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Multi-event Model Updating for Ship Structures with Resource-constrained Computing

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ABSTRACT

Naval structures are subjected to damage that occurs on short-term (i.e. impact) and long-term (i.e. fatigue) time scales. Digital twins of ship structures can provide real-time condition assessment and be leveraged by a decision-making framework to enable informed response management that will increase ship survivability during engagements. A key challenge in the development of digital twins is the development of methodologies that can distinguish the various fault cases. Moreover, these methodologies must be able to operate on the resource-constrained computing environments of naval structures while meeting real-time latency constraints. This work reports on recent progress in the development of a multi-event model updating framework specially designed to meet stringent latency constraints while operating on a system with constrained computing resources. The proposed methodology tracks structural damage for both impact and fatigue damage through a swarm of particles that represent numerical models with varying input parameters with set latency and computational restraints. In this work, numerical validation is performed on a structural testbed subjected to representative wave loadings. Results demonstrate that continuous fatigue crack growth and plastic deformation caused by impact can be reliably distinguished. The effects of latency and resource constraints on the accuracy of the proposed system are quantified and discussed in this work.

Keywords: model updating, modal analysis, digital twins, real-time

1. 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] Structural Health Monitoring (SHM)[2] and real-time model updating play a key role in the development of digital twins. 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 and allow for better management of the associated logistics tail.[3] For ship structures, two main methods are used that incorporate monitored data to estimate structure lifespan loads. The first focuses on monitoring the environment, while the second focuses on monitoring the structural response.[4] 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] Generally, faults in ship structures can manifest themselves at different time-scales including damage introduced on a short time-scale (i.e. impact) and those accrued on a long time-scale (fatigue, corrosion). The real-time model updating of ship structures during combat and impact events would lead to more robust naval systems.

Computational resources on Naval ships are limited and used for a variety of tasks, which depend on the ship's current condition, posture, and mission. Moreover, during combat engagements the computational resources required by structural digital twins may be re-allocated to more urgent needs such as radar signal processing,

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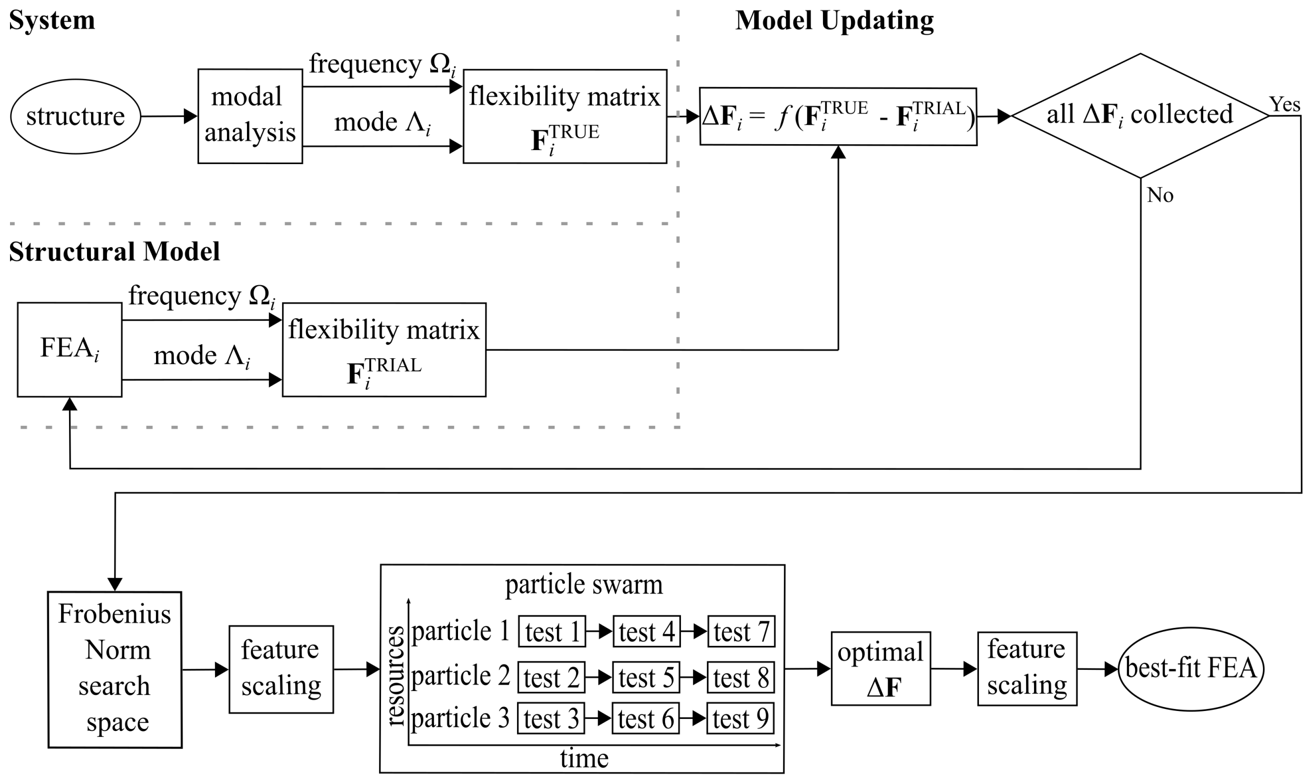

Figure 1: Methodology for the proposed real-time model updating scheme.

weapon system tracking, and control of power electronics.[5] With these limited computational resources spread between multiple tasks at any given time, it is important to only allocate the needed amount of computational resources for the shortest time possible. To achieve this constraint while updating multiple models of a ship component in real-time, a robust model-updating algorithmic framework with optimal parameters is needed.

Active structures such as Naval ships or ship components are expected to experience and respond to unmodeled dynamic events in real-time. To model these active structures in real-time, any model updating technique must learn and adapt to the measured data in real-time (under 100 ms) and across multiple timescales (impact to lifespan). The real-time structural model updating technique cannot depend on solely on offline training because not all combinations of damage events can be modeled. Thus, the real-time structural updating technique needs to have the ability to learn the structures state as the unmodeled high-rate dynamic event is happening.[6] The real-time multi-event updating framework proposed in this paper tracks the structure's state as it experiences an unmodeled dynamic event. The proposed framework uses a set of particles operating in parallel to update a linear structural model of a test structure through modal analysis. In this work, the number of particles solved in parallel are directly linked to the required computational resources while the system latency is driven by the number of iterations over which the particles are solved. This work provides three major contributions, 1) the introduction and validation of an algorithm for real-time model updating that is independent of pre-calculated data and offline training; 2) the algorithm tracking the active structure state while it is moving through a dynamic event, and; 3) investigating the effects of available computational resources on algorithm accuracy.

2. METHODOLOGY

The proposed methodology for multi-event model updating is presented in figure 1, while the testbed and damage tracking parameters are presented in figures 2 and 3 respectively. The algorithmic framework provides an accurate updated FEA model of the structure by minimizing the calculated error between the current estimated system

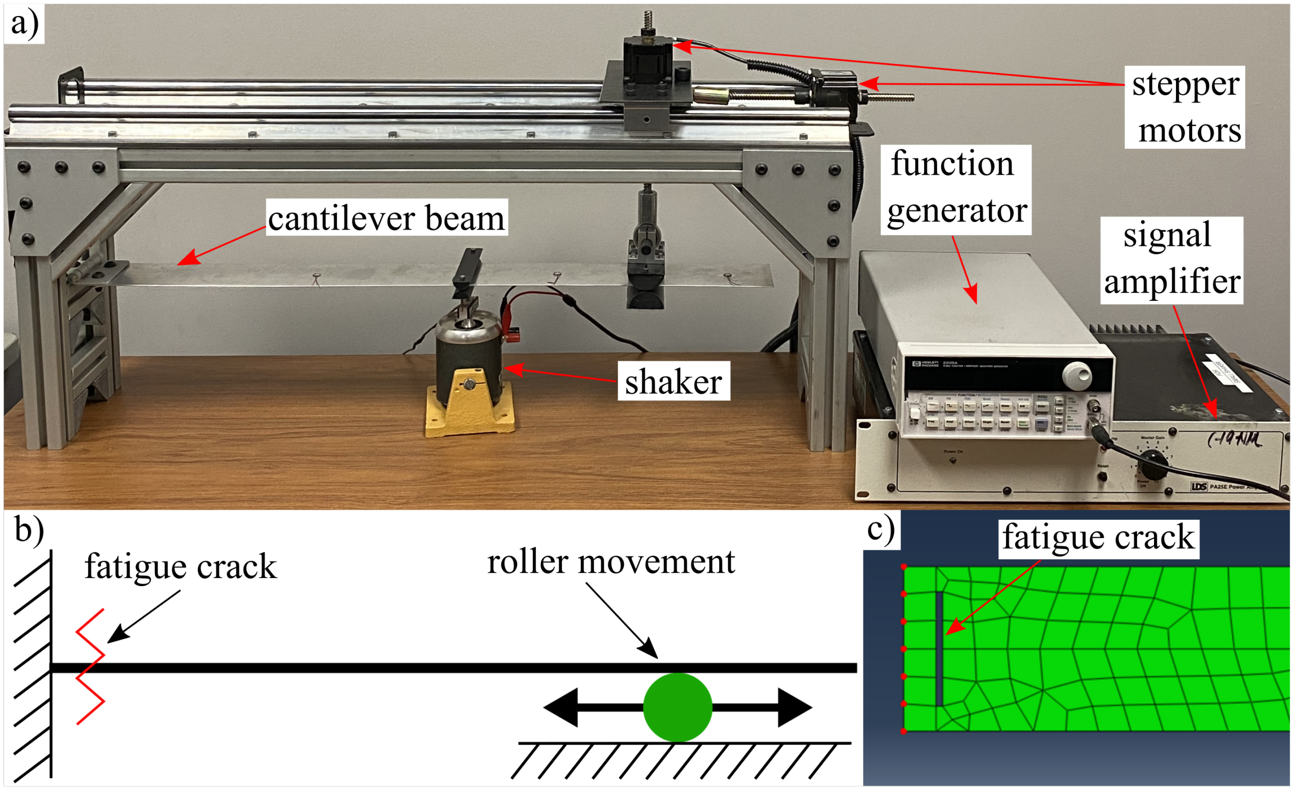

Figure 2: Testbed used for this work, showing: a) Physical testbed that consists of a cantilever beam with movable support on the right-hand-side and a shaker to represent the structure of interest; b) a 2-D representation of the structure showing the location of the fatigue crack and roller movement, and; c) FEA model with the fatigue crack modeled as a whole in the material.

state and a series of modified structure models. Changes to the structure's state (i.e. damage) is created by a fatigue crack that forms at the fixity of the structure and a slight change in the position of the roller support on the right-hand side. The current condition of the structure is calculated in real-time, while an un-modeled dynamic event moves through the structure, by selecting the best-fit FEA model solved for through a particle swarm approach. Since the particle swarm approach solves only a subset of the potential number of system states, the calculation time and computational resources are reduced while making the algorithmic framework more robust.

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

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

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.[7] $\Delta\mathbf{F}_{\text{trun}}$ 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.

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

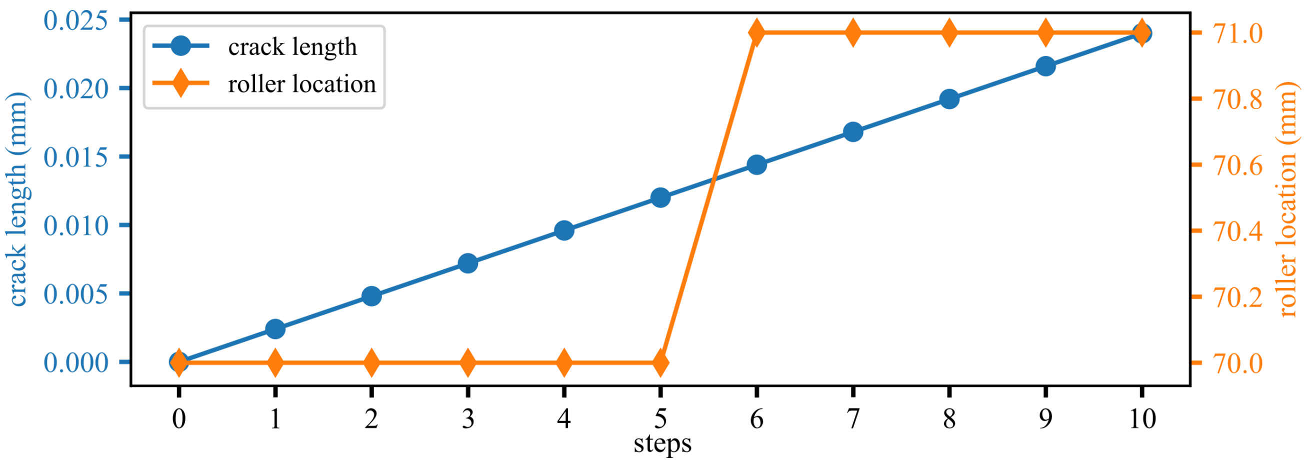

Figure 3: Continuously changing crack length (fatigue damage) and sudden boundary condition change (impact damage) experienced by the structure.

Though minimizing $\Delta \mathbf{F}_{\mathrm{trun}}$, the correlating $F_{\mathrm{turn}}^{\mathrm{trial}}$ model is taken as updated model of the structure.

In this work, a particle swarm optimizes $F_{\mathrm{turn}}^{\mathrm{trial}}$ by iteratively trying to improve the FEA model with regard to $\Delta \mathbf{F}_{\mathrm{trun}}$. Determining the optimal particle swarm parameters is important for this project due to the resource-constrained computing available onboard naval platforms. If non-optimal parameters are chosen, either the returned optimal location will result in a higher error (using fewer computational resources than need) or finding the optimal location after a longer-time frame (using more computational resources than needed). Both results are problematic, either a wrong solution is returned, or an unnecessary amount of limited computational resources are used over an extensive time frame. When optimal parameters are chosen, the computational resource and time constraint are balanced.

For this work, a testbed with a cantilever beam (figure 2) is used to represent a ship component. The testbed consists of a large 40x40 extruded aluminum frame securing a stepper motor that is attached to a hinged aluminum beam. The beam is 76.2 mm wide with a free length consisting of 914.4 mm and a thickness of 1.59 mm. Figure 2b) shows a 2D representation of the physical structure and the roller movement along the length of the cantilever beam while figure 2c) shows the developed FEA model. For this investigation, a 2D shell element with a defined thickness was used in the finite element model. Note that in this introductory work, the experimental mode shapes and frequencies are obtained from a ground-truth model. In future work, this data will be collected experimentally from the testbed.

Figure 3 reports the two considered damage conditions: a constant growing fatigue crack and a sudden impact that is represented by a sudden roller location change in the testbed. For steps 1–5 the crack length growth is constant while the roller remains in one location, but for step 6 the roller location suddenly changes while the crack growth remains constant. For the remaining steps, the roller locations remain at the same location while the crack length grows to its final length.

3. RESULTS

The Frobenius Norm search space surface plot for step 4 in figure 3 is presented in figure 4. The point of interest for this specific step is the global minimum coordinate that corresponds to a crack length of 0.010 mm, a roller location of 0.70 m, and a calculated error of 0. The calculated error is 0 because this coordinate location is the true value. Continuing, the global minimum of the Frobenius Norm search space produces the least error and is quickly and repeatably found by particle swarm using random particle starting locations. To determine the optimal particle-iteration combination for the particle swarm, a varying number of particles with a varying number of iterations were tested. For each test, the particle number increased by 2 while the iteration number increased by 5. This was done until there were 20 particles with 40 iterations. Once each test is completed, the results were investigated to determine which particle-iteration combination returned the global minimum. All the tested particle-iteration combinations are reported in figure 5, which shows the rapid decline in average error as the number of particles and iterations increase. Continuing, after the rapid decline in average error values a plateau occurs and each combination in this area returns the global minimum for every test but takes an increasing amount of time to complete.

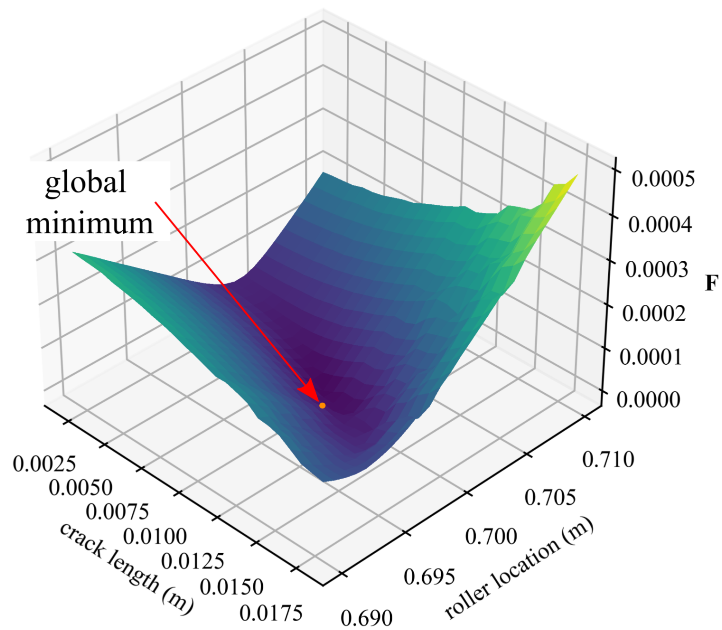

Figure 4: Search space with random particle swarm starting locations.

The chosen optimal particle-iteration combination is at the beginning of the plateau since it repeatedly returns the global minimum and takes the smallest quantity of computational resources to complete compared to the following particle-iteration combinations in the plateau. Naturally, many particle-iteration combinations repeatably found the global minimum. However only the certain particle-iteration combinations that found the global minimum were considered since some combinations used an increased quantity of limited computational resources and required a longer amount of time to complete the task. Of the considered combinations, the chosen optimal particle-iteration combination was found to be 10 particles and 25 iterations. This particle-iteration combination was found to be slightly more reliable compared to other combinations.

The results for varying particle-iteration combinations for each crack growth and roller location step are presented in figure 6, which shows the performance comparison between non-optimal and chosen optimal combinations. Here we can see the increase in the particle swarms' accuracy as the particle-iteration combination

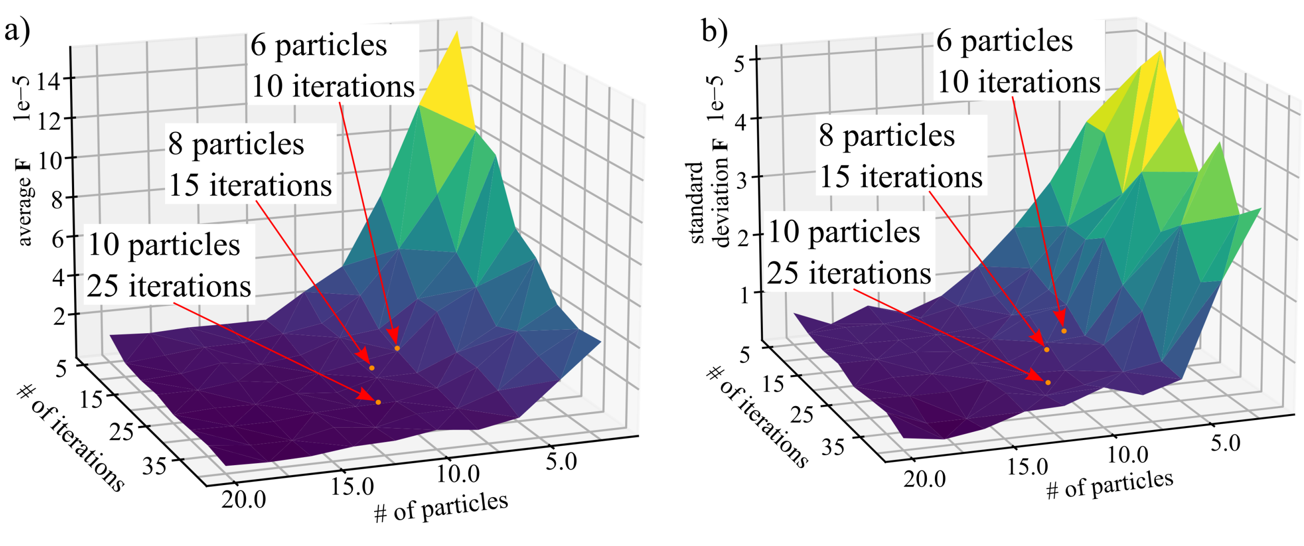

Figure 5: Performance results for a varying number of particles and iterations, showing: a) surface plot with average error, and; b) surface plot of the standard deviation of each considered test point.

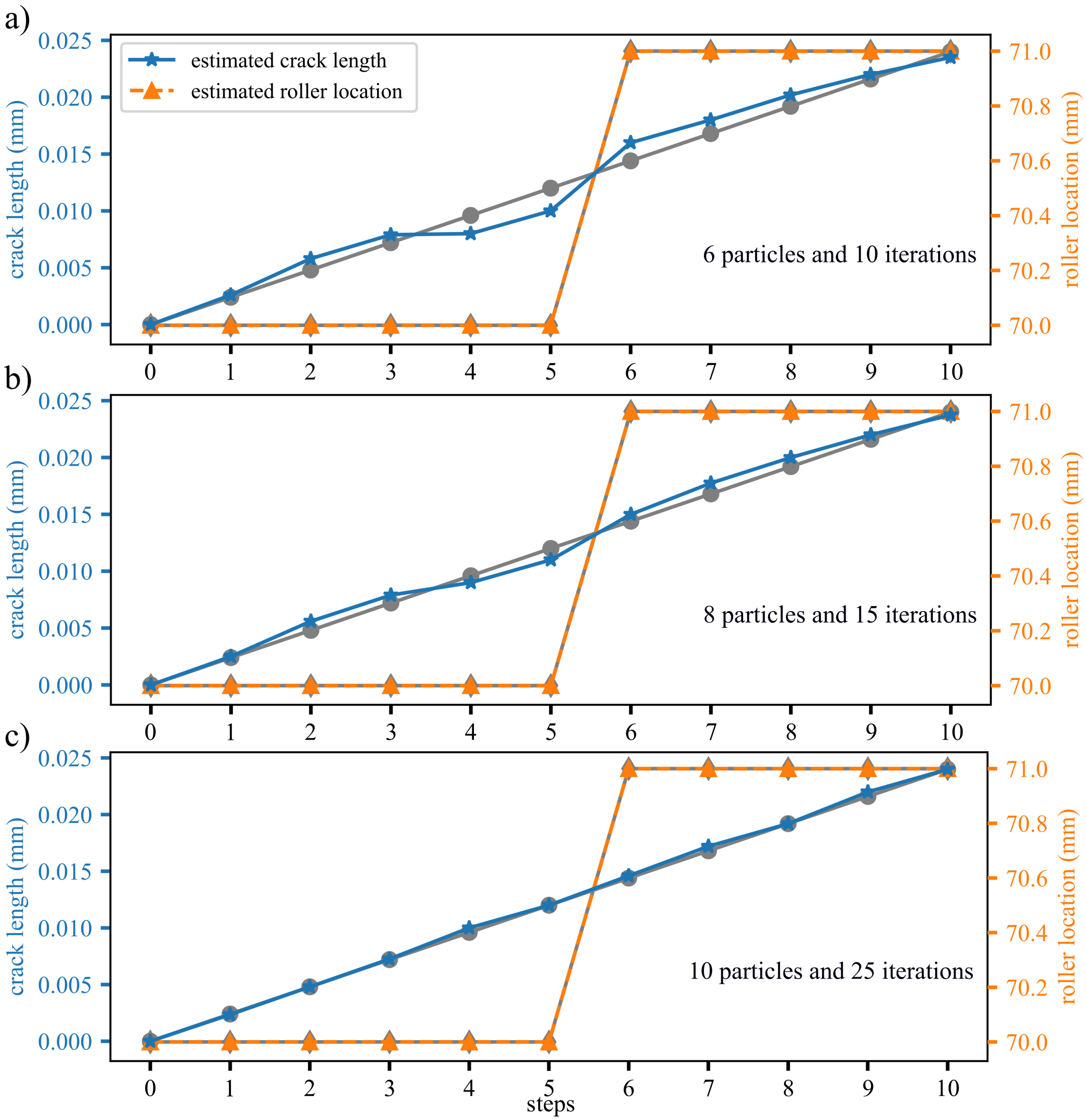

Figure 6: Particle swarm results for a varying particle-iteration combination range that starts at a less optimal combination and increases to the optimal combination, showing: a) 6 particles and 10 iterations, b) 8 particles and 15 iterations, and c) 10 particles and 25 iterations.

converges to the chosen optimal combination. Starting with figure 6a), a combination of 6 particles and 10 iterations return optimal locations that have significant error. However, increasing the particle-iteration combination to 8 and 15 respectively produces better results but there is a small amount of error present. Finally, the optimal combination of 10 particles and 25 iterations returns optimal locations with negligible error. The negligible error can be seen in figure 6c) for steps 4 and 7. Here, the error for both steps is so small that any increase in the particle-iteration combination for identification of more precise global minimums would come at the cost of significant increases of computational resources.

4. CONCLUSION

There is a need to develop real-time model updating methodologies for ship structures that consider the available computational resources. This work reports on the initial development of a multi-event model updating framework for structures. A cantilever beam testbed was developed to provide repeatable system conditions and assist in evaluating real-time model updating methodologies for structures such as naval ship components. The Frobenius Norm search space considered two damage cases: a slow-growing fatigue crack and sudden damage caused by an impact that resulted in a change of boundary condition of the model. The boundary condition change is a sudden movement of a roller connection on the cantilever beam. The convex optimization developed by this two-event model space was solved by using a particle swarm optimizer with a varying number of particle-iteration combinations. A series of 11 damage steps were investigated, and the particle swarm returned the found near-global minimum coordinate in the Frobenius Norm search space. With each near-global minimum correctly returned, the optimal parameters for the model are known. Thus, the structural model is updated with the near-global minimum coordinate data returned by the particle swarm. The preliminary results undertaken in this work resulted in an optimal particle-iteration combination of 10 and 25 respectively.

5. ACKNOWLEDGMENTS

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