShipRight, Ship Event Analysis (Llyods Register, 2021)	Not identified
CCS, Rules for Intelligent Ships (CCS, 2020)	Time interval shall be stated in configuration file
CCS, Hull monitoring and assistant decision--making system for operations in ice (CCS, 2018)	*Forecast for the next 1-2 hours
Class NK (Class NK, 2020)	4 hours

Stepping away from the state-identification problem and focusing on the development of probabilistic predictive models: Predictive and prognostic methods for support SDT has been the topic of continued research. Approaches including Bayesian updating, regression modelling, machine learning and artificial intelligence have been applied to the problem. Lee identified deterministic predictions for deterministic predictions for wave trains incident on a ship and the resulting ship motions were conducted (Jae-Hoon Lee, 2022) Nielsen et al (2022) investigated a hybrid maneuvering model for predicting the speed of a ferry under model uncertainty and varying operating conditions. The work demonstrated the applicability of neural networks to capture complex, nonlinear behaviour that is not an inherent component of first principle hydrodynamic models (Nielsen, 2022). A regression model based on the statistical characterization of vertical bending moments was developed and assessed for a notional combatant (Mondoro et. al 2023). The applicability and limitations of each of the methods is presented in the associated reports. The following case study was performed to highlight the complexities of developing predictive models for use in operational guidance.

Regressive and Machine Learning models were developed around the probabilistic characterization of structural loads acting on a vessel (Mondoro et. al 2023). The SDT was designed such that the model parameters included only retrospective data. The models were developed from training data that represented the response data of a notional vessel operating in a seaway. The models were then optimized to support the short term (1-5 minute) prediction accuracy. The models were then applied and assessed on the remainder of the data set. This paper reviewed the outcomes and generated the following finding and associated genericized case study:

When probabilistic models or predictive models are developed around the assumption that the ship is in a steady state, or even if it's assumed to be in a gradually developing state, its applicability to abrupt changes is limited. In some cases, limited refers to conservative (and potentially restrictive), while in others, it is non-conservative (and potentially dangerous). To aid in relaying these concepts, Figure 6 shows three scenarios:

1) The first scenario is an example of the ship operating and entering a storm (Figure 6 – top). There is a gradual change in the response parameter over time. Predictive models (model A and model B) may be useful as they are able to predict future response, with a small error margin. In the example shown, Model A is slightly more conservative that Model B.
2) The second scenario shows a scenario where a ship is operating in a seaway, then turns to continue operations in the same seaway but at a different relative heading. The middle row in Figure 6, shows how two models, developed for gradually changing conditions, perform when applied to this abrupt-change scenario. Model A leads to a time period where it is over-conservative. This information may cause the ship to adjust its operations, leading to a case where the ship is not being used to its fullest

extent. Model B, however, demonstrates how there can be a lag in the responsivity of the model, leading to periods where the SDT is providing non-conservative outputs, and the ship is being provided a false sense of security (if the probabilistic value is the only thing being considered).

3) The third scenario is also a scenario where a ship is operating in a seaway, then turns to continue operations in the same seaway but at a different relative heading. The bottom row in Figure 6, shows how the same two models. The scenario highlights the fact that the conservative nature of the models may not be ubiquitous across all scenarios: Model A is non-conservative in this scenario, while Model B is over-conservative.

The case study had been conducted around a single response parameter. Complex structural systems, like ship hulls, however, should be assessed on the system level. This enables a one, clear guidance recommendation to be made that considers the response of the vessel and the different failure mechanisms. This is covered in the next section.

6.0 PERFORMANCE BASED DECISION SUPPORT

SDTs that support operational guidance lend themselves to a performance-based structural evaluation approach. This allows for the demand (deterministic, probabilistic, and/or predictive), capacity (component and/or system as quantified through low- or high- fidelity models), and risk tolerance to be included. This allows the SDT to recognize the important of different situations, such as peace-time or war-time, and address those situations appropriately. Likewise, it can be designed to support operations in normal weather or rough weather, where risk tolerance levels may also differ. It allows for different considerations to be made if the ship is manned or unmanned, thus incorporating the fact that there are difference consequences of failure.

For SDTs, performance based decision support first involves the identification of the state that the vessel is in:

- Routine / Under Duress (Peacetime / Wartime)
- Manned / Unmmanned
- “Normal Weather” / “Heavy Weather” (Day-to-Day / Near & Hurricanes)

This helps establish the imperative for operations, consequences, and risk tolerances. Each branch may have different performance based criteria. That is, the safety margin for the “peacetime-manned-normal weather” branch may be different from the safety margin for the “wartime-unmanned-normal weather” branch.

Next, performance based decision support requires a definition of capacity. This is typically done by first defining what failure is. Failure is commonly defined as “a state of inability to perform a normal function” (Merriam-Webster.com, 2022), with structural failure, defined as “a change in state such that the structure no longer provides a required function (load carrying or otherwise) or impacts some specified system performance to an unacceptable degree.” (Hess, 2003). The structural components and structural systems of naval and marine ships support a wide variety of functions such as enabling the transfer of loads from the shell to the primary hull girder, supporting foundations and equipment and transferring their loads to the primary hull girder, resisting hull girder bending. A failure covers component failure (e.g., material yielding, buckling, fracture, etc.) and system failures (e.g., progressive collapse, non-linear buckling, disproportionate collapse, etc.).

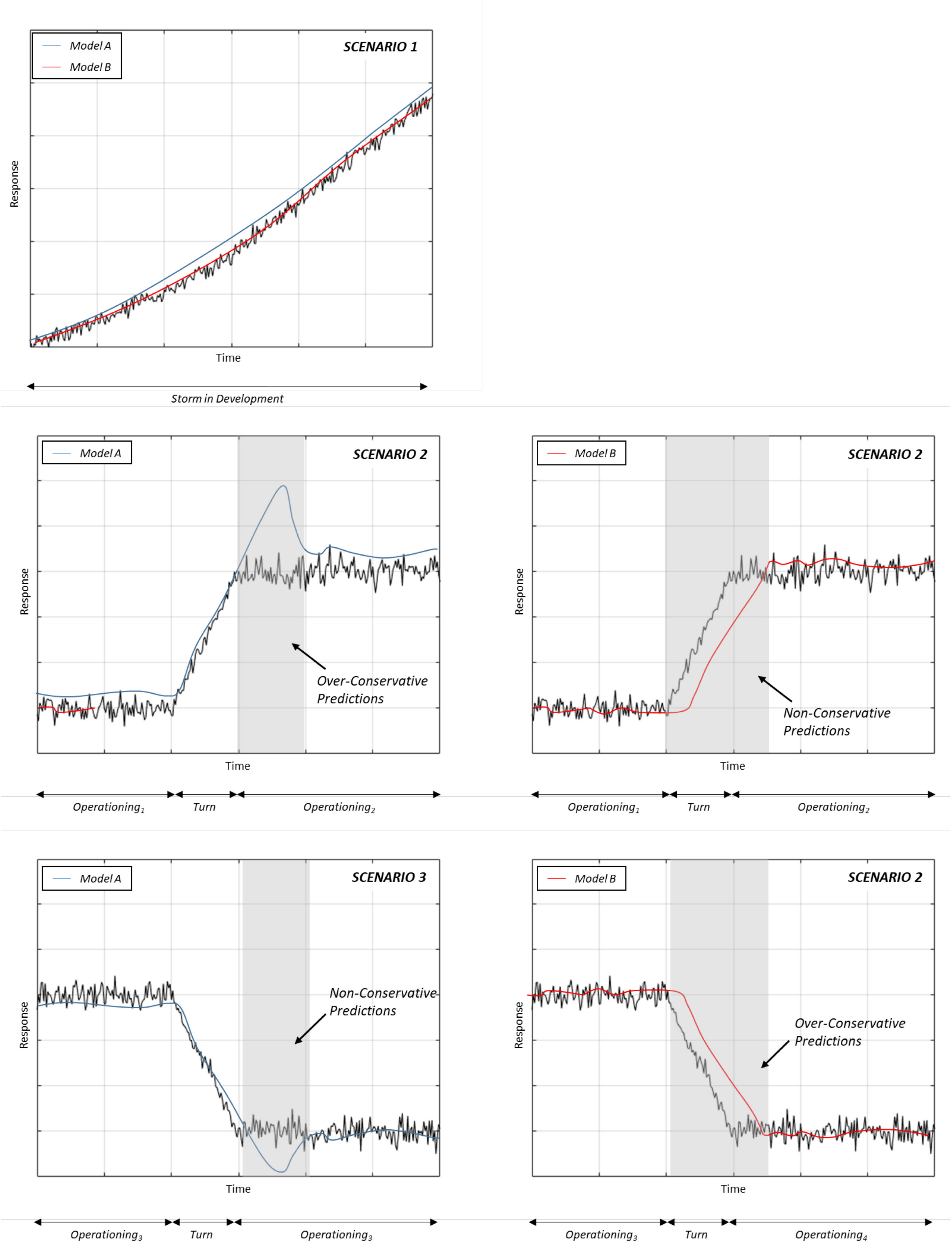

Figure 6: Performance of predicting models in difference scenarios.

Structural failure models can include (1) system-levels models structured around component failures and (2) explicit quantification of system performance. The first includes defining the individual components and their failure mechanisms, then, describing the system's performance as a series, parallel, or series-parallel model with all of the components included (Ang and Tang, 2007). The second is as previous described, a complex nonlinear analysis of the full structural system to evaluate for failure, load shedding, and progressive collapse. While the later more appropriately accounts for the physics in the failures, the variability inherent in the problem drives this approach towards a probabilistic characterization of the structural capacity. The probabilistic, nonlinear analysis of a large system becomes computationally expensive (if it has enough data on the stochastic parameters to be run at all).

This paper puts forth a logic tree framework for use when developing SDT solutions. First and foremost, the SDT must be developed to be able to place itself if the correct branch:

- Peacetime – Manned – Normal Weather
- Peacetime – Manned – Heavy Weather
- Peacetime – Unmanned – Normal Weather
- Peacetime – Unmanned – Heavy Weather
- Wartime – Manned – Normal Weather
- Wartime – Manned – Heavy Weather
- Wartime – Unmanned – Normal Weather
- Wartime – Unmanned – Heavy Weather

Until the point in time where a robust probabilistic solution that can account for steady state, gradual changes in state, and abrupt changes exists, the SDT must also have the ability to identify what state it is in:

- Steady state
- Gradual changes in state
- Abrupt changes

Then, a performance based structural assessment path can be developed for each path. This is conceptualized for the "Peacetime – Manned – Heavy Weather" branch in Figure 7. In this figure, there are separate paths that a posed for each of the states:

- For the steady state, deterministic data provides valuable information on what the ship has recently been subjected to, and probabilistic data is useful for accounting for the natural variability in the response. Both could be used. In each case, the components included in the definition of the system would be evaluated, and then assimilated into the system level assessment. The deterministic and probabilistic evaluation would then have to be fused to provide a clear output from the SDT.
- For the gradual change branch, the same process could be applied, although now including the predictions.
- For the abrupt change branch, the deterministic value may be the only useful data to include in the evaluation. However, since it is the only data that is being used, the margin being mapped to the structural evaluations may be different from that used in the deterministic branch of the steady state (or gradual change) branch)

The logic tree implicitly prescribes a system level structural assessment that is developed from a series, parallel, or series-parallel model containing the different components. Discussion on how that would be developed and validated is outside of the scope of this paper.

This logic tree also implies that there is a systematic method to ingrate deterministic assessments (i.e., based only on retrospective data), probabilistic assessments (that account for the current variation in the response) and predictive assessments (that track and account for trends over time). This is a challenge problem focused on risk and risk tolerances. Further discussion on this is needed for the development of a SDT, but falls outside of the scope of this paper,

It is worth noting that the performance based approach allows for the SDT to account for monitoring data and the different branches of the situation. This is fundamentally different from Design. In the design stage, rules and standards have to holistically account for all of the branches at once, and all of the potential loading scenarios. The rules and standards often lack the clear enumeration of how load variability is included, how material variability is accounted for, how strength variability is included, or how consequences and risk tolerances play a part the criteria. This makes it extremely challenging pull out the core requirements for structural assessment when it comes to digital twins and related products (such as monitoring systems).

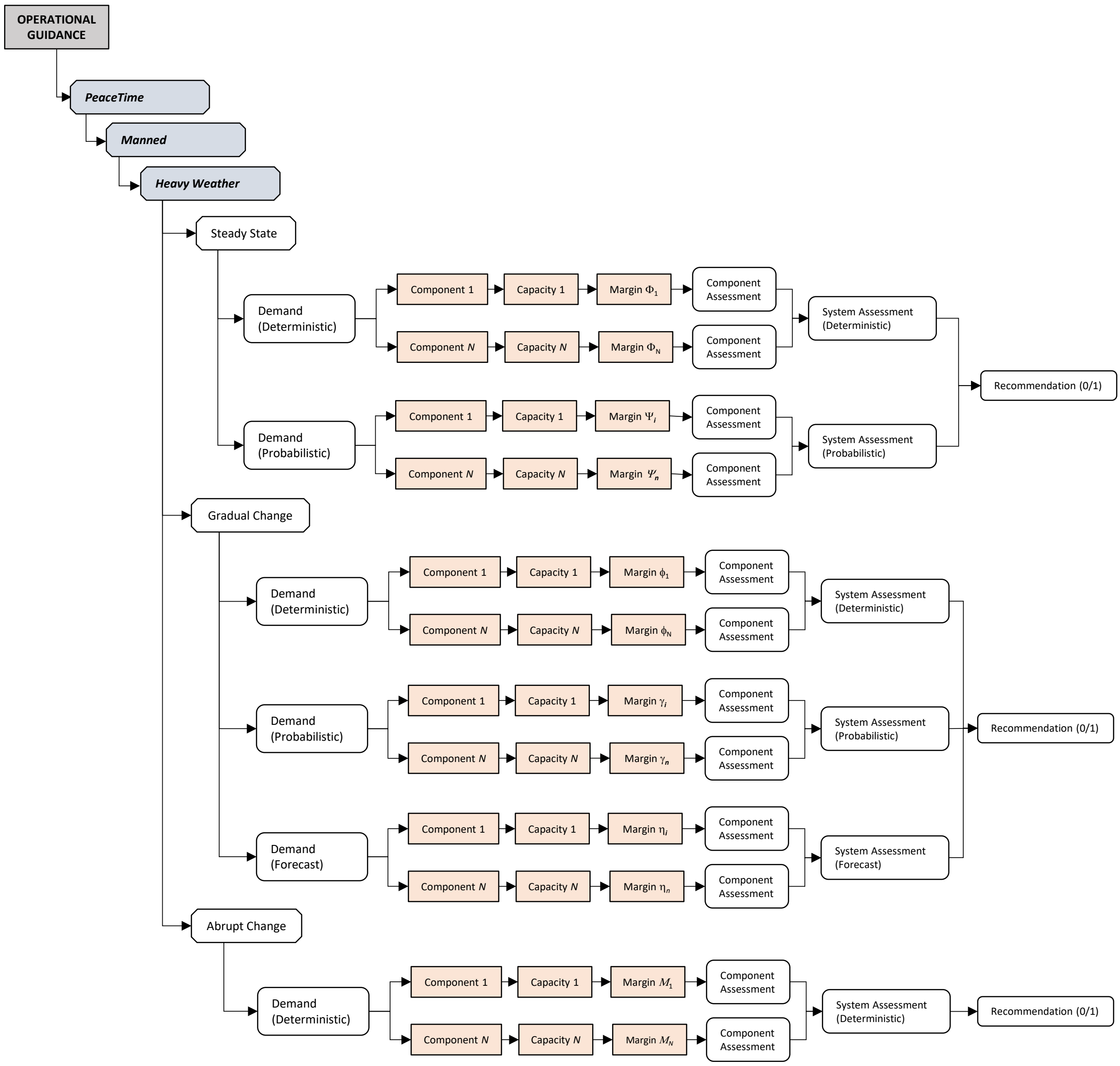

Figure 7: Logic tree for SDT with a performance based structural assessment approach.

7.0 CONCLUSION

This paper identifies critical features associated with the structural digital twin for use for shipboard operational guidance. A digital twin has the possibility of fusing data with physics based models to support decisions. This paper highlights the need to clearly scope the requirements for the digital twin (i.e., the objective) and the requirements of the digital twin (i.e. the resources and model parameters). This paper also provided a case study on the use of digital twins that has a probabilistic-predictive solution to supporting operational guidance.

The design of a SDT requires a clear understanding of scope, especially since digital twins are an emerging capability that has the ability to take a wide variety of forms to support a single question (and there are also a wide variety of questions SDTs can support). The objective is essential to down scope to a tractable problem. The objective is where the requirement of the system gets set. As proposed in this paper, this includes the intended use, the timeliness of the outputs, the time horizon used for the assessments, the consequences of failure, the type of operations (peacetime, wartime, both), and the level of integration of the SDT with humans. The resources establish the constraints to the SDT design problem, and the model parameters are the input variables needed. Often times, the definition of the constraints and model parameters becomes an iterative process with cost and the uncertainty bounds of the SDT as conflicting objectives that are trying to be jointly optimized.

SDTs for operational guidance are intended to provide awareness to the crew (or autonomy system) on the structural performance of the vessel. This awareness can be based solely on what the vessel has already been subjected to. But researchers and class societies place higher expectations on these products to include a probabilistic understanding on the current response and (in some cases) a predictive assessment of what the response will be in the near future. This paper discussed some of the trappings when using only retrospective data as model parameters for the digital twin. The case study demonstrated that these types of models have challenges with abrupt changes in the response (such as those stemming from turns, changes in speed, or emergence from (or entrance into) a sheltered area. As such, there is a need for a robust solution to be developed that can work in those scenarios, or the use a logic tree where the SDT can identify which branch it should be in.

Lastly, the SDT for operational guidance must have a systematic method in place for evaluating the structural performance of the vessel. This paper put forth the use of performance-based structural engineering concepts to support SDTs. The advantage of this approach allows the best available information on demand to be used (i.e., deterministic retrospective data collected, probabilistic quantifications, and predictive values). It allows for the consequences of failure to be uniquely defined for the operational scenarios. And it allows for a system level assessment of the structure to be performed and a single recommendation or single status point provided to the operator (human or autonomy system). The system level assessments can be done rapidly though a surrogate model that uses component level assessments. Or it can be designed to capture the full complexity of the structural system, the redundancies, the load paths, the progressive collapse. One thing that can be sure, the criteria implemented in the SDT will be different from the design stage, since the SDT capitalizes on the known data (i.e., reduction in uncertainty from the design stage).

The design of a SDT is a challenging endeavour. A clear understanding of the objectives, resources, model parameters, and risk tolerances is essential.

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