Online Structural Model Updating for Ship Structures Considering Impact and Fatigue Damage

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ABSTRACT
Naval ship structures (i.e. supports, hull, driving machinery etc.) have various damage states that develop on short-term (i.e. impact) and long-term (i.e. fatigue) time scales. An up-to-date digital twin of ship structures that can deliver condition assessment in real-time would empower a real-time decision-making framework to undertake informed response management.Together, the digital twin and decision maker will increase ship engagement survivability during combat events and reduce the severity of long-term fatigue effects. A core challenge in digital twin development is the advancement of reliable methodologies that distinguish the short-term and long-term damage states. Furthermore, these methodologies must effectively assimilate large amounts of data into physics-based or data driven prognostics models while operating on the naval structure's resource constrained computing environments and considering stringent real-time latency constraints. This work details the experimental validation of a specially designed multi-event model updating framework that meets strict real-time latency constraints while operating on a system with limited computational resources. The proposed methodology tracks both impact and fatigue structural damage using a particle swarm that represents numerical models with varying input parameters; given set constraints for latency and computational resources. Experimental validation of the proposed methodology is undertaken using data collected from a structural testbed designed to provide responses representative of a ship subjected to fatigue and impact; considering a pre-determined wave loading. Results demonstrate that a physics-based model of the structure can be updated in realtime while distinguishing between plastic deformation caused by impact and continuous fatigue crack growth. Latency effects, resource-constrained accuracy, and parameter optimization of the proposed system are quantified and further discussed in this work.

Keywords: model updating, resource-constrained, digital twins, real-time, parameter optimization

INTRODUCTION

The development of digital twins and the subsequent management of next-generation structures, such as naval structures, will play a critical role in their utilization over a complete life-cycle [1]. Additionally, as for the development of digital twins, Structural Health Monitoring (SHM) [2] and real-time model updating compose the majority of the Digital Twin development. Digital Twins without SHM or real-time model updating have hindered capabilities, accuracy, and usefulness. Moreover, if a digital twin lacks adequate real-time model updating capabilities they are unable to respond, assess, or quantify the damage caused by high-rate dynamic events. This prevents the calculations of remaining useful structural health and prognostics which are key components needed for decision-making. Real-time model updating can contain a mixture of physics-based and data-driven models which together allow for the proactive identification of the likelihood of failure; allowing for better management of the associated logistics tail [3]. For ship structures, there are two main methods to estimate structure lifespan loads that use monitored data. Each lifespan estimation is a unique monitoring method with a specific focus. The first focuses on monitoring the environment, while the second focuses on monitoring the structural response [4]. More specifically, the ship's immediate and future surroundings are paired with sea state or wave conditions. For example, monitoring ship routing and using sensing approaches that observe and estimate wave environments in real-time (including using wave height radar) can be used to update a life-cycle model of the ship structure [4]. Considering the majority of ship structure faults manifest themselves on varying time scales that consist of damage initiation on a very short time scale (i.e. impact) and damage accumulation on a long time scale (i.e. fatigue, corrosion). The real-time ship structure model updating implemented during combat and impact occurrence would lead to increases in naval system robustness.

Naval ships are equipped with an exceptionally limited amount of computational resources that are continuously allocated to an extensive range of intensive tasks that are highly dependent on the ship's current condition, posture, and mission. Moreover, the computational resources required by structural digital twins may be reallocated to more urgent needs during combat engagements such as radar signal processing, weapon system tracking, and control of power electronics [5]. Considering these limited onboard computational resources, it is necessary to allocate the needed amount of computational resources for the shortest time possible, as these limited computational resources are split between multiple intensive tasks at any given time. To update a ship component with multiple models in real-time while achieving this constraint, an optimal parameter model-updating algorithmic framework is needed.

Naval ships and structural ship components are active structures that are expected to experience and react to unmodeled high-rate dynamic events in real-time. To model active structures in real-time, any model updating methodology must use measured data to learn and adapt in real-time (under 100 ms) while operating across multiple time scales (impact to lifespan). Moreover, the real-time structural model updating technique is unable to have a sole dependency on offline training since there are unmodeled damage event combinations that exist. Therefore, the real-time structural updating technique needs to have the ability to learn the structure's state as the unmodeled high-rate dynamic event is happening [6]. This paper reports preliminary experimental results for the multi-event real-time ship structure modeling approach proposed by the author [7]. The proposed real-time multi-event framework tracks the Ship Structure and Fatigue Environment (Ship-SAFE) testbed state while it is subjected to an unmodeled dynamic event. Continuing, this proposed framework employs a swarm of particles that function together in parallel to update a linear structural model of the Ship-SAFE testbed using modal analysis. For this work, there are two direct relations to note that involve the particle swarm. The first relation is between the number of particles working together in parallel and the required computational resources, while the second relation is between the system latency and the number of iterations each of the particles is solved over. The major contribution of this work is the inclusion of data obtained from experimental modal analysis data in the proposed real-time multi-event model updating framework.

BACKGROUND

The proposed multi-event model updating methodology is presented figure 1 while the Ship-SAFE testbed and its damage tracking parameters are depicted in figure 2. This algorithmic methodology results in an accurately updated Finite Element Analysis (FEA) model of the Ship-SAFE beam by minimizing the error present between the current estimated system state and a sequence of altered structure FEA models. Since the fatigue crack growth occurs near the structure's left fixity and the roller support has a small position change on the right side, the structure's state changes as a result (i.e. damage). Continuing, as an unmodeled dynamic event travels through the structure, the current system state is calculated in real-time by selecting the best-fit FEA model that is solved with a particle swarm approach. Moreover, the required computational resources and calculation time is reduced while increasing the robustness of the algorithmic framework as the particle swarm approach only solves a subset of a large number of potential system states rather than using all the computational resources to solve every possible system state.

The real-time algorithmic framework for multi-event FEA model updating is presented in figure 1 and consists of n number of solved FEA models, each with varying independent input boundary conditions and damage state. Continuing, Equation (1). shows that the extracted mode and frequency data is used in the truncated flexibility matrix. Where d_i is a mass normalization constant for the i^{th} mode, $\bar{\phi}_i$ is the mode shape matrix, and ω_i is related to the modal frequencies matrix [8]. Next, $\Delta\mathbf{F}_{\mathrm{trun}}$ is the difference computation between the flexibility matrices of the true (damaged) structure and the trial FEA model. $\mathbf{F}_{\mathrm{turn}}^{\mathrm{true}}$ is the

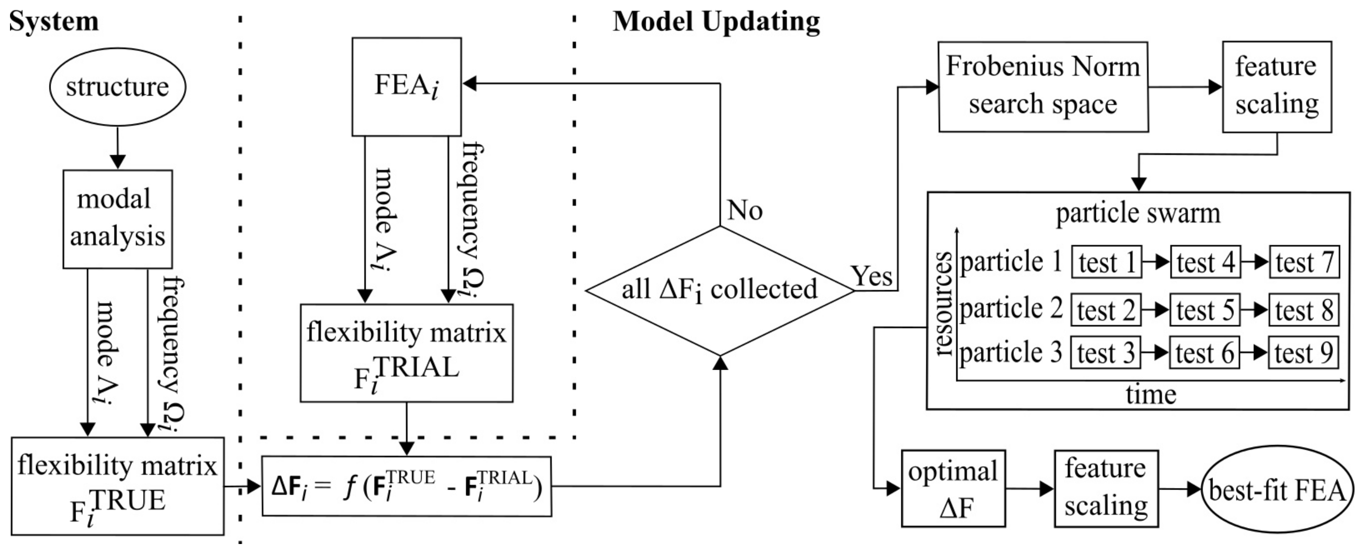


Figure 1: Methodology for the real-time multi-event model updating framework used in this work.

true (damaged) matrix, and $\mathbf{F}_{\text{turn}}^{\text{trial}}$ is the trial FEA model. Lastly, by minimizing $\Delta\mathbf{F}_{\text{trun}}$, the correlating $F_{\text{turn}}^{\text{trial}}$ model is used as the updated model for the structure.

Continuing, figure 1 shows the algorithmic framework for real-time multi-event FEA model updating and consists of n number of constructed FEA models with varying independent boundary conditions and damage cases. Next, Equation (1) shows frequency and mode data are extracted and used in a truncated flexibility matrix.

$$\mathbf{F}_{\text{trun}} = \sum_{i=1}^{n} \left(\frac{d_i}{\omega_i}\right)^2 \bar{\phi}_i \, \bar{\phi}_i^{\text{T}} \tag{1}$$

Where d_i is a mass normalization constant for the i^{th} mode, $\bar{\phi}_i$ is the mode shape matrix, and ω_i is related to the modal frequencies matrix [8]. $\Delta\mathbf{F}_{\text{trun}}$ is computed as the difference between the flexibility matrices of the true (damaged) structure and the trial FEA model. $\mathbf{F}_{\text{turn}}^{\text{true}}$ is the true (damaged) matrix, and $\mathbf{F}_{\text{turn}}^{\text{trial}}$ is the trial FEA model.

$$\Delta\mathbf{F}_{\text{trun}} = \mathbf{F}_{\text{turn}}^{\text{true}} - \mathbf{F}_{\text{turn}}^{\text{trial}} \tag{2}$$

For this work, $F_{\text{turn}}^{\text{trial}}$ is optimized using a particle swarm by iteratively improving $\Delta\mathbf{F}_{\text{trun}}$ for the FEA models. An important aspect of this project is determining the particle swarms' optimal parameters since naval ship environments have constrained computational resources. If non-optimal parameters are used, many inefficiencies occur but only the two main issues are discussed. The first is finding the optimal FEA model parameters after an extended time frame (using excessive computational resources), while the second is a returned optimal location that results in higher error (using insufficient computational resources). Continuing, both inefficiencies are very problematic, in either case, a high error solution is returned, or an excessive amount of the naval ship's computational resources are allocated over an extensive time frame. To balance both time constraints and computational resource parameters the optimal combination is determined and used for this work.

This work used the Ship-SAFE testbed cantilever beam (figure 2) to represent a ship component. The testbed consists of a large 40x40 extruded aluminum frame that secures a stepper motor that is attached to a fixed aluminum beam. The thin aluminum beam is 76.2 mm wide with a free length consisting of 914.4 mm and a thickness of 1.59 mm. Moreover, Figure 2b shows a 2D representation of the physical testbed with the roller movement along the length of the beam while figure 2c shows potential steps for a typical crack length and roller location test. For the finite element model, a defined thickness 2D shell element was used for computational efficiency.

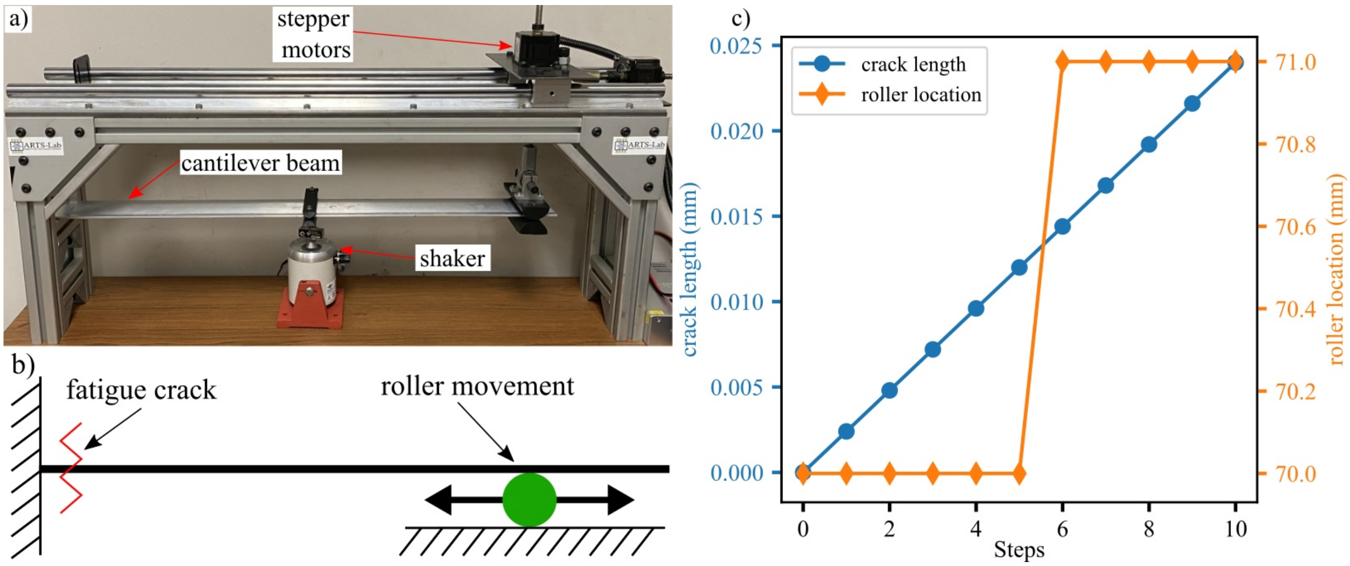


Figure 2: Ship-SAFE testbed used for this work, showing: a) Physical testbed that consists of a cantilever beam with movable support on the right-hand-side and a shaker to represent the structure of interest; and b) a 2-D representation of the structure showing the location of the fatigue crack and roller movement.

Table 1: Damage cases for the Ship-SAFE testbed considered in this work.

	roller location (m)	crack length (m)
damage case 1	0.700	0.0080
damage case 2	0.710	0.0100

The two damage cases that can be considered by the Ship-SAFE are: 1) fatigue crack growth and 2) a sudden impact represented by a sudden change in roller location. To expand, consider the temporal tracking parameters reported in figure 2c. For steps 1-5 the roller location is held at a single location while the fatigue crack length growth is constant, on step 6 the roller location is suddenly changed (representing an impact that happens on a short time scale) while the crack length growth remains at a constant rate. After the impact damage, the roller location remains at the new location while the crack length grows to its final state by step 10. However, in this preliminary work, experimental results for only two damage cases are used. The damage cases are presented in Table 1.

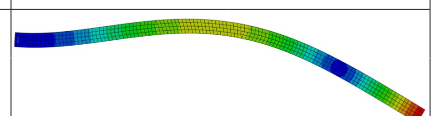
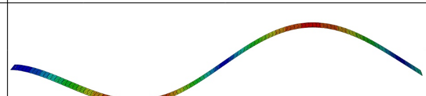
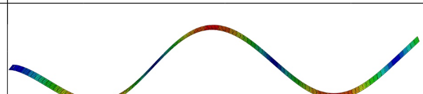
Mode	Frequency	Mode Type	Shape
1	36.036 Hz	Bending - Y	
2	69.790 Hz	Bending - Z	
3	224.81 Hz	Bending - Y	
4	225.92 Hz	Bending - Z	
5	470.05 Hz	Bending - Z	

Figure 3: First five mode shapes of the FEA model for the Ship-SAFE testbed

ANALYSIS

The first five numerical mode shapes of the Ship-SAFE cantilever beam are presented in figure 3. The specific modes of interest for this work are the vertical bending (Bending - Z) modes, which are modes 2, 4, and 5 from figure 3, since the input conditions act in the verti-

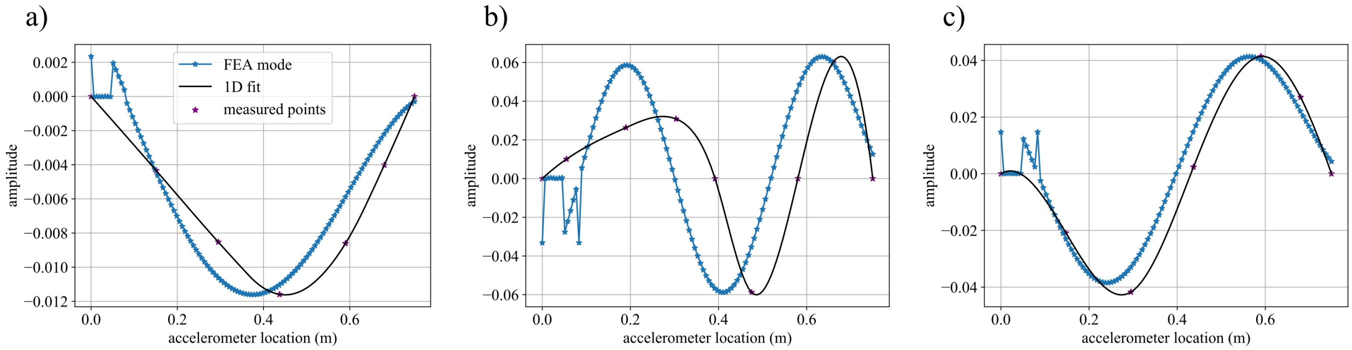


Figure 4: Experimental and numerical mode comparisons for the first three modes.

cal bending direction. Continuing, the vertical bending
modes were experimentally validated by placing accelerometers on the beam in figure 2a. The vertical mode shape comparison between the numerical and experimental modes is shown in figure 4. Continuing, figure 4 is composed of the following: 1) scaled FEA modes, 2) accelerometer measuring points, 3) interpolation points, 4) 1-D fit through measured and interpolation points. Together these aspects provide a visual mode comparison that is later mathematically evaluated using two separate methods. To initially determine the optimal curve fitting method, many fitting methods were explored such as: linear, 3-6 degree polynomial, log, 1-D fit, sine, and cosine. For this first test only the measured points were used for each fitting method, this test resulted in the 1-D fit as the most optimal fitting method. Next, each of the methods was tested again with an interpolation point on various locations and compared to each other, with the best results coming from the 1-D fit again. Lastly, the results from each 1-D fit method were compared, with the best fit resulting from the 1-D fit with an interpolation point. It is important to note that the misplaced nodes for the FEA modes are caused by the fatigue crack in the model.

Since the optimal fit method is determined, the numerical and experimental modes can be compared. Starting with mode 1,

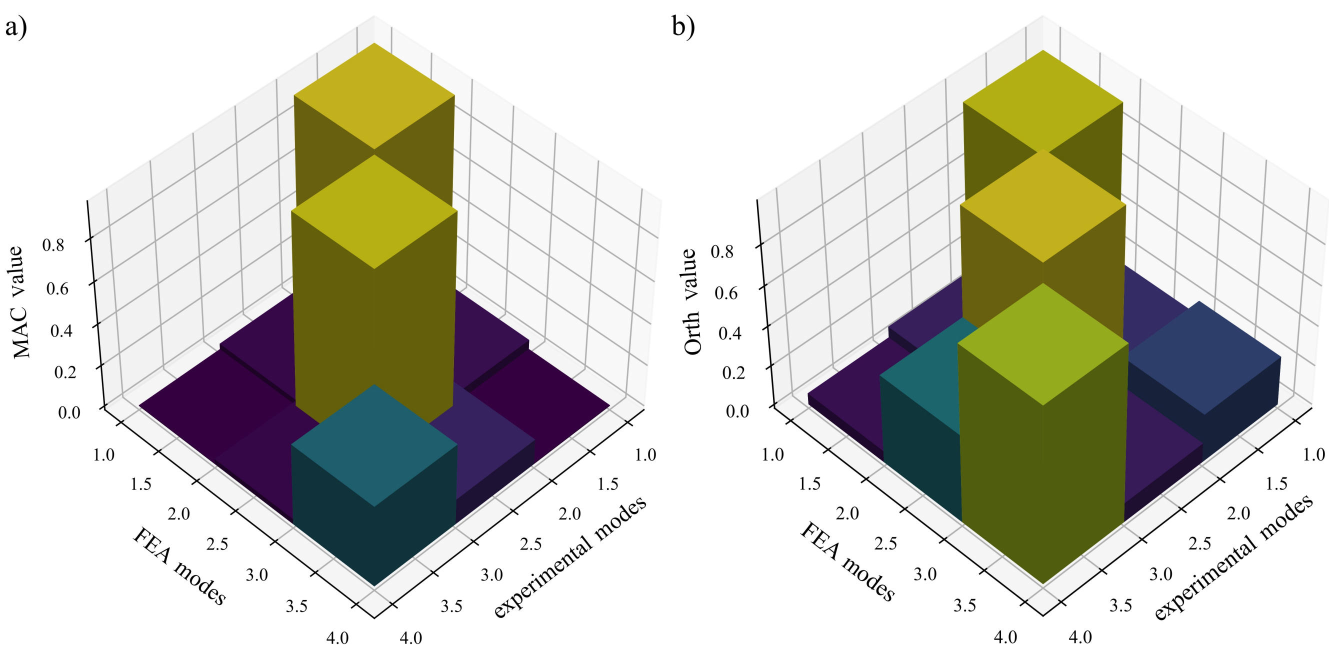


Figure 5: Experimental and numerical mode shape comparison results, showing a) Modal Assurance Criterion (MAC) plot, and b) Orthogonality plot.

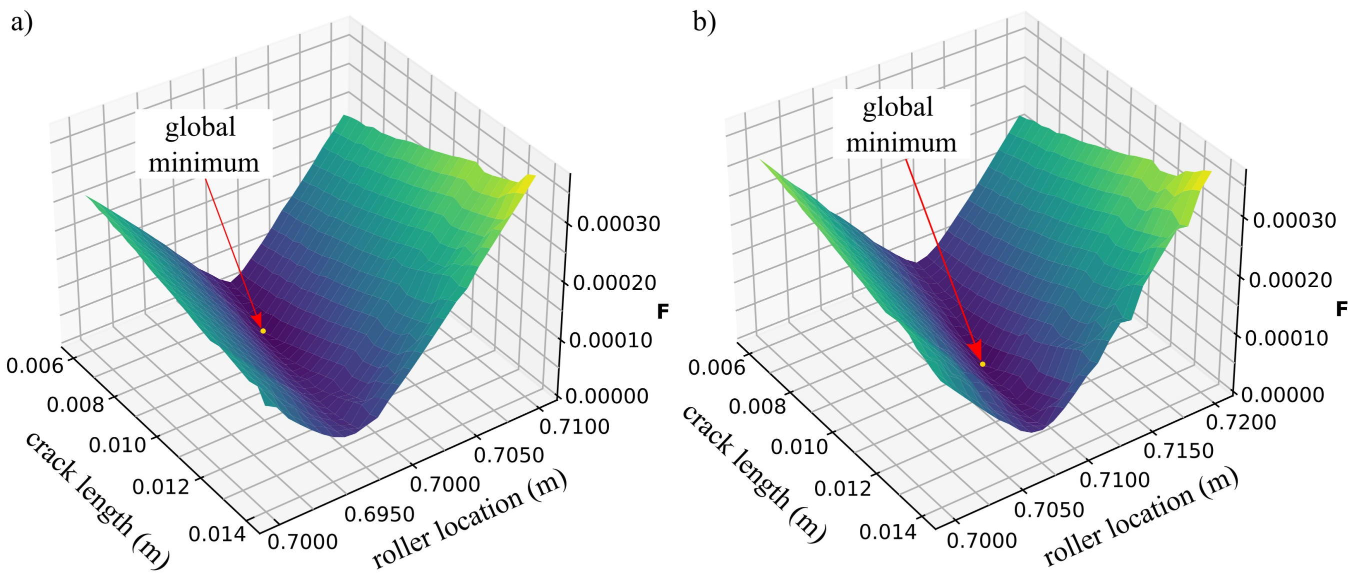


Figure 6: Experimental Frobenius Norm search space surface plot showing a) damage case 1 and b) damage case 2.

there is a good fit between the experimentally measured and numerical mode with only a small shift present. Moving to mode 2, the fit between each is better than in mode 1 but a small shift is still present. Finally, in mode 3 the fit comparison between each method is less than that in the previous modes, this is caused by a larger shift and larger difference for the first peak. To quantify and show the comparisons between the numerical and experimental modes two methods were chosen. The first method is a Modal Assurance Criterion (MAC) plot, which provides a decent degree of mode shape consistency. The second method is an Orthogonality check, which determines whether a mode can be constructed by a linear combination of other modes. Both methods were used to evaluate the first three vertical bending modes and are shown in figure 5. Here the MAC plot shows a good correlation between modes 1 and 2 with a lesser correlation for mode 3, while the Orthogonality plot shows a high correlation for modes 1, 2, and 3 with a small correlation between experimental mode 3 and numerical mode 2. This small correlation is likely apparent since both are bending modes and are similar in shape.

The MAC and Orthogonality plots both have a strong diagonal, which indicates a good correlation between like modes from the numerical and experimental methods while having weaker off-diagonal values indicating less correlation between unlike modes (i.e. mode 1 and mode 2).

The experimental Frobenius Norm search space surface plots are presented in figure 6. Where figure 6(a) is damage case 1 and figure 6(b) is damage case 2, as detailed in Table 1. The global minimum coordinate for each damage state is of interest as it corresponds to the true state of the structure that produces the smallest calculated error. Moreover, the global minimum of the experimental Frobenius Norm search space is found through a particle swarm implementation that uses random particle starting locations in the search space [7]. This search method results in a global minimum that is quickly, reliably, and efficiently determined by optimizing the particle swarm parameters. Of the tested particle-iteration parameter combinations, the optimal combination found in the authors prior work to 10 and 25 for a number of particles and number of particle iterations respectively was reused in this work [7]. Results obtained are reported in Table 2. These results show that the proposed real-time multi-event model updating framework is capable of tracking multiple error types in the considered experimental structure.

Table 2: Results for the considered damage cases.

	ground truth (m)		estimated (m)		error (%)		
	roller location	crack length	roller location	crack length	roller location	crack length	**F**
damage case 1	0.700	0.0080	0.700	0.0076	0	5.26	8.60E-06
damage case 2	0.710	0.0100	0.71	0.0103	0	-2.91	7.20E-06

CONCLUSION

There is an essential need for the development of a real-time model updating methodology for ship structures that considers impact damage, and fatigue damage without neglecting the ships computational resources. This work reports on the initial development of a multi-event model updating framework for ship structures that examine impact and fatigue damage. To provide repeatable structure conditions and evaluate the real-time multi-event model updating framework for naval ship structures, a cantilever beam testbed was developed. The experimental Frobenius Norm search space surface plots contained two damage inputs. The first considered damage case is a steady slow growing fatigue crack and the second is sudden impact damage that results in a boundary condition change. This boundary condition change caused by the impact is represented as a sudden roller connection movement on the cantilever beam. The convex experimental Frobenius Norm search space developed by the two damage events was solved using a particle swarm optimizer with experimentally determined optimal parameters. Two damage steps were investigated and the particle swarm optimizer returned near-global minimum coordinates in the Frobenius Norm search space. With near-global minimum coordinates correctly returned for both steps, the optimal parameters for the structure are known. Thus, the structural model could be updated with correct values for fatigue crack length and changes in connections (i.e. roller location). The preliminary work undertaken in this work resulted in an updated structural model with a near-global minimum returned by a particle swarm optimizer.

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