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PREDICTIVE HEALTH ANALYSIS FOR FUTURE MAINTENANCE PLANNING IN AGING CONTAINERSHIP HULL STRUCTURES WITHIN DIGITAL HEALTHCARE ENGINEERING SYSTEMS

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ABSTRACT

Aging ships and offshore structures face significant risks from corrosion, fatigue cracking, and mechanical damage, worsened by harsh marine environments and remote operations. Ensuring their safety and sustainability requires innovative solutions, leveraging automated technologies, digital solutions and advanced communication systems. This paper introduces the Digital Healthcare Engineering (DHE) system, a proactive, real-time monitoring and artificial intelligence (AI)-driven framework for managing the structural health of aging vessels and the well-being of seafarers. The AI-enhanced DHE system includes five modules: (1) Module 1: On-site real-time monitoring and digitalization of structural health parameters, (2) Module 2: Transmission of collected data to a land-based analytics center via low Earth orbit (LEO) satellites, (3) Module 3: Advanced analytics and simulations through digital twin technology, (4) Module 4: AI-driven diagnostics with automated maintenance recommendations, and (5) Module 5: Predictive health analysis for future maintenance planning. This study focuses on Module 5, which uses damage data to predict corrosion wastage and fatigue crack propagation, assess structural strength reduction, and optimize maintenance schedules. A case study on a hypothetical 25,800 TEU containership powered by small modular reactors (SMRs) demonstrates the system's practical benefits in enhancing the safety and operational sustainability.

Keywords: AI-enhanced Digital Healthcare Engineering (DHE) system; aging containership hull structures; digital twins; predictive health analysis, age-related degradation

1. INTRODUCTION

As ships and offshore structures age, they face compounded challenges that threaten their structural integrity. Age-related degradation – manifesting as in-service damage such as corrosion wastage, fatigue cracking, and mechanical denting – progressively undermines their operational reliability. Moreover, continuous exposure to hostile and remote ocean environments amplifies the risks of hazardous conditions such as rogue waves.

In the maritime industry, a range of strategies have been adopted to prevent catastrophic accidents arising from structural failures. These include: (i) designing hull structures with adequate safety margins, (ii) implementing periodic inspections on an annual basis, (iii) conducting rigorous dry-docking surveys every five years, (iv) monitoring stress through strain gauges, (v) performing proactive risk assessments, and (vi) leveraging weather hindcast data to optimize navigation routes. While such measures have undoubtedly reduced risk and extended the service life, they remain insufficient to address the multifaceted challenges associated with aging ships.

The large size and complex geometry of ships, combined with extended inspection intervals, create significant barriers to effective structural health management. Additionally, the unpredictable and harsh conditions of the maritime environment — including rough waves, changing operational conditions, and remote locations — further complicate efforts to maintain structural integrity [1-3]. These realities highlight the urgent need for innovative approaches to overcome the limitations of conventional methods, ensuring the structural integrity of aging vessels in uncertain environments. Artificial intelligence (AI)-enhanced Digital Healthcare Engineering (DHE) system has been conceptualized as an advanced framework for efficiently managing structural health of aging structures by leveraging the transformative potential of digital and communication technologies [4].

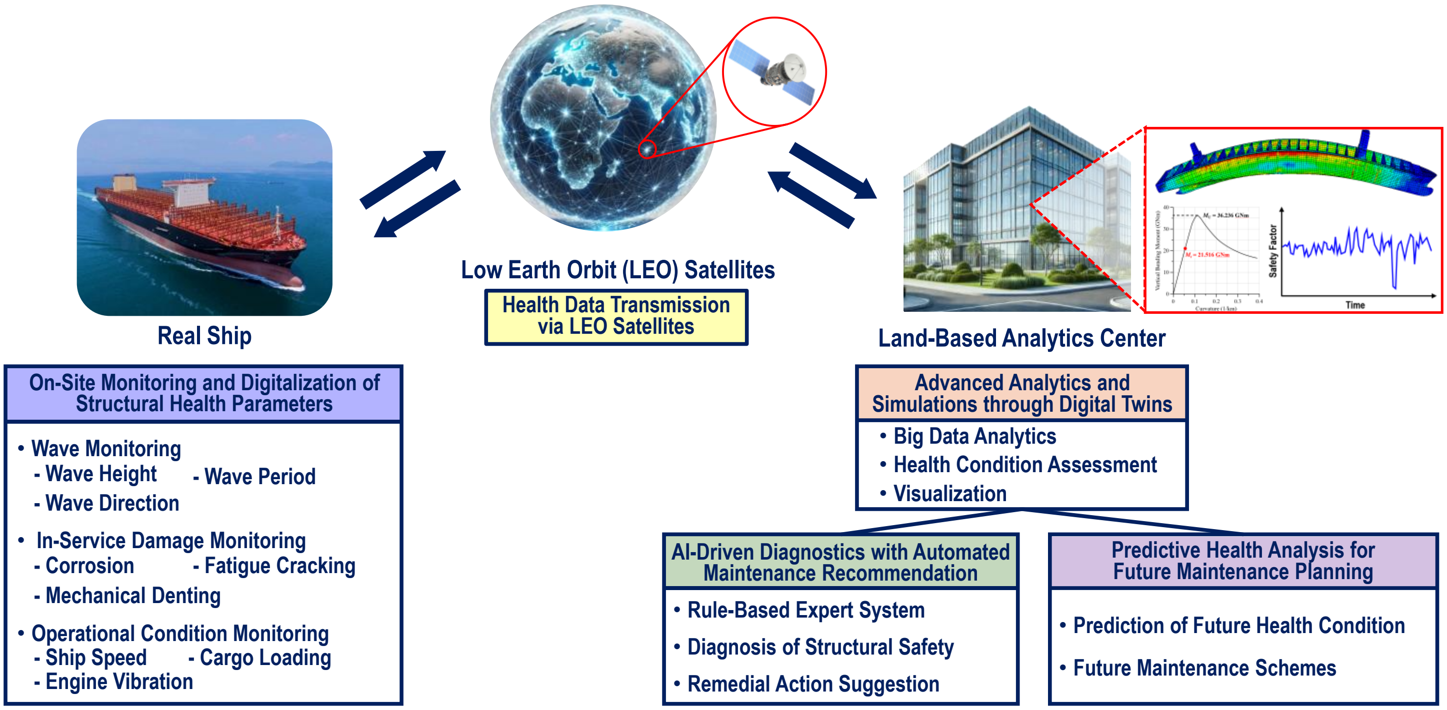


FIGURE 1: FRAMEWORK OF AN AI-ENHANCED DHE SYSTEM FOR AGING CONTAINERSHIP HULL STRUCTURES [5].

Unlike traditional structural health monitoring systems that rely on periodic inspections and limited sensor data, the DHE system offers continuous, high-resolution insights by integrating advanced digital twin models, AI-driven analytics, and predictive health analysis. The AI-enhanced DHE system is composed of five key modules, as outlined below:

- Module 1: On-site monitoring and digitalization of structural health parameters
- Module 2: Transmission of collected data to a land-based analytics center via low Earth orbit (LEO) satellites
- Module 3: Advanced analytics and simulations through digital twin technology
- Module 4: AI-driven diagnostics with automated maintenance recommendations
- Module 5: Predictive health analysis for future maintenance planning.

Each module of the AI-enhanced DHE system plays a critical role in facilitating the real-time healthcare of aging ships and addressing the challenges outlined earlier. On-site monitoring (Module 1) ensures the collection of accurate health parameters such as wave profile, in-service damage, and operational conditions including ship speed and engine vibration. The health data, transmitted via Module 2, serves as the foundation for digital twin simulations (Module 3), which leverage computational fluid dynamics (CFD) and nonlinear finite element analysis (NLFEA). The integration of AI techniques in Module 4 accelerates diagnostics and maintenance planning. Meanwhile, Module 5 focuses on predicting future health conditions, offering insights into long-term trends to support optimal maintenance scheduling and ensuring remedial actions are implemented before structural degradation results in catastrophic failures. The overall framework of the AI-enhanced DHE system, supported by these five modules, is illustrated in Figure 1.

It is crucial to understand the advancements and limitations of existing research in the developing an AI-enhanced DHE system for aging engineered structures. Comprehensive literature reviews have explored the application of DHE systems for ships and offshore structures [6], offshore pipelines [7], and land-based liquified natural gas (LNG) tanks [8]. These reviews reveal significant advancements in real-time monitoring and data communication. However, challenges persist in areas such as digital twin modeling, the integration of AI-driven diagnostics, and the prediction of future health conditions. To address these gaps, Kim and Paik [5] proposed a digital twin model integrated with AI-driven diagnostics within the DHE system. Additionally, digital twin models employing various methodologies have been developed for ship hull structures by researchers such as Fujikubo et al. [9] and Lee et al. [10].

Building upon the foundational framework of the AI-enhanced DHE system, this study focuses on the development of Module 5: predictive health analysis for future maintenance planning. Details about other DHE modules can be found in the literature [5-8]. Section 2 presents advanced mathematical models for predicting age-related degradation over time, including corrosion wastage and fatigue crack propagation. To demonstrate the practical application of this approach, Section 3 presents a case study involving a hypothetical 25,800 TEU (twenty-foot equivalent unit) containership powered by small modular reactors (SMRs), highlighting how predictive health analysis contributes to the structural healthcare of aging ship hull structures.

2. MATHEMATICAL MODELS FOR PREDICTING TIME-DEPENDENT CORROSION WASTAGE AND FATIGUE CRACK PROPAGATION

The increasing complexity of structural health management for aging ships necessitates the adoption of proactive and data-driven approaches to mitigate risks arising from age-related deterioration and uncertain ocean environments. Module 5 of the DHE system is designed to address these challenges by incorporating predictive health analysis, enabling the accurate prediction of structural degradation and the timely implementation of maintenance strategies.

This section presents the advanced mathematical models employed in the predictive health analysis module, focusing on corrosion wastage and fatigue crack propagation.

2.1 Corrosion Wastage

Corrosion is a significant type of in-service damage that progressively degrades aging ship hull structures by reducing their cross-sectional area over time, thereby diminishing their load-carrying capacity and compromising overall structural integrity. Prediction of corrosion rates is essential for evaluating corrosion damage in engineered structures. Numerous corrosion models for predicting corrosion rates have been proposed in the literature, broadly classified into two categories [11,12]: physical and empirical models. Physical models estimate corrosion rates based on the underlying physical processes of corrosion, incorporating various environmental and material-specific factors [13]. However, for the DHE system of aging ships, it is impractical to account for the multitude of factors required to determine corrosion rates for numerous locations across the entire ship hull. Conversely, empirical models predict corrosion rates using historical data of metal's cross section loss. Since the corrosion data collected from Module 1 can be effectively utilized, empirical models are particularly well-suited for implementation within the DHE system. This section presents an advanced empirical method for formulating time-dependent corrosion wastage models, utilizing a statistical analysis of historical corrosion loss data.

Figure 2 presents the procedure for developing an empirical corrosion wastage prediction model. After corrosion data is collected from Module 1, encompassing parameters such as location, depth, and degree of pitting intensity (DOP), the data undergoes statistical analysis to uncover underlying trends and patterns.

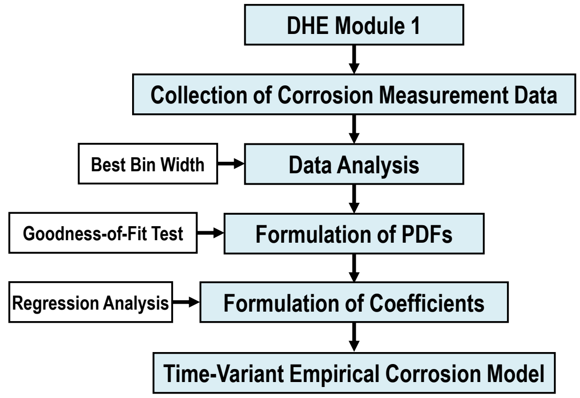
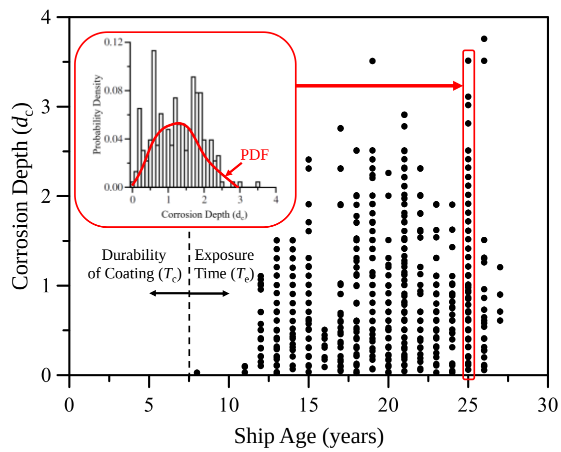
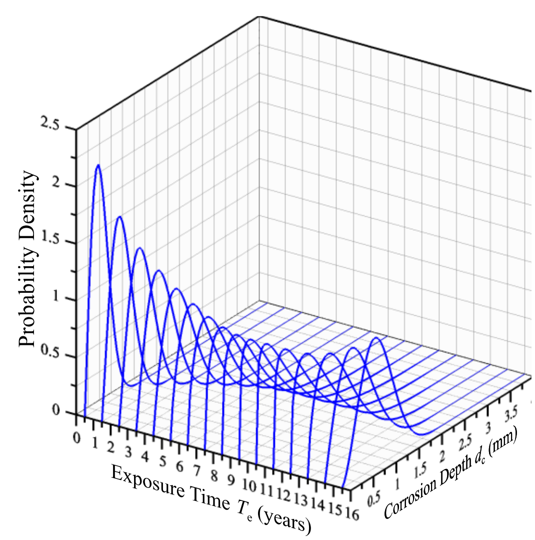


FIGURE 2: PROCEDURE FOR THE DEVELOPMENT OF A TIME-VARIANT EMPIRICAL CORROSION PREDICTION MODEL IN MODULE 5 OF THE DHE SYSTEM.



(a) MEASUREMENT DATABASE



(b) PROBABILITY DENSITY DISTRIBUTIONS FITTED TO THE MEASUREMENT DATABASE

FIGURE 3: PROBABILISTIC CHARACTERISTICS OF CORROSION WASTAGE PROGRESS [14].

Corrosion wastage exhibits varying probabilistic characteristics over time, as shown in Figure 3. Probability density functions (PDFs) are instrumental in capturing and representing the statistical variability within the measurement data. The selection of bin width (i.e., the interval size for grouping data) significantly influences the statistical properties of the dataset. Therefore, it is essential to determine the best bin width that maximizes the mean value while minimizing the coefficient of variation (COV), as described by Paik [1]. Various PDFs are available for formulating empirical models, and goodness-of-fit (GOF) tests, such as the Anderson-Darling (A-D) or Kolmogorov-Smirnov (K-S) methods, can be employed to determine the most suitable PDF for the given dataset.

The Weibull distribution is widely recognized as the most suitable PDF for time-dependent corrosion measurement datasets, as demonstrated in several studies [11,15,16]. However, other types of PDFs may also be determined as the best fit, depending on the specific characteristics of the data. Once the best-fit PDFs are determined for each corrosion dataset, corresponding to the ship's age or the exposure time following coating breakdown, a time-variant empirical corrosion prediction model can be developed through regression analysis using the coefficients of the PDFs. Figure 4 illustrates an example of an empirical model formulated through regression analysis of the Weibull distribution's coefficients [15].

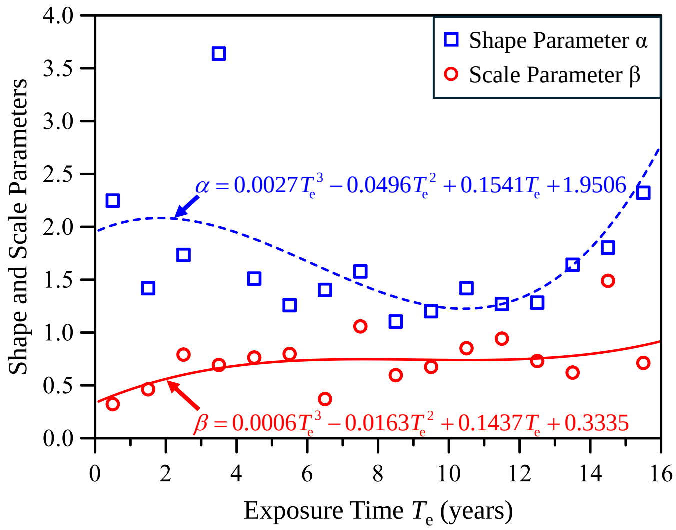


FIGURE 4: FORMULATION OF AN EMPIRICAL CORROSION PREDICTION MODEL BASED ON THE WEIBULL DISTRIBUTION'S COEFFICIENTS.

Lastly, cumulative density functions (CDFs) are employed to estimate corrosion depth as a function of exposure time. Equations 1 and 2 define the CDF of the Weibull distribution and its application in determining corrosion depth over time [15,16]. It is noted that, due to variations in the characteristics of corrosion progress under different environmental conditions, specific corrosion models must be formulated to reflect the unique conditions at various locations on the hull structure.

$$\mathrm{CDF} = 1 - \exp\left[-\left(\frac{d_c(T_e)}{\beta(T_e)} \right)^{\alpha(T_e)} \right] \tag{1}$$

$$d_c(T_e) = \beta(T_e) \cdot \left[-\ln(1 - \mathrm{CDF}) \right]^{\frac{1}{\alpha(T_e)}} \tag{2}$$

where d_c is corrosion depth, α and β are shape and scale parameters of the Weibull distribution, and T_e is exposure time in years.

2.2 Fatigue Crack Initiation and Propagation

Fatigue cracking is another critical type of in-service damage and one of the most prevalent failure mechanisms observed in engineered structures. Once initiated, fatigue cracks progressively grow under cyclic loading, potentially leading to catastrophic structural failure as a result of a significant reduction in ultimate strength. In addition, fatigue cracking often occurs at stress levels significantly lower than the design threshold, making it challenging to address. Fatigue cracking progresses through three distinct stages, as illustrated in Figure 5: crack initiation, crack propagation, and failure (fracture). The initiation phase is influenced by various factors, including geometry, material properties, cyclic loading conditions, local stresses, and environmental effects. The initiation of macro cracks is usually predicted using the S-N curve approach, which is often combined with the Palmgren-Miner rule to assess the cumulative fatigue damage resulting from cyclic loading.

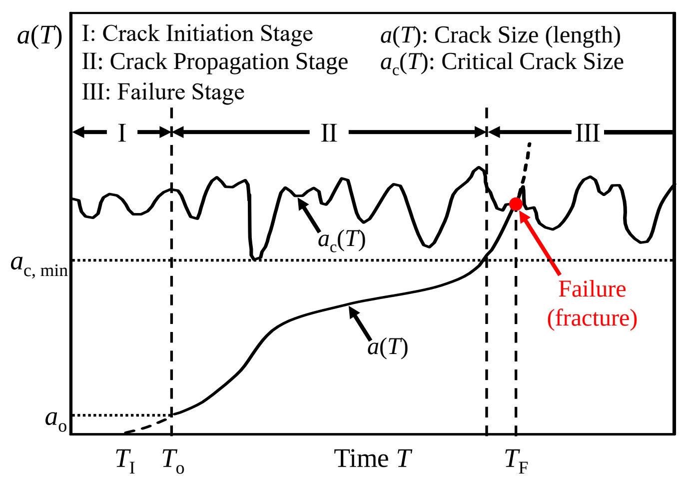


FIGURE 5: A SCHEMATIC OF CRACK INITIATION AND GROWTH FOR A STRUCTURE OVER TIME [15].

Crack growth rate is a key factor in predicting crack propagation using a fracture mechanics approach. A critical parameter in this analysis is the range of the stress intensity factor ΔK at the crack tip, which is used to model the relationship between loading conditions and crack growth behavior. As shown in Figure 6, the crack growth rate versus ΔK curve exhibits distinct characteristics across the three fatigue growth stages. ΔK_{th} represents the threshold value of ΔK, indicating the minimum level required for a crack to propagate. Donahue et al. [17] proposed a crack growth relationship for the threshold region, as follows.

$$\frac{da}{dN} = C\left(\Delta K - \Delta K_{th}\right)^m \tag{3}$$

where da/dN is the crack growth per cycle, and C and m are constants determined through material tests.

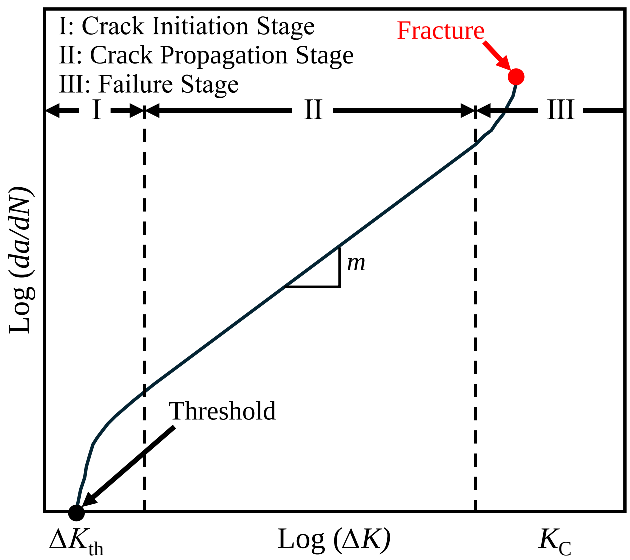


FIGURE 6: A SCHEMATIC REPRESENTATION OF THE DISTINCT CHARACTERISTICS OF THE CRACK GROWTH RATE VERSUS ΔK CURVE ACROSS THE THREE CRACK GROWTH STAGES.

In the crack growth stage II, cracks typically propagate with a linear trend on a log-log plot (Figure 6). The crack growth rate in this regime is commonly estimated using the Paris-Erdogan law [18], as defined in Equation 4, which is derived from the principles of linear elastic fracture mechanics (LEFM). However, when plastic deformation at the crack tip dominates crack growth, elastic-plastic fracture mechanics (EPFM) becomes more applicable. EPFM approaches often utilize concepts such as crack tip opening displacement (CTOD) or the J-integral method for more accurate predictions. Further details on these methods can be found in Paik [14].

$$\frac{da}{dN} = C\left(\Delta K\right)^m \tag{4}$$

where $\Delta K = F\Delta\sigma\sqrt{\pi a}$ for stiffened steel panels [14], $\Delta\sigma$ is the stress range, a is the crack size (length), and F is a geometric parameter relying on the loading and configuration of the crack body. For steel plates with cracks under axial tension, F is calculated using the following equations [2,14]:

i) for a center crack,

$$F = \left(\sec\frac{\pi a}{b}\right)^{1/2} \tag{5}$$

ii) for a unilateral crack,

$$F = 30.38\left(\frac{a}{b}\right)^4 - 21.71\left(\frac{a}{b}\right)^3 + 10.55\left(\frac{a}{b}\right)^2 - 0.23\left(\frac{a}{b}\right) + 1.12 \tag{6}$$

iii) for bilateral cracks,

$$F = 15.44\left(\frac{a}{b}\right)^3 - 4.78\left(\frac{a}{b}\right)^2 + 0.43\left(\frac{a}{b}\right) + 1.12 \tag{7}$$

where a and b represent crack length and plate breadth, respectively.

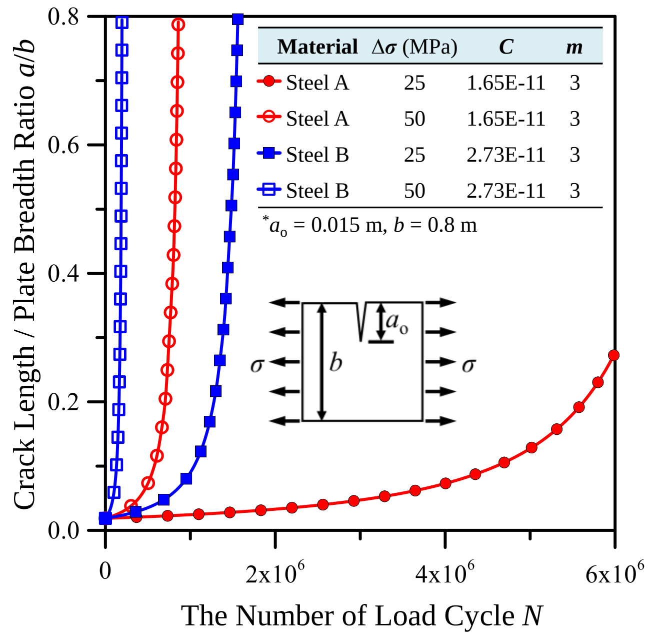


FIGURE 7: COMPARISON OF CRACK GROWTH PREDICTIONS UNDER VARYING MATERIAL CONSTANTS AND LOADING CONDITIONS.

In the DHE system, fatigue crack data collected onboard through Module 1 is utilized to predict crack propagation. It is assumed that the detected cracks are in the stage II, as cracks identified during hull inspections are typically large enough to be categorized within this regime. The number of load cycles is determined using Equation 8. By combining Equations 4 and 8 and performing integration, the crack length can be defined in closed form as a function of time T after the initiation of cracking [2]. Equations 9 and 10 provide the crack length prediction formulas for cases where the material constant m equals 2 and where it does not, respectively. Figure 7 presents a comparison of crack growth predictions obtained using the proposed formulas under varying material constants and loading conditions [19].

$$N = \frac{T \times 365 \times 24 \times 60 \times 60}{t} = T\omega \tag{8}$$

where T is the time in years after the initiation of the cracking and t is the period of wave occurrences, usually assumed to be between 6 and 10 seconds.

i) $m \neq 2$

$$\left[a_o^{1-m/2} + \left(1 - \frac{m}{2}\right) C \left(\Delta\sigma F \sqrt{\pi}\right)^m T\omega \right]^{\frac{1}{1-m/2}} \tag{9}$$

ii) $m = 2$

$$a_o \exp\left[C \Delta\sigma^2 F^2 \pi \right] T\omega \tag{10}$$

where a_o is the initial crack size and a is the crack size at time T.

3. PREDICTIVE HEALTH ANALYSIS WITHIN THE DHE SYSTEM – APPLIED EXAMPLE WITH A 25,800 TEU CONTAINERSHIP POWERED BY SMRS

3.1 Module Framework and Data Processing

The predictive health analysis module (Module 5) within the DHE system integrates real-time monitoring data, predictions of time-variant in-service damage, advanced computational simulations, and maintenance scheduling algorithms. This module builds upon foundational inputs from earlier modules, including on-site monitoring (Module 1) and data transmission (Module 2). The collected data serves as the basis for formulating empirical models to predict time-dependent corrosion wastage and fatigue crack propagation, as detailed in Section 2. These predictions are then utilized in the module's health analysis framework to optimize maintenance planning and extend the lifespan of aging vessels.

Considering the predicted in-service damage, CFD (or hydrodynamic analysis) and NLFEA are employed to compute the loads and load effects on aging hull structures. Kim and Paik [5] developed a digital twin model for aging containerships using MAESTRO software [20], which provides powerful tools for hydrodynamic analysis and NLFEA. This study employs the same software for the development of Module 5, focusing on predictive health analysis. Based on the loads calculated through hydrodynamic analysis, the residual ultimate strength of both local components (plates and stiffened panels) and global components (hull girders) is evaluated using NLFEA. ALPS/ULSAP [21] and ALPS/HULL [22] codes are specifically designed for the ultimate strength analysis of stiffened panels and hull girder structures, respectively. These tools are integral to the MAESTRO's NLFEA process, providing precise ultimate strength and the failure modes of the structures. The hydrodynamic analysis and NLFEA modules within MAESTRO have been extensively validated in the literature [1,2,5,20-25].

Predictive health analysis offers valuable insights for structural health management, including trends in residual ultimate strength and key performance indicators (KPIs) such as remaining service life (RSL) and the safety factor η, which is defined in Equation 11. By integrating structural health data with considerations for maintenance costs and operational downtime, this module enables the recommendation of optimized maintenance schedules that enhance both efficiency and cost-effectiveness. The overall process for predictive health analysis and future maintenance planning within Module 5 is illustrated in Figure 8.

$$\eta = \frac{C}{D} > \eta_{cr} \tag{11}$$

where C is the maximum load-carrying capacity (i.e., ultimate strength), D is the applied loads, η is the safety factor, and η_{cr} is the critical safety factor predefined by classification societies or operators for ensuring the structural safety. η should always be greater than η_{cr} to ensure the safety of the target structures.

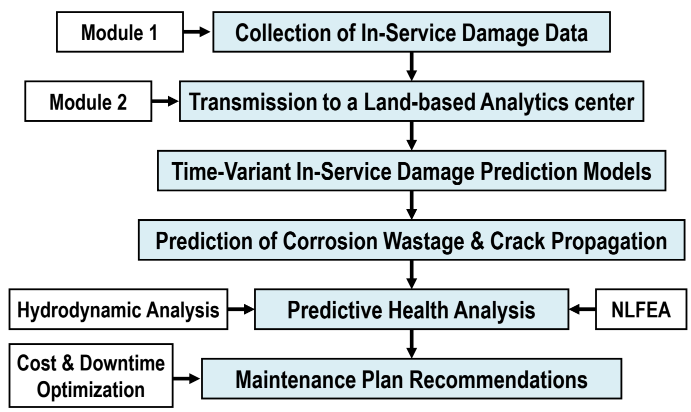


FIGURE 8: PROCESS FOR PREDICTIVE HEALTH ANALYSIS AND MAINTENANCE PLANNING IN MODULE 5 OF THE DHE SYSTEM.

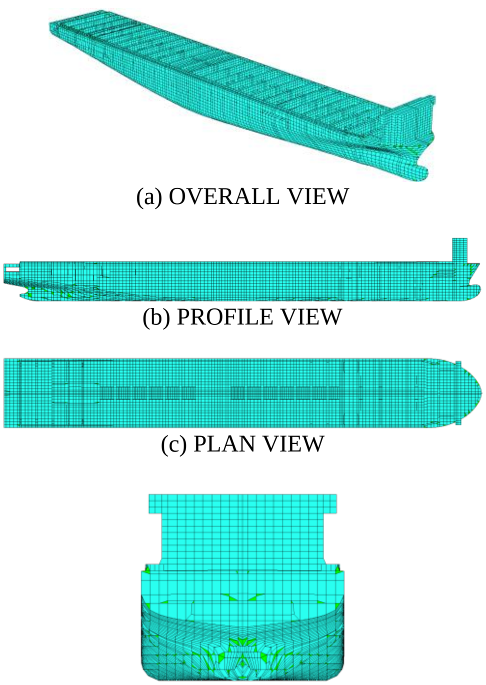
3.2 Applied Example: 25,800 TEU Containership Powered by SMRs

The DHE system is expected to be highly effective for the lifetime healthcare of ship hull structures and will particularly prove its worth in the application to autonomous and/or advanced vessels. In this paper, a 25,800 TEU SMR-powered containership was selected as the target ship due to its significant capital expenditure (CAPEX) and the potentially catastrophic outcomes of accidents resulting from inadequate healthcare. This selection also reflects the growing demand for advanced healthcare systems capable of managing structural integrity in next-generation vessels, where extended service lives of up to 50 years are considered to offset the increased CAPEX associated with green energy system, while enabling operation with minimal human intervention.

TABLE 1: PRINCIPAL DIMENSIONS OF THE 25,800 TEU SMR-POWERED CONTAINERSHIP MODEL.

Parameter	Dimension
Length between perpendiculars (L_{BP})	413.0 m
Breadth (B)	61.4 m
Depth (D)	33.1 m
Draught (d)	18.5 m
Block coefficient (C_b)	0.66
Full load displacement (Δ)	334,662 tonnes

A three-dimensional model of the target vessel was developed as a case study to demonstrate the predictive health analysis capabilities within the proposed DHE system, as illustrated in Figure 9. Further details on the ship's design can be found in Kim et al. [26]. The principal dimensions of the ship are provided in Table 1, and the ship was assumed to be fully loaded. For this analysis, the MAESTRO software was utilized to create the model and conduct hydrodynamic analysis as well as NLFEA for assessing structural health, as discussed in the previous section.



(a) OVERALL VIEW

(b) PROFILE VIEW

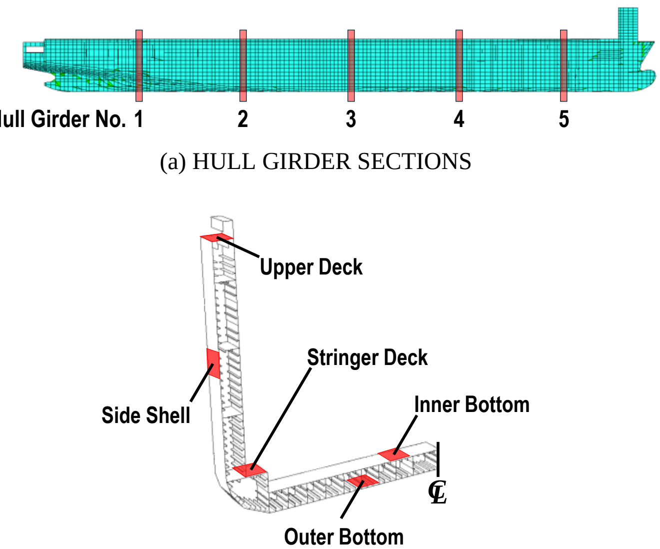
(c) PLAN VIEW

(d) BODY PLAN VIEW

FIGURE 9: THREE-DIMENSIONAL MODEL OF THE 25,800 TEU CONTAINERSHIP POWERED BY SMRS FOR HYDRODYNAMIC ANALYSIS AND NLFEA.

The AI-enhanced DHE system is designed to provide comprehensive structural healthcare, addressing both local components and the global structure. Accordingly, predictive health analysis must be performed for all structural members. However, due to page limitations, a representative example was selected, focusing on 5 hull girder sections and 5 stiffened panels at the midship section to demonstrate the predictive health analysis, as shown in Figure 10.

In the DHE system, wave profiles and in-service damage are measured on-site in real-time or at regular intervals – daily, weekly, or monthly – and transmitted to a land-based analytics center for further analysis. In this study, however, it is assumed that the data is already transmitted, as the focus is on illustrating the predictive health analysis within Module 5. The time-variant corrosion prediction models were developed for each structural component using the measurement data from Paik et al. [27], while crack propagation models were based on random initial crack sizes and material constants provided in ABS [19]. Ideally, however, both datasets should have been collected directly from the target ship for integration into the DHE system. For this analysis, it is also assumed that the ship is 5 years old and has no corrosion protection applied.



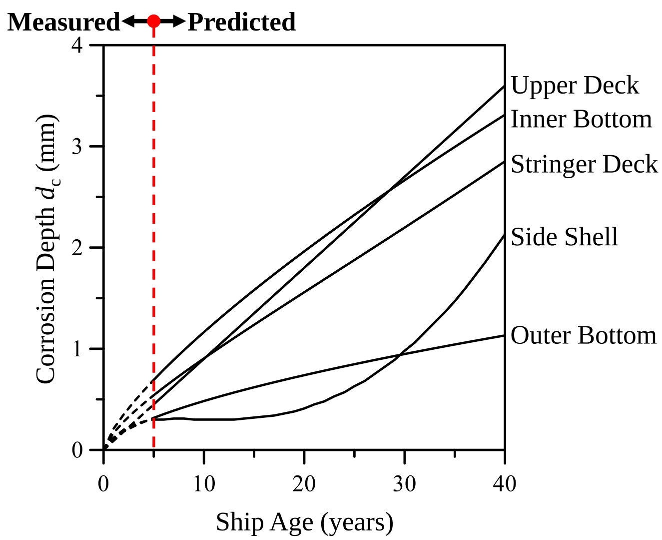
(a) HULL GIRDER SECTIONS

(b) STIFFENED PANELS AT MIDSHIP

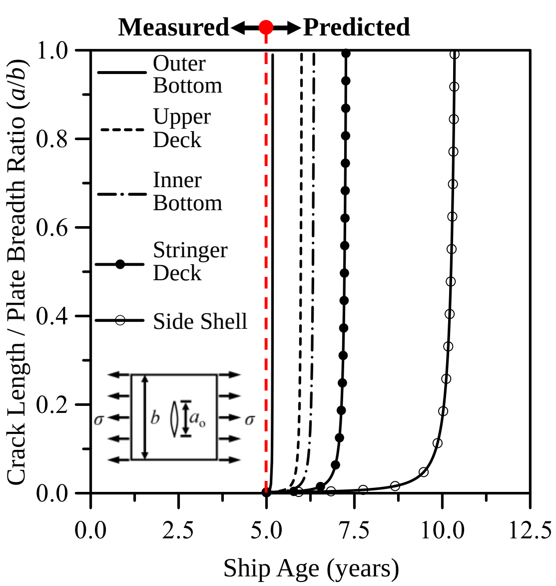
FIGURE 10: SELECTED HULL GIRDER SECTIONS AND STIFFENED PANELS FOR THE DEMONSTRATION OF THE PREDICTIVE HEALTH ANALYSIS WITHIN THE DHE SYSTEM.

Figure 11 compares the predicted corrosion progress and crack propagation of the selected stiffened panels over time, as determined using the methods described in Section 2. The results indicate that both corrosion progress and crack propagation vary significantly based on the location of the stiffened panels, influenced by different environmental and loading conditions. Notably, crack propagation was found to be particularly rapid, often leading to failure within 5 years. Figure 12 shows examples of reduction trends in the ultimate strength of stiffened panels. The residual ultimate strength of the stiffened panels was calculated using ALPS/ULSAP, incorporating the effects of predicted corrosion wastage and fatigue crack propagation. In Figure 12, σ_u and σ_{uo} represent the residual ultimate strength and the intact ultimate strength, respectively. The results in Figures 11 and 12 underscore that future structural safety issues can be effectively managed through the predictive health analysis in Module 5.

Figure 13 shows the ultimate strength reduction trends of the selected hull girder structures, derived from the predicted corrosion wastage progression. For this analysis, ALPS/HULL was employed to perform a progressive collapse analysis of the hull girder structures. Fatigue cracks were excluded from this analysis due to the lack of reliable measurement data. Consequently, the residual hull girder strength (M_u) in a real ship may be significantly lower than the results presented in Figure 13, as evidenced by the pronounced impact of crack propagation on residual strength shown in Figure 12.



(a) CORROSION WASTAGE PROGRESS



(b) FATIGUE CRACK PROPAGATION

FIGURE 11: PREDICTED CORROSION PROGRESS AND CRACK PROPAGATION IN THE SELECTED STIFFENED PANELS.

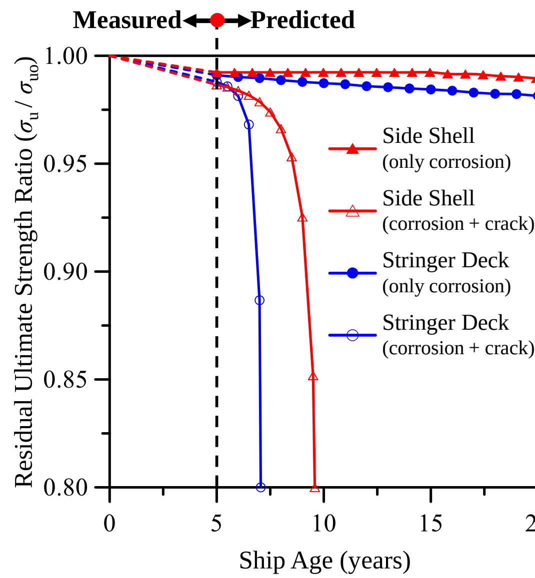


FIGURE 12: REDUCTION TRENDS IN THE ULTIMATE STRENGTH OF STIFFENED PANELS.

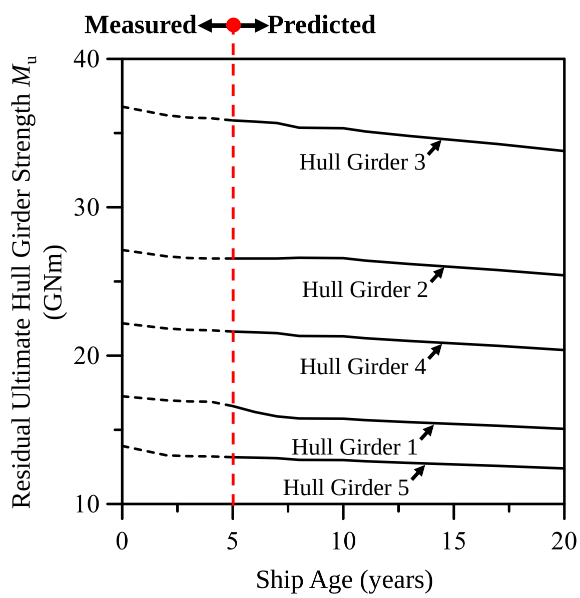


FIGURE 13: REDUCTION TRENDS IN THE ULTIMATE STRENGTH OF HULL GIRDER STRUCRURES.

The prediction of the safety factor, as defined in Equation 11, plays a crucial role in preventing catastrophic accidents caused by age-related degradation and harsh weather conditions. Both weather hindcast data and the results of residual ultimate strength analysis are utilized to estimate the safety factor of hull structures. Figure 14 presents a schematic example of the predictive health analysis conducted within Module 5, which is based on the safety factor derived from the predicted health data.

Module 5 of the DHE system is designed to provide early warnings about structural safety and deliver essential data for optimizing maintenance planning. In addition to the presented structural health data, the remaining service life (RSL) proves invaluable for proactive maintenance planning. The concept of RSL is applicable to various structural health parameters, as defined in Equation 12. By integrating these structural health insights with the maintenance cost optimization framework illustrated in Figure 15, Module 5 delivers a robust tool for ensuring structural safety and cost-effective maintenance strategies.

$$\mathrm{RSL} = \frac{x_{\mathrm{cr}} - x}{\dot{x}} \tag{12}$$

where x is the structural health parameter (e.g., corrosion depth, crack length, and safety factor), x_{cr} is the critical threshold of x, and $\dot{x}$ is the degradation rate of x.

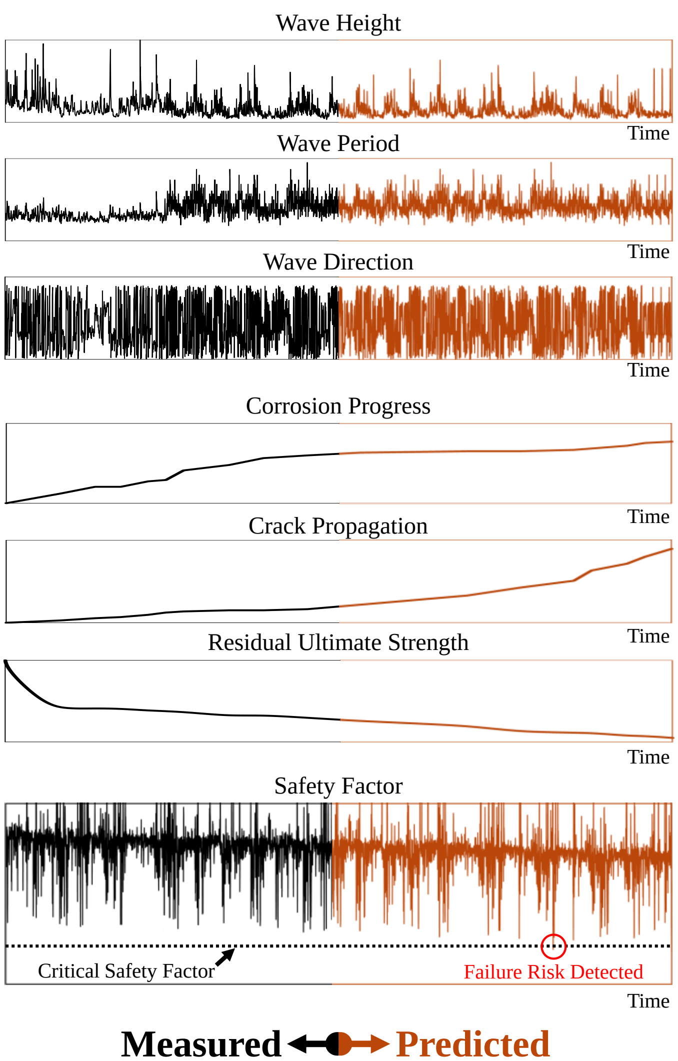


FIGURE 14: A SCHEMATIC EXAMPLE OF THE PREDICTIVE HEALTH ANALYSIS CONDUCTED WITHIN MODULE 5.

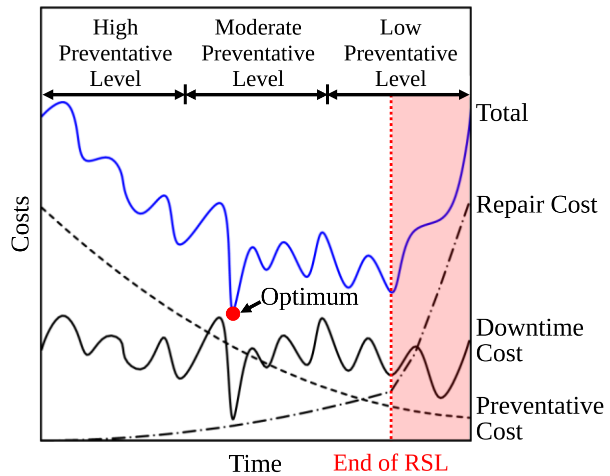


FIGURE 15: SCHEMATIC OF MAINTENANCE COST OPTIMIZATION.

4. CONCLUSION

Aging ships and offshore structures face increasing risks due to age-related degradation, compounded by harsh ocean environments and extended inspection intervals, which challenge conventional structural health management strategies. The DHE system addresses these challenges by leveraging on-site monitoring, data transmission, advanced digital twin models, AI-driven analytics, and predictive health analysis to provide continuous, high-resolution insights into structural health.

This study introduced a predictive health analysis framework within Module 5 of the DHE system to provide early warnings on structural safety and critical data for optimizing maintenance planning. This framework incorporates time-variant models for corrosion and fatigue crack propagation to predict structural degradation accurately. To demonstrate its applicability, the framework was tested using a hypothetical 25,800 TEU SMR-powered containership model. The case study highlighted the effectiveness of the predictive health analysis in evaluating residual ultimate strength and safety factors, offering valuable insights for proactive maintenance and extending the service life of aging ships. However, as the AI-enhanced DHE system fundamentally relies on the measurement data obtained from Module 1, the reliability of Module 5's predictive results may be reduced during the early operational stages before a sufficient dataset has been accumulated. Future studies should address practical approaches, such as incorporating historical data from similar vessels, to mitigate this limitation.

The primary concern in nuclear shipping is the risk of radioactive contamination resulting from environmental extremes and accidents. Real-time monitoring and AI-enhanced DHE systems are essential to improve the safety and operational sustainability of SMR-powered aging ships—including hull structures, machinery, and seafarer well-being [28]. Future work will focus on completing the development of each DHE module and integrating them into a unified prototype. This prototype will be applied to an operating vessel to verify the system's functionality and assess its accuracy under realistic conditions.

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