Spring 2023

Timing Deterministic Structural Model Updating Considering Impact and Fatigue Damage

Jason Michael Smith Jr.

Timing Deterministic Structural Model Updating Considering Impact and Fatigue Damage

by

Jason Michael Smith Jr.

Bachelor of Science in Engineering
University of South Carolina, 2021

Submitted in Partial Fulfillment of the Requirements

For the Degree of Master of Science in

Mechanical Engineering

College of Engineering and Computing

University of South Carolina

2023

Accepted by:

Austin Downey, Director of Thesis

Sourav Banerjee, Reader

Cheryl L. Addy, Interim Vice Provost and Dean of the Graduate School

ABSTRACT

Naval ship structures such as support trusses, hull sections, driving machinery, and load-bearing beams are subjected to various damage states that develop on short-term (i.e. impact) and long-term (i.e. fatigue) timescales. Naval structures fitted with a structural health monitoring system with damage detection abilities will enable appropriate real-time adjustments to the ships' posture and control policies and thus have increased survivability and lethality. A digital twin can provide real-time condition assessment of naval structures when conjoined with a decision-making framework will increase naval ship survivability through informed response management. A fundamental challenge for the development of digital twins is reliable methodology advancement that is able to distinguish short-term damage from long-term damage states. Moreover, the methodology advancement must efficiently update vast amounts of data into data-driven or physics-based models while efficiently computing on the naval ships resourced constrained environments and meeting stringent latency constraints. This work details the numerical and experimental validation of a particularly designed framework for multi-event model updating that meets stringent latency constraints while computing on a system with limited computational resources. The proposed framework tracks impact and fatigue structural damage through a particle swarm implementation that represents numerical models with various input parameters with set latency constraints and available computational resources. The proposed methodology is used to conduct experimental validation using data measured from a structural testbed designed to provide representative ship responses subjected to impact and fatigue events while considering a pre-determined wave loading condition. Results demonstrate that a structural physics-

based model can be updated in real-time while differentiating plastic deformation caused by impact events from continuous fatigue crack growth. Latency effects, resource-constrained computation accuracy, parameter optimization, and process robustness of the proposed framework are quantified and discussed further in this work.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

$\boldsymbol{F}_{trun}$ Denotes the truncated flexibility matrix.

d_i Denotes a mass normalization constant for the ith mode.

ω_i Denotes the modal frequency matrix.

$\bar{\phi}_i$ Denotes the mode shape matrix.

^{T} Denotes a transpose of a vector or matrix.

Δ Denotes the change between state one to state two.

$\boldsymbol{F}_{turn}^{true}$ Denotes the flexibility matrix of the true damaged structure.

$\boldsymbol{F}_{turn}^{trial}$ Denotes the flexibility matrix of the is the trial FEA model.

LIST OF ABBREVIATIONS

FBA .... Flexibility Based Approach

FEA .... Finite Element Analysis

MAC .... Modal Assurance Criterion

NDT .... Nondestructive Testing

Ship-SAFE .... Ship Structure and Fatigue Environment

SHM .... Structural Health Monitoring

CHAPTER 1

INTRODUCTION

The development of digital twins with the subsequent management of next-generation structures, such as naval structures, will play a fundamental role in their operation throughout their life cycle [1]. Continuing, Structural Health Monitoring (SHM) [2] and model updating in real-time compose most of the digital twin development. Without these two aspects, SHM or real-time model updating, Digital Twins are less complex but at a cost of available capabilities, usefulness, and reduced accuracy. More specifically, digital twins are unable to properly detect, assess, respond, or quantify damage caused by high-rate dynamic events. Continuing, this prevents core decision making components from being calculated such as a naval structures' remaining useful health and prognostics. Real-time model updating can be composed of a mixture of models, such as physics-based and data driven types that together enable the proactive identification of failure occurrence; thus, allowing for informed management of the associated logistics tail [3]. Specifically, for ship structures, there are two main frameworks to estimate a structure lifespan loads that use monitored data. Each lifespan estimation has a specific focus that uses a unique method for monitored data, with the first focusing on monitoring the environment while the second focuses on monitoring the ships structural response [4]. Moreover, the immediate and future ship surroundings are paired with the current wave conditions or sea state. For example, monitoring ship routing while using sensing approaches that observe and estimate wave environments in real-time, including wave height radar, can be used to update a life-cycle model of the ship structure [4]. The majority of ship structure failures and faults are manifested on varying timescales consisting of initial damage caused by impacts that occurs on a very short time scale and accumulated damage caused by fatigue or corrosion that occurs on a much longer time scale. The real-time structural model updating framework onboard naval ships would increase naval system robustness when implemented during combat and impact occurrences.

However, naval ships have an exceptionally limited amount of computational resources which are actively allocated to an extensive range of resource intensive tasks that have a direct dependency on the current condition of the ship and its surroundings. Moreover, the structural digital twin may reallocate its limited computational resources to critical or more urgent tasks during combat engagements such as radar signal processing, weapon system tracking, control of power electronics [5]. With these limited computational resources onboard the naval ships, it is necessary to allocate only the required amount of computational resources for each task until its complete. Moreover, only allocating the needed amount of computational resources for the shortest time possible, as these limited computational resources are divided amongst various intensive computing task at any given time. To achieve an updated ship component using multiple models in real-time while operating under this stringent constraint, a model-updating algorithmic framework with optimal parameters is required.

Active structures such as naval ships and structural ship components actively encounter unmodeled high-rate dynamic events and are expected react accordingly. Active structure real-time modeling methodologies must incorporate measured data to enable real-time (under 100 ms) learning and adaptation while operating on multiple, impact to lifespan, time scales Furthermore, only incorporating a dependency on offline training for the real-time structural model updating framework will result in inaccurate models since the damage is a combination of unmodeled events. Thus, the real-time structural updating framework must incorporate the ability to learn the state of the structure as it experiences the unmodeled high-rate dynamic event [6]. This paper reports experimental results for the multi-event real-time ship structure modeling approach. The real-time multi-event framework tracks the Ship Structure and Fatigue Environment (Ship-SAFE) testbed state as it is subjected to an unmodeled dynamic event. Continuing, the framework updates a linear structural model of the Ship-SAFE testbed using modal analysis by utilizing a swarm of particles that function in parallel. In this work there are two direct relations that involve the particle swarm's robustness. The first direct relation is the number of required particles that work together in parallel and the required amount of computational resources, while the second relation is between the number of iterations each particle is solved and the resulting system latency.

This works major contributions are, 1) the introduction and validation of a real-time model-updating algorithm that is free of offline training and any pre-calculated data; 2) the algorithm tracking the Ship-SAFE testbed state while it experiences a dynamic event; 3) investigating the effects of limited computational resources on the algorithm accuracy; 4) the inclusion of experimental modal analysis data obtained from the Ship-SAFE testbed.

CHAPTER 2

LITERATURE REVIEW

Real-time model updating is an important aspect of digital twin technology, especially for naval ship and ship structures. Continuing, a core difference between a model and a digital twin Is that models only provide information on a structures' expected behavior without any feedback from the physical structure, whereas a digital twin uses multiple models that provide information on a structures behavior and the structure provides continuous updates the models though various data collection methods. This work aims to update a structural model by using measured data from a physical structure using a flexibility-based approach. Additionally, the calculations between the model and structure flexibility are reduced by implementing a truncated flexibility matrix that reduces the search space for the particle swarm optimization. Moreover, the flexibility-based approach only creates a subset of potential system states which reduces the search space the particle swarm needs to optimize.

2.1 NAVAL SHIPS: DIGITAL TWIN AND SHM

Digital twins have been defined in the past as a "digital representation of a physical object" but for affordability the digital twin has advances into system-of-systems model where each of the twins will convey information amongst themselves [3]. Moreover, having multiple digital twins each based on different data inputs. For example, a baseline twin based on physics-based model behavior, a load-based twin that uses the operating context rather than the asset response, a ML proxy where behavior is based on data-driven modeling, and a benchmark twin where we use a model of the asset in conjunction with actual data to monitor the system for expected behavior [3].

If a digital twin is implemented with hull, mechanical and electrical (HM&E) it can inform viable information such as propulsion system health, predict ship speed, and numerous other things [3].

With this the main purpose of a digital twin is to provide a real-time system health of the vessel [3]. There are many ways to determine the health of a structure by implementing Structural Health Monitoring (SHM). More specifically, integrating structural health monitoring data with multi-scale, multi-physics, probabilistic models can be used to help track the status of assets and aid in decision support [4].

Integrating SHM with the digital twin by monitoring the response from the structure would give the system a qualification of lifetime load and reduces significant amount of uncertainty with fatigue damage estimation [4]. The power of a digital twin comes into play when we can leverage our best understanding of the ship’s current condition and use that to evaluate future performance [3].

2.2 SEARCH SPACES: FBA AND PARTICLE SWARM

The Flexibility Based Approach (FBA) evaluates an error function using the properties of the model and the flexibility matrix to formulate an objective function based on the difference between the flexibility matrices that correspond to the true and trial models [7].

The FBA has many benefits and is a robust framework. The benefit of using the FBA is that it allows for the inclusion of lower order modes to be included in the truncated flexibility matrix while also proved effective even when large pruning rates were adopted as a way of attaining computational speed-up [7]. Continuing, Kurata et al. shows that at the core of Bayesian model updating method the ability to evaluate the closeness of the hypothesized model to the real structure is vital and using FBA was proven to be the better objective function against direct mode-based approach (DMBA) as it was more accurate in locating the crack damage [7].

A PSO system attempts to balance exploration and exploitation by combining local and global search methods [3], this is accomplished by using a population-based search procedure where there are a given number of particles that move around the search space using PSO equation parameters to determine the trajectory of each particle [8].

CHAPTER 3

BACKGROUND

This proposed work numerically and experimentally validates an algorithm for tracking fatigue crack growth and roller location parameters on the Ship Structure and Fatigue Environment testbed in real-time. This is accomplished by employing a multi-event structural model updating framework to the models and Ship-SAFE testbed. Details of the Ship-SAFE testbed, numerical model, and multi-event structural model updating algorithm are further discussed in the following sections.

3.1 SHIP-SAFE EXPERIMENTAL TESTBED AND MODEL

The numerical model created for this work is based on the Ship-SAFE testbed that was initially developed to simulate a naval ship structural component. Moreover, the Ship-SAFE testbed was specifically designed and constructed for simulating naval ship structure damage cases: a movable roller boundary condition attached to a stepper motor to simulate an impact and a continuous fatigue crack growth. The Ship-SAFE testbed is expedient when modeling naval ship structure damage cases since it enables a quick and repeatable test parameter alteration. Continuing, the roller boundary condition can quickly and accurately be changed for each testing step. In this work both damage cases are utilized and tracked using the structural multi-event modeling updating algorithm. The experimental testbed configuration is shown in figure 3.1 a).

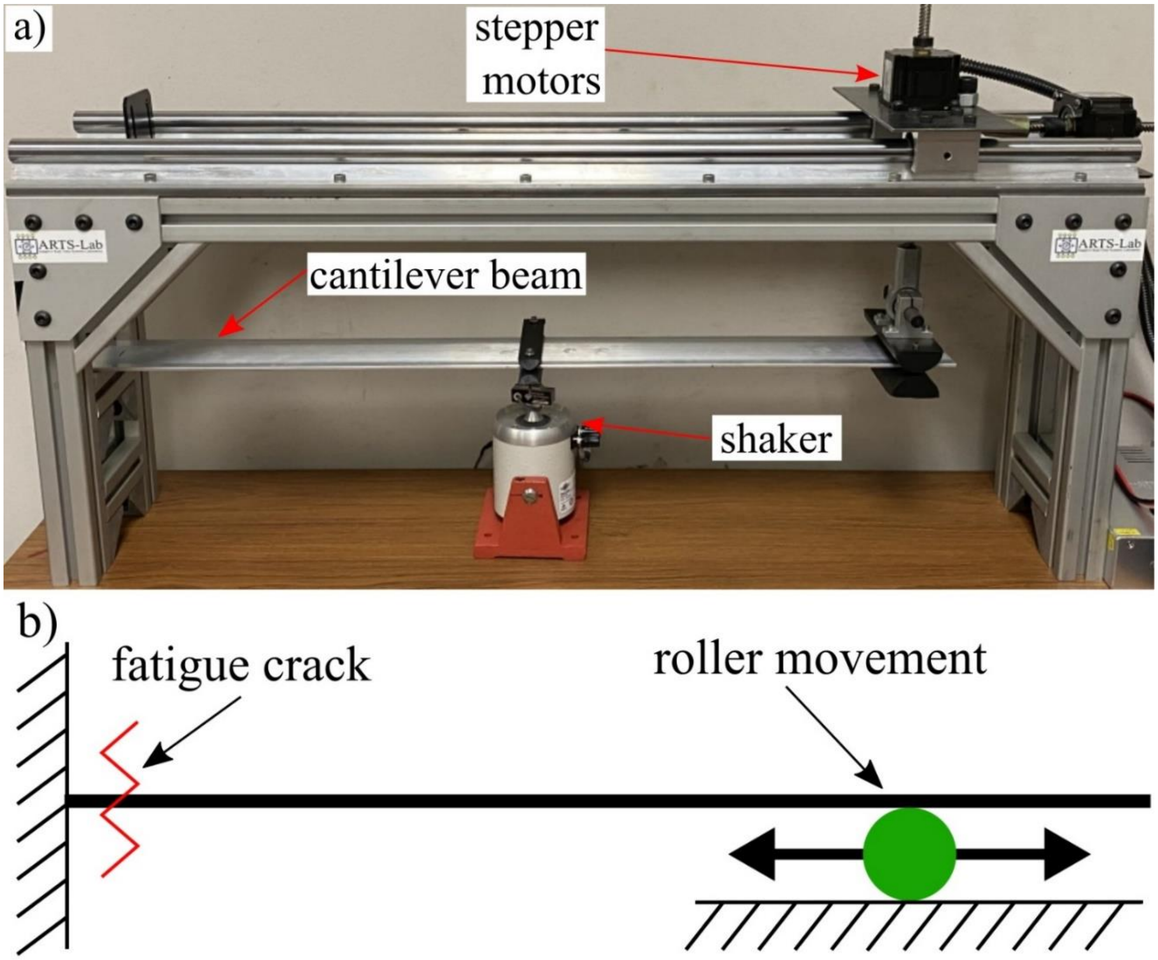


Figure 3.1 Ship-SAFE testbed used in this work.

The Ship-SAFE testbed configuration is equipped with 4 accelerometers mounted at various locations along the length of the cantilever beam with a free length of 914.4 mm, a width of 76.2 mm and a thickness of 1.59 mm (figure 3.1 a)). Continuing, the cantilever beam is attached to a large 40x40 extruded aluminum frame that also secures a stepper motor used to control the roller boundary condition. Adjusting the roller boundary condition for each testing step simulates damage to the system that is a user defined system input, which results in a change to the measured system acceleration output. Since the damage is simulated, the roller boundary condition is leveraged for its accuracy and repeatability during testing. Figure 3.1 b) shows a 2D representation of the physical Ship-SAFE testbed and how each damage case acts on the cantilever beam. The design also features a movable shaker that allows for Nondestructive testing (NDT) such as wave impact simulation and experimental modal testing.

3.2 MULTI-EVENT STRUCTURAL MODEL UPDATING

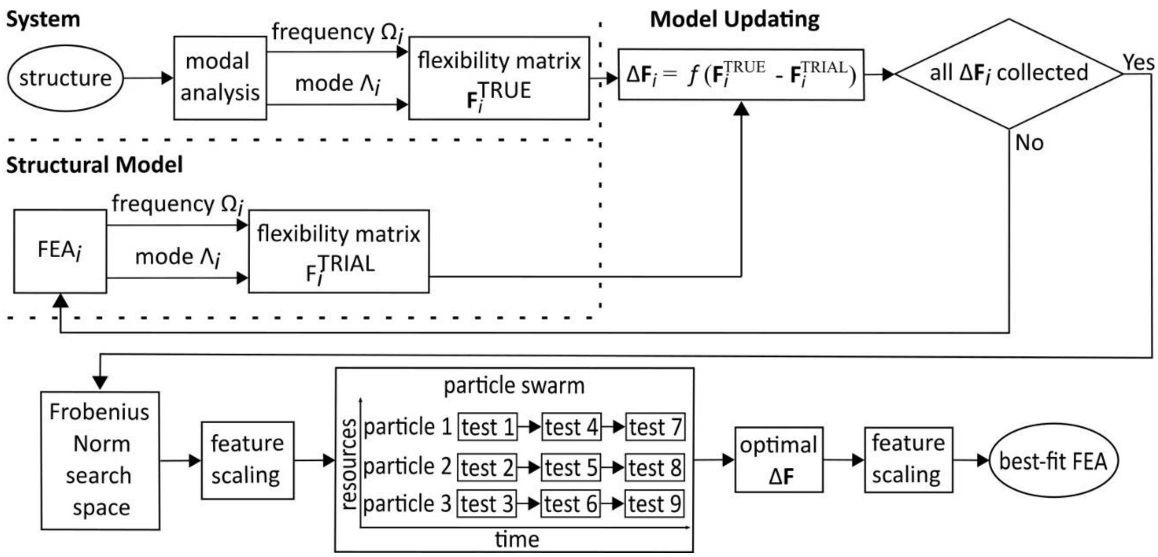


Figure 3.2 Multi-event model updating flowchart.

The real-time multi-event algorithmic framework for FEA model updating is presented in figure 3.2 and is composed of n number of solved FEA models (the subset of potential system states), with each consisting of varying independent boundary condition inputs and damage states. Continuing, the mode and frequency data is extracted and used in the truncated flexibility matrix (equation 1), where d_i is a mass normalization constant for the i^{th} mode, $\overline{\phi}_i$ is the mode shape matrix, and ω_i is related to the modal frequencies' matrix [7]. $\Delta\mathbf{F}_{trun}$ is the difference between the flexibility matrices of the damaged (true) structure and the FEA model trial, while $\mathbf{F}_{\text{turn}}^{\text{true}}$ is the damaged (true) matrix, and $\mathbf{F}_{\text{turn}}^{\text{trail}}$ is the trial FEA model. Lastly, $\Delta\mathbf{F}_{\text{trun}}$ is minimized and the corresponding $\mathbf{F}_{\text{turn}}^{\text{trial}}$ model is selected for the updated structure model.

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

Moreover, figure 3.2 shows the algorithmic framework for the multi-event FEA model updating in real-time and uses a various number of modified FEA models each constructed with slightly varying input parameters, independent roller boundary condition and damage cases respectively. Specifically, equation (1) utilizes the extracted frequency and mode data to construct the truncated flexibility matrix that is later leveraged to compute the difference between the structure and model (equation 2) used in the updating process.

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

In this work, $\boldsymbol{F}_{\text{turn}}^{\text{trial}}$ is optimized by utilizing a particle swarm procedure that improves $\Delta\mathbf{F}_{\text{trun}}$ using an iterative search approach. Utilizing more iterations and/or more particles will result in increased accuracy while trading for a longer computation time and higher allocated computational resources. Thus, a core aspect of this multi-event model updating framework is determining the optimal particle swarm parameters since naval ship environments are equipped with systems that have constrained computational resources. If optimization is not conducted, then non-optimal parameters are used which results in many inefficiencies occurring. However, for this work only two main issues are discussed; the first is finding the optimal FEA model parameters after an excessive time frame (i.e allocating excessive computational resources), while the second issue is the particle swarm returning an optimal location that results in high error (i.e., allocating insufficient computational resources). Furthermore, both of these inefficiencies are extremely problematic, either accurate FEA model parameters are returned at the cost of using excessive limited computational resources or a solution with high error is returned due to insufficient use of computational resources. To balance both time constraints and computational resource parameters, the optimal particle swarm parameters are determined and used in this work.

In summary, the multi-event FEA model updating consist of three mains parts: 1) a flexibility matrix calculation for the structure and model, 2) an error calculation between the structure and model using the calculated flexibility matrices for each, and 3) an optimized particle swarm that quickly and accurately returns optimal model parameters. The optimized particle swarm consist of governing equation optimizations and particle-iteration optimization that together result in a robust solving procedure.

3.3 NUMERICAL MODEL TYPE SELECTION

For the real-time multi-event model updating framework, an initial FEA model was constructed that modeled the Ship-SAFE cantilever beam. The initial model consisted of a 3D beam with appropriate dimensions, the far-left edge is completely fixed, and a roller constraint was placed on the right side of the FEA model. Figure 3.1 b) shows how each section of the beam is constrained. This model represented the Ship-SAFE beam very accurately but considering the resource constrained aspect of the real-time multi-event model updating framework, a reduction in computation time is needed. With this, a 2D shell element FEA model is constructed to simplify the model and reduce computation time, the model is constrained at the same locations as the 3D model. The output data (frequency and modes) from each model are almost identical, with the differences between each model type being very miniscule the 2D model was chosen due to its faster computation time. With this the fatigue crack starting location and growth directions are finalized near the left fixity while stating in the center of the beam and growing toward each edge (figure 3.3).

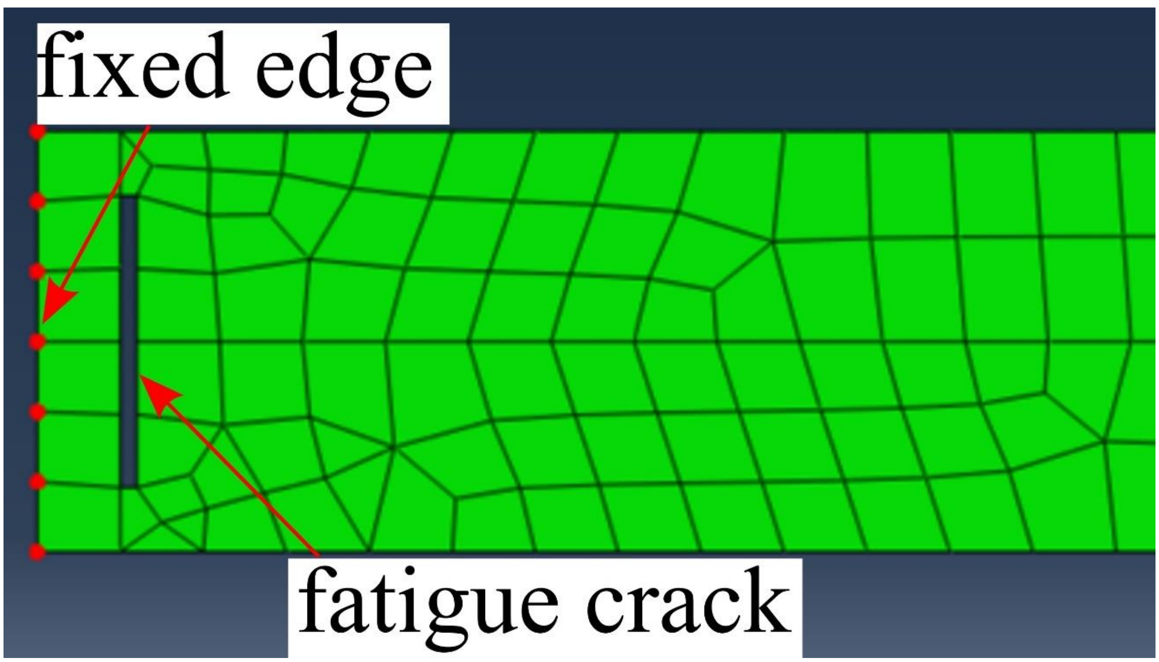


Figure 3.3 Ship-SAFE FEA model used in this work.

For this work the fatigue crack is a linear discontinuity in the material that grows in steps. Moreover, the fatigue crack isa material removal with a rectangular geometry that grows in a linear fashion toward the beam’s edges. As the crack increases in length the FEA mesh needs to be updated, for this the auto mesh option is utilized but only when the element angles become too small. Moreover, the FEA model is only re-meshed when the existing mesh has elements with extremely small angles that will result in less accuracy at those locations. Inaccuracy for elements around the fatigue crack is a core issue when determining mode shapes, the output nodal data at these locations can result in very inaccurate displacements. Figure 3.3 shows elements around the crack edges that have small angles and most likely will need to be re-meshed if the crack increases in length any further.

In summary, the FEA model is finalized as a 2D shell element model to reduce the required computational resources to solve the model and computation time. This is done by utilizing a less complex model type (2D shell instead of 3D solid) that provides near identical output results when considering natural frequencies and mode shapes when re-meshing only when small element angles are achieved.

CHAPTER 4

METHODOLOGY

Once the Ship-SAFE structure is constructed and the FEA model is created, the methodology procedure can be divided into two main sections: the numerical and experimental (figure 3.2 System and Structural model sections). The numerical model procedure (figure 3.2 Structural model section) can be further broken down into two additional sub processes: selecting roller location and starting crack length. Lastly, the experimental procedure (figure 3.2 System section) can be decomposed into three procedures: acceleration data, FFT and measured natural frequencies.

The experimental procedure will be further discussed in Section 4.1, the Frobenius Norm search space will be covered in Section 4.2 and the real-time model updating will be discussed in Section 4.3. The model type and creation were covered entirely in Section 3.3.

4.1 EXPERIMENTAL PROCEDURE

The experimental procedure is conducted to determine the “true” system response of the Ship-SAFE testbed with varying roller boundary condition locations. To accomplish this, acceleration data was collected from 4 locations (used for frequency comparisons) along the beam’s length. Before processing the acceleration data, a filtering process is needed. Here, a Hanning window is applied to the time-series data to smooth it before a Fast Fourier Transform (FFT) is applied. After applying the Hanning filtering, the natural frequencies of the Ship-SAFE cantilever beam are obtained by taking the FFT of the filtered acceleration data. With the determined natural frequencies, the experimental modes shapes can be measured. This is done by using the 4 accelerometers and measuring the response at each natural frequency. Together this creates the "true" response of the system that is then compared to various solved FEA models to create the Frobenius Norm search spaces, which is discussed further in Section 4.2.

The experimental data collected from the Ship-SAFE testbed allows for the evaluation and validation of the real-time multi-event structural model updating algorithmic framework. With this, the framework can be expanded to more complex structures with the goal of accurately updating the structural model using experimental natural frequencies and mode shapes through a Flexibility Based Approach (FBA).

4.2 FBA

The purpose of the FBA is to create the Frobenius Norm search space for the particle swarm to compute on. This is done to quickly determine the best model parameters for the current structure state. Figure 3.2 shows the FBA procedure for each model and structure (System and Structural model sections). Here, the only needed data is frequency and modal to compute the flexibility matrix (Equation 1). Once this is obtained for each of the model and structure (Section 3.3 and 4.3 details obtaining the data) the difference between the structure and model flexibility matrix is computed to create the Frobenius Norm search space. Moreover, the search is composed of various solved models each with varying parameters and each flexibility matrix is compared to the structures flexibility matrix to determine error. With the search space completed a

Particle Swarm Optimization (PSO) is implemented to quickly determine the best model parameters for the current structure state to update the model for a more accurate representation of the structure.

4.3 PSO

The PSO purpose is to select the model quickly and accurately in the Frobenius Norm search space that best represents the physical structure. This is a core aspect of the real-time multi-event structural model updating framework since naval ships have extremely resource constrained environments. If the PSO is unable to compute quickly and consistently return accurate results, then the updated model will be inaccurate while using more computational resources to compute. Various optimization methods are employed and tested to determine the best PSO governing equation parameters, particle number, and iteration numbers while considering computation time and returned result accuracy. This is discussed further in the Results and Analysis chapter.

4.4 REAL-TIME MODEL UPDATING

The real-time model updating can be completed in three major steps: 1) creating the Frobenius Norm search space, 2) featuring scaling the search space (and later inverse featuring scaling) and, 3) PSO implementation on the scaled Frobenius Norm search space. Once the Frobenius Norm search Space is created (detailed in Section 4.2) feature scaling is implemented to the entire search space, which scales each axis for its initial values to a range of 0-1. This process normalizes the independent axis's which makes the gradient of the Frobenius Norm search space smother and allows the PSO to reach a minimum quicker. The smoothing also helps remove any local minimums in the search space the PSO might get “stuck” in. Moreover, the PSO operates on a smoother gradient Frobenius Norm search space created by feature scaling and is less likely to return a local search space minimum rather than a global minimum that would result in higher error. Lastly, the scaled model values returned by the PSO are inverse feature scaled to obtain the actual optimal model parameters, which are then used to correct the structural model.

CHAPTER 5

RESULTS AND DISCUSSION

The first five numerical mode shapes of the Ship-SAFE cantilever beam are shown in figure 5.1. For this work the specific modes of interest, due to the nature of the structure and the type of forces it experiences, are the vertical bending modes (Bending – Z modes) 2, 4 and 5 from figure 5.1 which will be referred to as modes 1, 2 and 3. Moreover, the structure experiences dominate vertical input conditions thus creating bending modes. Continuing, the three bending modes are experimentally validated by placing 4 accelerometers on the Ship-SAFE cantilever beam in figure 3.1 a). The vertical bending mode shape comparison between the experimental Ship-Safe cantilever beam and the numerical FEA model of the beam is shown in figures 5.2 mode 1, 5.3 for mode 2 and 5.4 for mode 3. Continuing, figures 5.2, 5.3, and 5.4 are composed of the following features: 1) Scaled numerical mode, 2) accelerometer measuring locations, 3) an interpolation point, and 4) a 1-D fit using the acceleration locations and interpolation point. Each of these features provide a visual mode comparison that shows the accuracy of the model. This comparison is later evaluated mathematically using two methods.

5.1 EXPERIMENTAL MODE SHAPE CURVE FITTING

To determine the optimal curve fitting method, many methods were explored such as 3-6 degree polynomial, linear, 1-D fit, sin, cosine and log. Initially, only the measured points were used to test each fitting method and resulted in the 1-D fit as the most optimal fitting method for each of the modes. For a more complete test, each of the methods was test again but with the addition of the interpolation point and resulted in the 1-D fitting method being the most optimal for each mode. To compare the best fit method, 1-D fit using only measured points vs 1-D fir with interpolation point, both 1-D fit results were compared to each other resulting in the best fit method of a 1-D fit using the interpolation point. An important aspect to note is the numerical modes with misplaced nodes, which are cause by the fatigue crack in the model.

5.2 MODE SHAPE COMPARSIONS

With the optimal fit method determined, the experimental and numerical mode shapes can now be compared. Starting with vertical bending mode 1 in figure 5.2, there is a good fit between both modes with only a small visible shift. Moving to figure 5.3 for mode 2, there is still a small visible shift in the modes, but it is a better overall fit that mode 1. Lastly, mode 3 shown in figure 5.4, the comparison between the modes is less than the first two vertical bending modes with a larger shift and difference in the first peaks. To evaluate the experimental and numerical mode comparisons more accurately, two mathematical methods were chosen. The first method is the Modal Assurance Criterion (MAC) plot that provides a good statistical indicator and degree of consistency between the mode shapes while the second method is Orthogonality plot which provides an indicator of how likely a mode can be constructed from a linear combination or other modes. For example, it provides a value that shows how likely mode 3 is to be constructed from a linear combination of modes 1 and 2. Both methods were utilized to evaluate the three bending modes and are shown in figure 5.5 and 5.6 for the MAC plot and orthogonality plot respectively. The Mac plot in figure 5.5 shows a strong correlation for vertical bending modes 1 and 2 but with a lesser correlation for vertical bending mode 3, while orthogonality plot in figure 5.6 shows a strong correlation for vertical bending modes 1, 2 and 3 but also with a small correlation between the experimental vertical bending mode 3 and the numerical vertical bending mode 2. This small correlation between these modes is likely due to the similar mode shape and that they are consecutive bending modes. Moreover, the only difference between these bending modes is a single peak thus they are similar in nature.

Both the MAC and Orthogonality plot show strong diagonals, which indicates good correlation between like mode. Moreover, like modes such as experimental mode 1 compared to numerical mode 1 and experimental mode 2 compared to numerical mode 2 etc. Continuing, each also show weak off diagonals indicating less correlation between unlike mode (i.e mode1 and mode 3).

5. 3 EXPERIMENTAL DAMAGE CASES

The Frobenius Norm search space shown in figure 5.7 presents damage case 1 while damage case 2 is shown in figure 5.8, damage case 3 is presented in figure 5.9, damage case 4 is shown in figure 5.10 and lastly damage case 5 is shown in figure 5.11. Each of these damage cases is detailed in Table 5.1. For each damage state the area of interest in the global minimum as it corresponds to the true state of the Ship-SAFE cantilever beam that produces the least amount of error. Furthermore, the global minimum of the experimental Frobenius Norm search space is searched for and determined by a PSO implementation that utilizes random particle starting locations in the search space. The optimized particle swarm implementation results in a global minimum that is quickly, reliably, and efficiently returned. Continuing, the optimized particle swarm has a tested optimal particle-iteration combination of 10 particles and 25 iterations. Results obtained from the optimized particle swarm are presented in Table 5.2 and show that the proposed real-time multi-event model updating framework is capable of tracking multiple damage states in the experimental Ship-SAFE structure.

Table 5.1: Damage cases for the Ship-SAFE testbed considered for this work.

	roller location (m)	crack length (m)
damage case 1	0.700	0.0060
damage case 2	0.700	0.0080
damage case 3	0.710	0.0100
damage case 4	0.710	0.0120
damage case 5	0.710	0.0140

Table 5.2: Results for considered damage cases used in this work.

	ground truth (m)		estimated		error		
	roller location	crack length	roller location	crack length	roller location	crack length	**F**
damage case 1	0.700	0.0060	0.700	0.0065	0	-8.33	9.02E-06
damage case 2	0.700	0.0080	0.700	0.0076	0	5.26	8.60E-06
damage case 3	0.710	0.0100	0.710	0.0103	0	-2.91	7.20E-06
damage case 4	0.710	0.0120	0.710	0.0114	0	5.00	2.21E-06
damage case 5	0.710	0.0140	0.710	0.0143	0	-2.14	2.09E-06

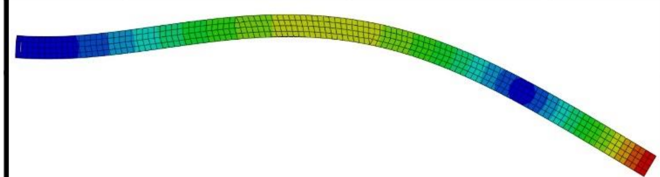
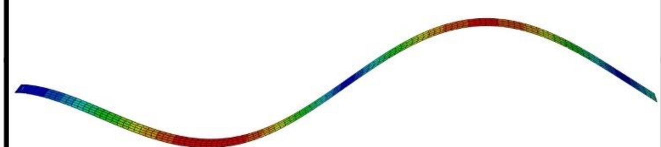
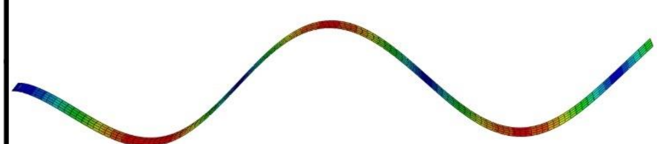
Mode	Mode Type	Frequency	Shape
1	Bending - Y	36.036 Hz	
2	Bending - Z	69.790 Hz	
3	Bending - Y	224.81 Hz	
4	Bending - Z	225.92 Hz	
5	Bending - Z	470.05 Hz	

Figure 5.1 First 5 mode shapes of the Ship-SAFE testbed FEA model

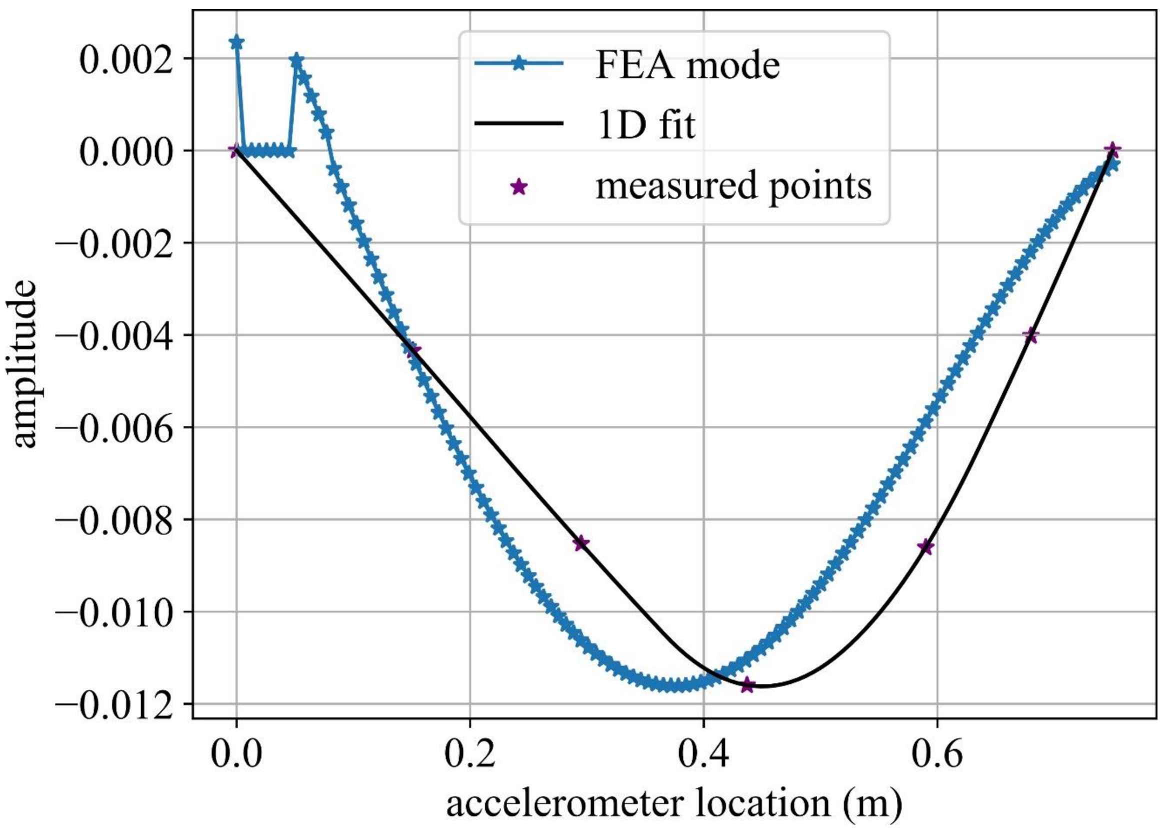


Figure 5.2 Mode 1 experimental and numerical mode comparison

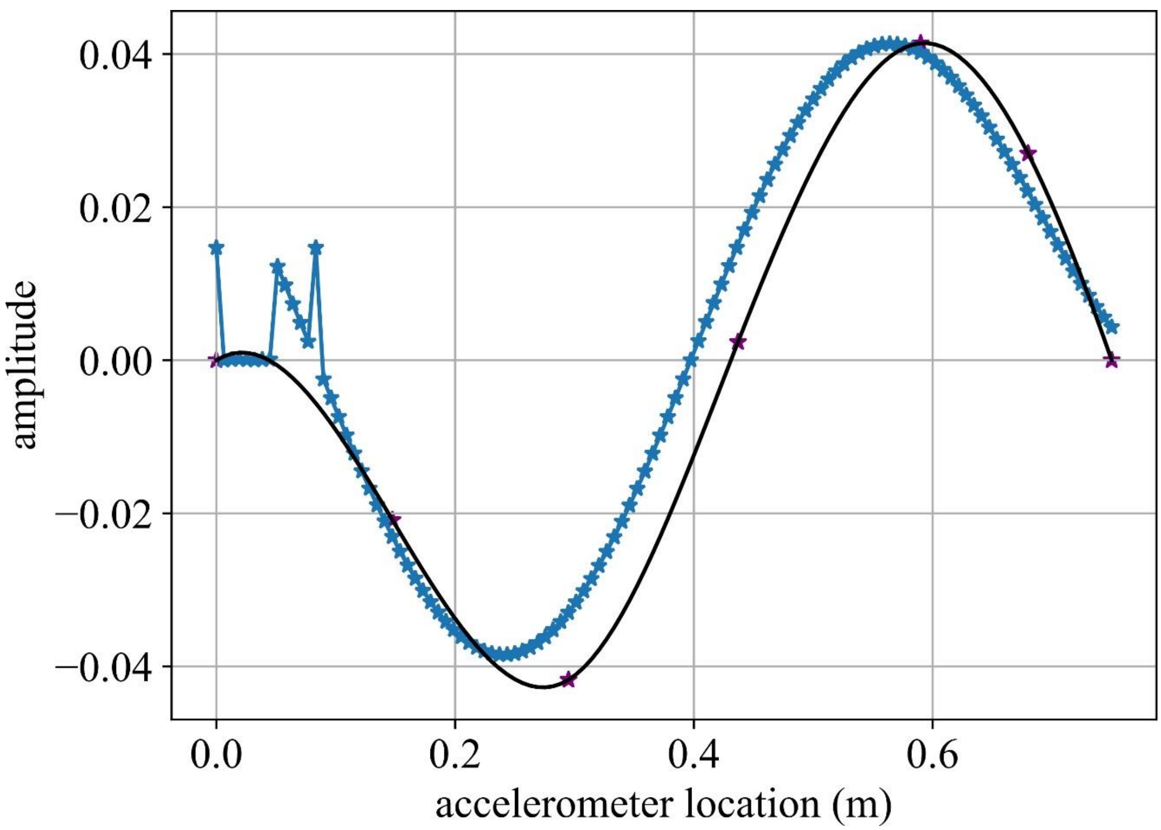


Figure 5.3 Mode 2 experimental and numerical mode comparison

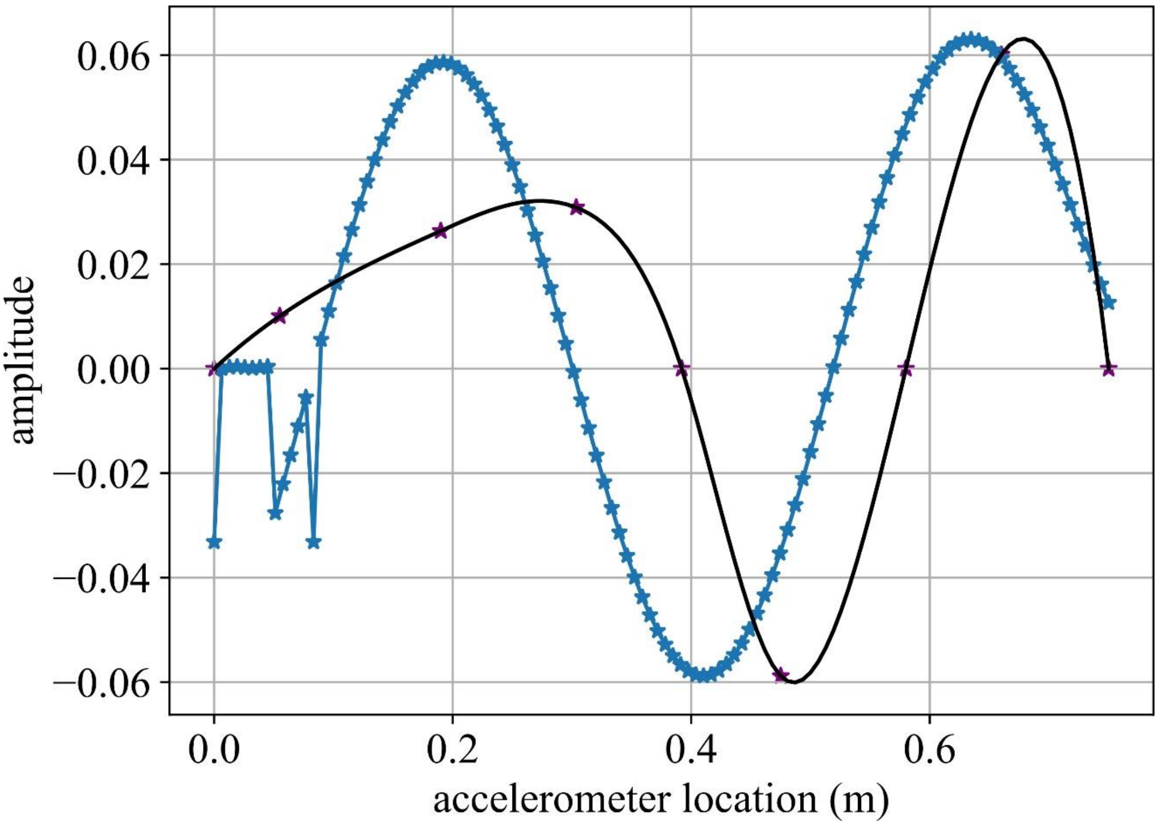


Figure 5.4 Mode 3 experimental and numerical mode comparison

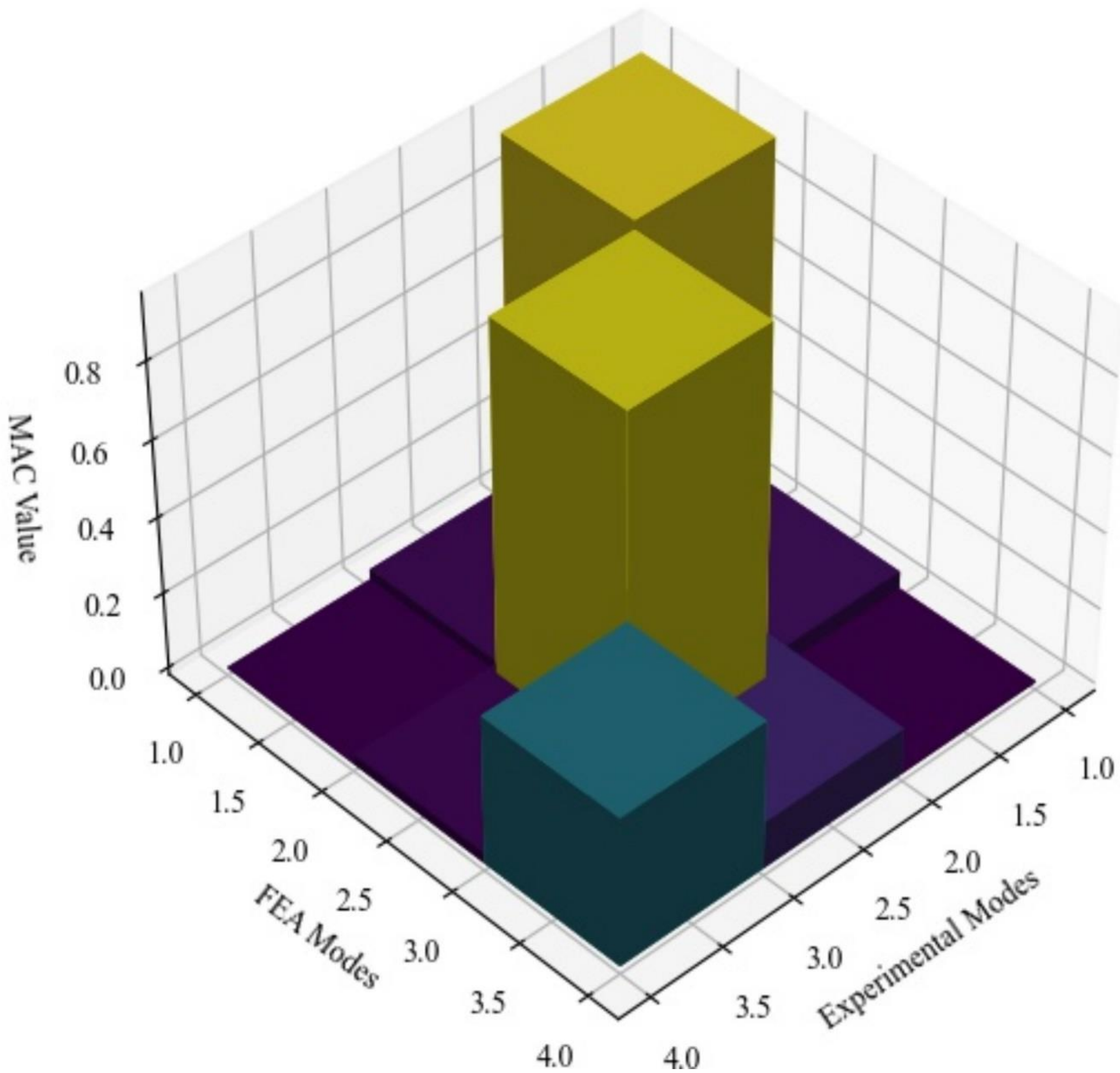


Figure 5.5 Experimental and numerical MAC plot results

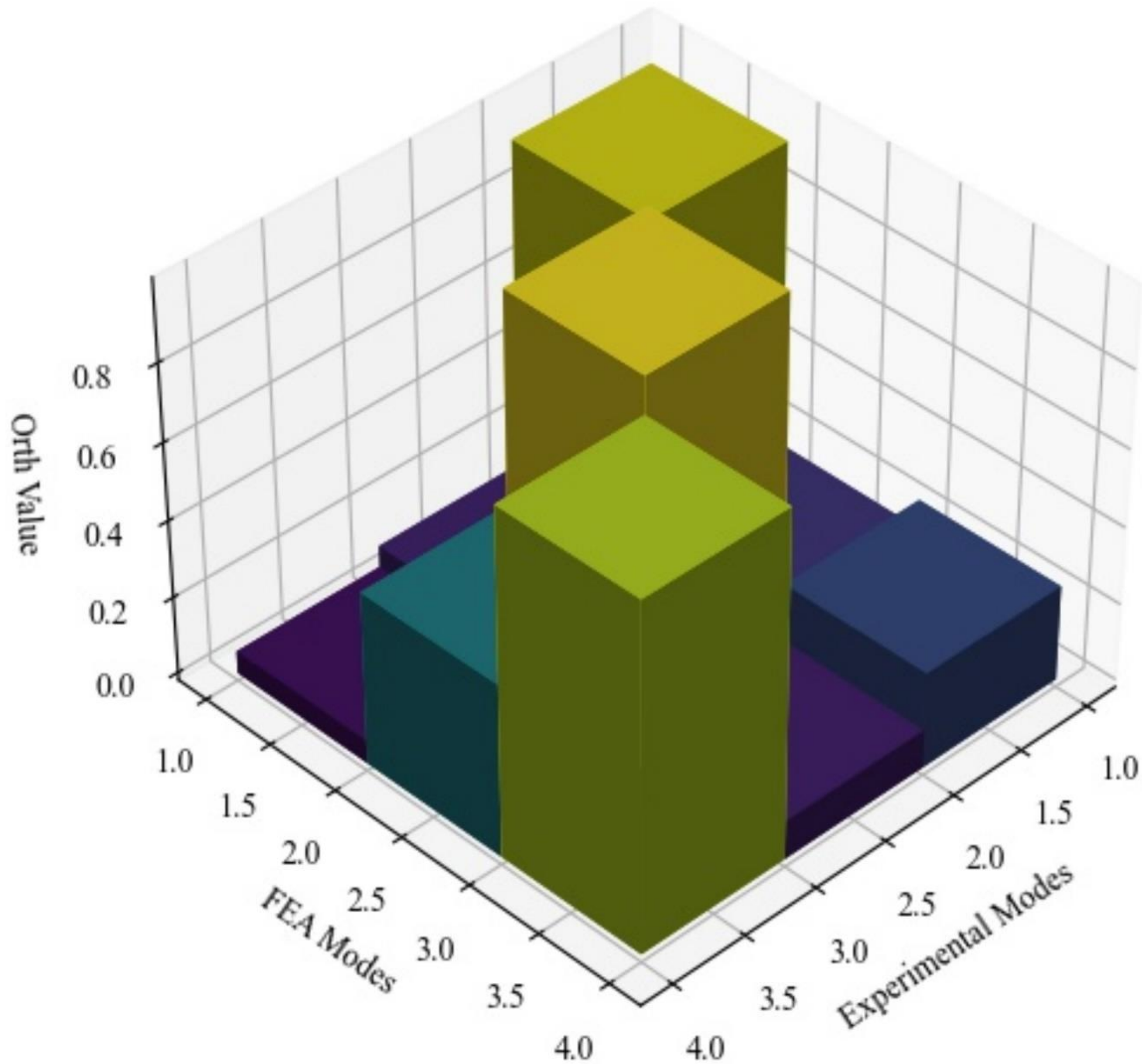


Figure 5.6 Experimental and numerical orthogonality plot results

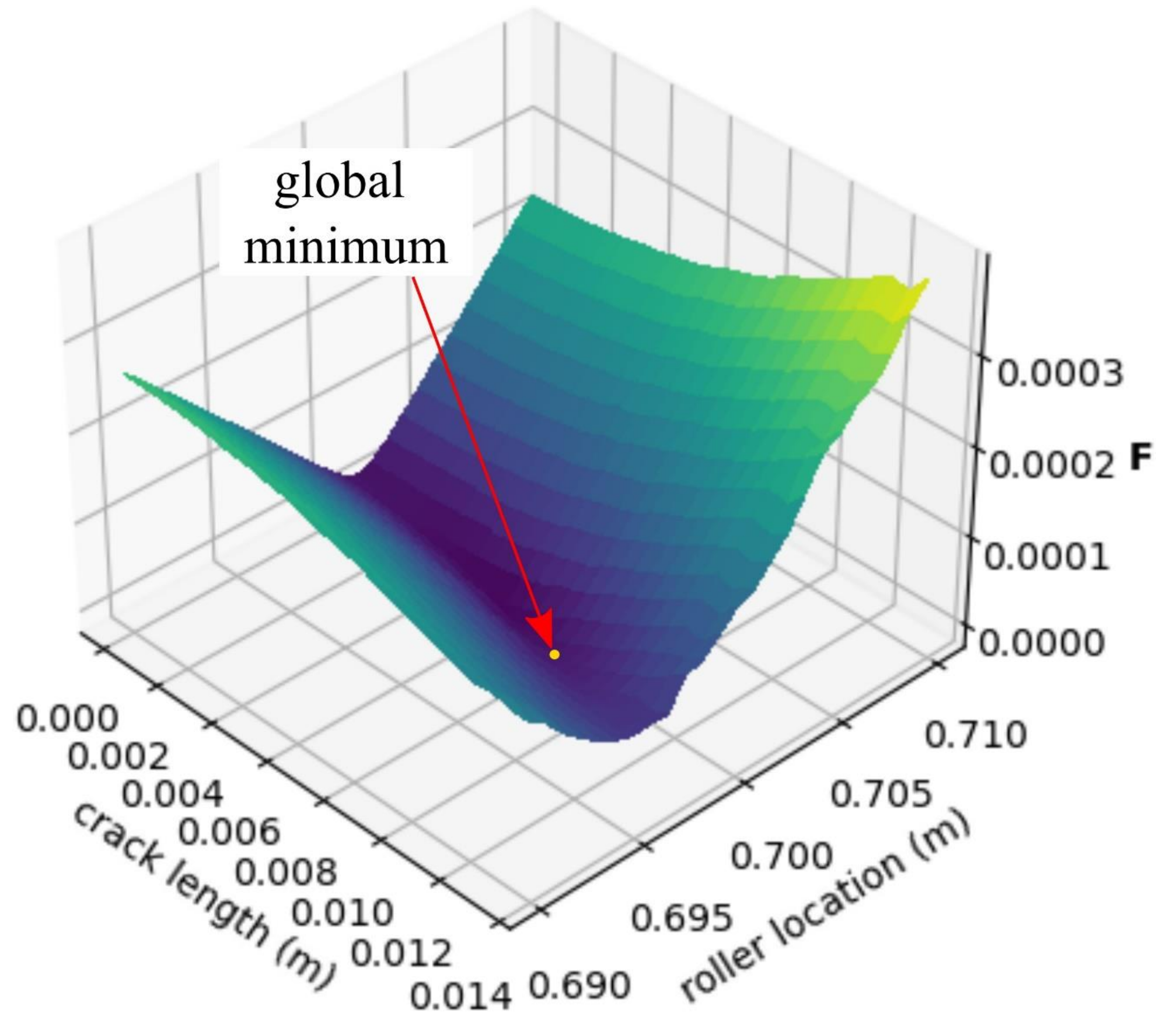


Figure 5.7 Experimental search space showing damage case 1.

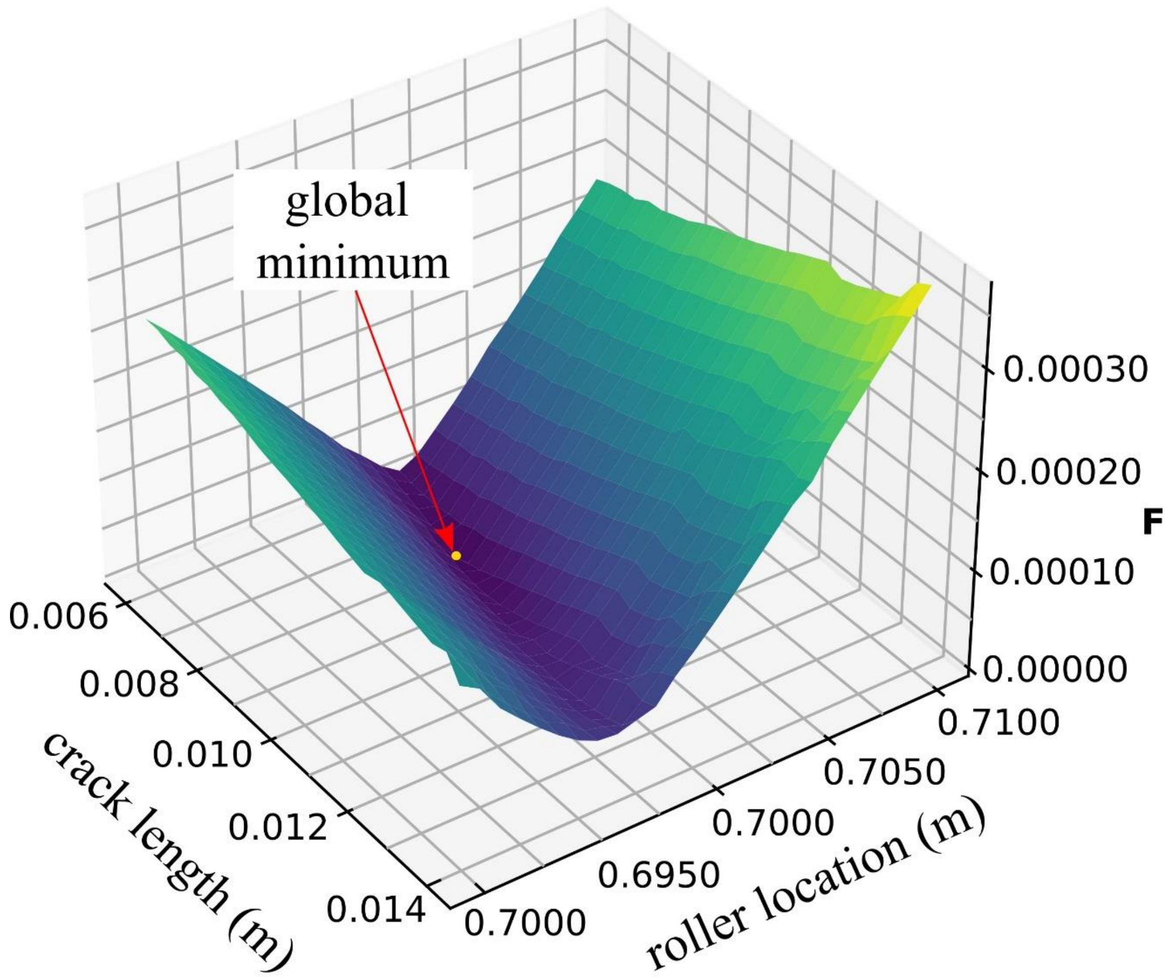


Figure 5.8 Experimental search space showing damage case 2.

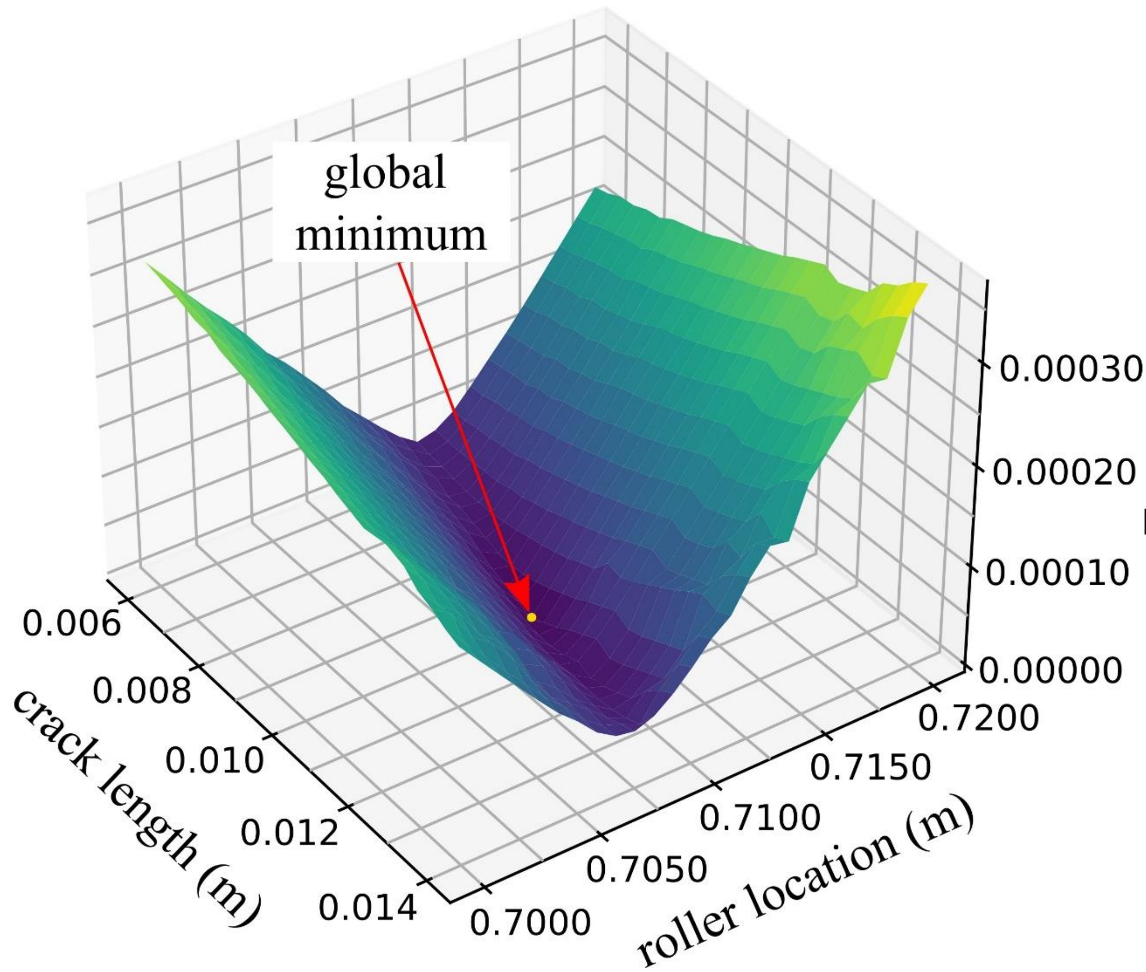


Figure 5.9 Experimental search space showing damage case 3.

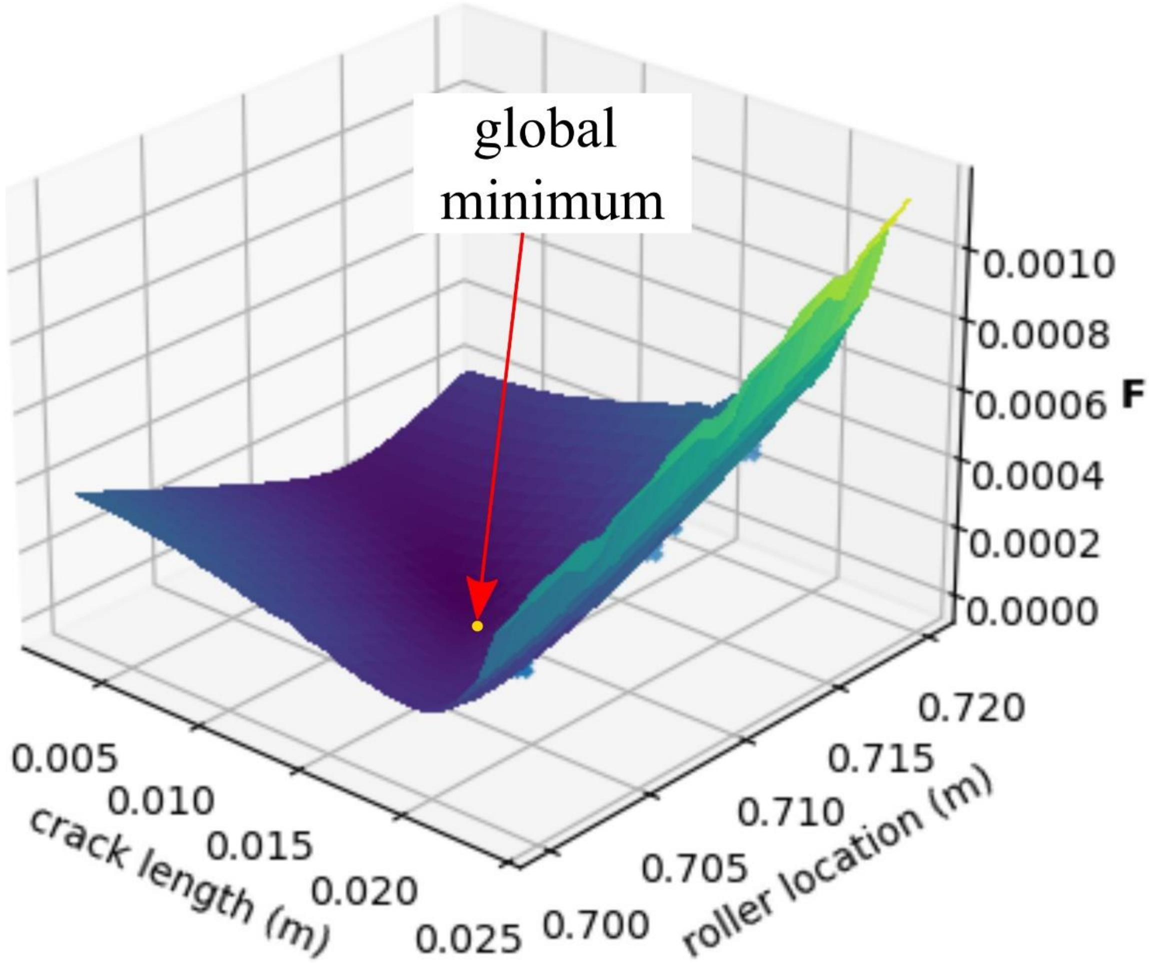


Figure 5.10 Experimental search space showing damage case 4.

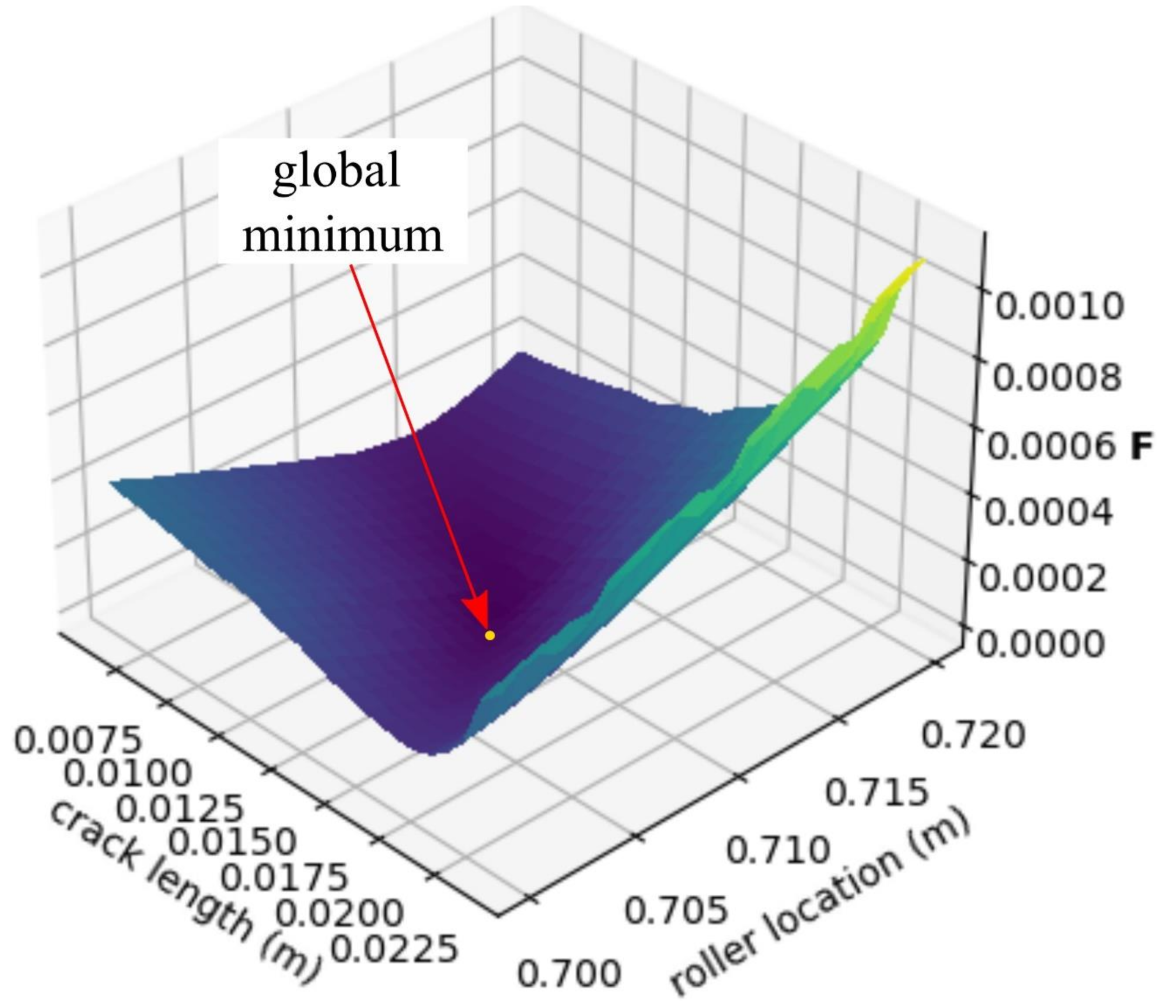


Figure 5.11 Experimental search space showing damage case 5.

REFERENCES

[1] Okasha, Nader M., and Dan M. Frangopol. “Integration of Structural Health Monitoring in a System Performance Based Life-Cycle Bridge Management Framework.” Structure and Infrastructure Engineering, 2010, pp. 1–18., https://doi.org/10.1080/15732479.2010.485726.

[2] Worden, Keith, et al. “The Fundamental Axioms of Structural Health Monitoring.” Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, vol. 463, no. 2082, 2007, pp. 1639–1664., https://doi.org/10.1098/rspa.2007.1834.

[3] Drazen, David, et al. “Use of Digital Twins to Enhance Operational Awareness and Guidance.” Computer Applications and Information Technology in the Maritime Industries, vol. 18, 2019, pp. 334–351.

[4] Mondoro, Alysson, and Benjamin Grisso. “On the Integration of SHM and Digital Twin for the Fatigue Assessment of Naval Surface Ships.” Structural Health Monitoring 2019, 2019, https://doi.org/10.12783/shm2019/32203.

[5] Schoder, Karl, et al. “Evaluation Framework for Power and Energy Management Shipboard Distribution Controls.” 2017 IEEE Electric Ship Technologies Symposium (ESTS), 2017, https://doi.org/10.1109/ests.2017.8069311.

[6] Downey, Austin, et al. “Millisecond Model Updating for Structures Experiencing Unmodeled High-Rate Dynamic Events.” Mechanical Systems and Signal Processing, vol. 138, 2020, p. 106551., https://doi.org/10.1016/j.ymssp.2019.106551.

[7] Kurata, Masahiro, et al. “A Probabilistic Model Updating Algorithm for Fatigue Damage Detection in Aluminum Hull Structures.” ASME 2010 Conference on Smart Materials, Adaptive Structures and Intelligent Systems, Volume 2, 2010, https://doi.org/10.1115/smasis2010-3838.

[8] Ender Ozcan and Chilukuri K. Mohan. “Analysis of a simple particle swarm optimization system”. In Intelligent Engineering Systems Through Artificial Neural Networks, Volume 8. jan 1998.