Damage identification of offshore jacket platforms in a digital twin framework considering optimal sensor placement

Authors: Mengmeng Wang, Atilla Incecik, Shizhe Feng, M.K. Gupta, Grzegorz Królczyk, Z Li, Z Li

Date: 2024-04-01T00:00:00+00:00

Abstract

A new digital twin (DT) framework with optimal sensor placement (OSP) is proposed to accurately calculate the modal responses and identify the damage ratios of the offshore jacket platforms. The proposed damage identification framework consists of two models (namely one OSP model and one damage identification model). The OSP model adopts the multi-objective Lichtenberg algorithm (MOLA) to perform the sensor number/location optimization to make a good balance between the sensor cost and the modal calculation accuracy. In the damage identification model, the Markov Chain Monte Carlo (MCMC)-Bayesian method is developed to calculate the structural damage ratios based on the modal information obtained from the sensory measurements, where the uncertainties of the structural parameters are quantified. The proposed method is validated using an offshore jacket platform, and the analysis results demonstrate efficient identification of the structural damage location and severity.

Full Text

Preamble

Damage Identification of Offshore Jacket Platforms in a Digital Twin Framework Considering Optimal Sensor Placement

Mengmeng Wang^{a,b}, Atilla Incecik^{b}, Shizhe Feng^{c}, M.K. Gupta^{d}, Grzegorz Królczyk^{d}, Z Li^{d,}
^{a}Department of Marine Engineering, Ocean University of China, Qingdao 266100, China
^{b}Department of Naval Architecture, Ocean, and Marine Engineering, University of Strathclyde, Glasgow G11XQ, United Kingdom
^{c}School of Mechanical Engineering, Hebei University of Technology, Tianjin

300130, China
^{d}Faculty of Mechanical Engineering, Opole University of Technology, Opole, 45758, Poland
Corresponding author

Abstract

A new digital twin (DT) framework with optimal sensor placement (OSP) is proposed to accurately calculate modal responses and identify damage ratios of offshore jacket platforms. The proposed damage identification framework consists of two models: an OSP model and a damage identification model. The OSP model adopts the multi-objective Lichtenberg algorithm (MOLA) to optimize sensor number and location, achieving a balance between sensor cost and modal calculation accuracy. In the damage identification model, the Markov Chain Monte Carlo (MCMC)-Bayesian method is developed to calculate structural damage ratios based on modal information obtained from sensory measurements, where uncertainties of structural parameters are quantified. The proposed method is validated using an offshore jacket platform, and the analysis results demonstrate efficient identification of structural damage location and severity.

Keywords: Optimal sensor placement, Damage identification, Digital twin, Offshore jacket platform

1. Introduction

With increasing dependence on renewable energy, offshore wind energy development has grown rapidly, evidenced by new installation capacity of 21.1 GW in 2021—more than triple that of 2020 [**?**]. This rapid growth brings significant safety challenges for offshore wind structures, which are directly exposed to harsh ocean environments [**?**] where corrosion and fatigue loads cause frequent structural damage [**?**, **?**]. To protect these structures, real-time health monitoring and early-stage damage identification are essential [**?**]. Recently, digital twin (DT) technology \cite{6-8} has provided a promising solution for structural health monitoring (SHM). A DT can create a mirrored model (called a DT virtual model) to simulate physical unit dynamics in real-time \cite{9-11}, enabling SHM implementation.

A DT-based SHM framework generally includes four modules: a structure unit, a DT virtual model, a DT database, and an SHM model. The structure unit serves as the basis for constructing the DT virtual model; the virtual model conducts simulations and analyses to collect structural dynamic responses; the database stores sensory measurements and virtual model outputs to enable dual information exchange between the structure unit and virtual model; and the

SHM model monitors structural health condition in real time, detects damages, and issues timely alerts for maintenance and repairs. This DT-based SHM framework provides a comprehensive tool for offshore wind structures. However, its development remains in an infant stage. Existing efforts have focused on building the DT virtual model, while very limited work addresses the SHM model within the DT framework [?]. The key challenge is that existing DT frameworks assume modal information of offshore wind structures is correct and effective, ignoring model uncertainties—yet these uncertainties play a crucial role in precise damage identification. Consequently, addressing this issue is critical when developing DT-based SHM frameworks.

Since the 1970s, damage identification has evolved considerably, with researchers attempting various methods for damage detection and identification (location and severity) in offshore jacket platforms, such as the cross-model cross-mode (CMCM) method, machine learning \cite{12–15}, modal strain energy method, and others. However, most damage identification methods are deterministic and cannot quantify uncertainties in damage detection. To mitigate negative effects of uncertainties on damage identification, probabilistic methods are often employed to quantify their impact on accuracy [?]. Bayesian methods are widely used probabilistic approaches in literature for model updating, modal identification, and damage detection [?, ?]. Huang et al. [?] combined Bayesian analysis with modal data to identify weakening of structural component stiffness. Yin et al. [?] introduced a numerical and experimental Bayesian framework for damage identification in 2D frames. Huang et al. [?] numerically implemented the Bayesian method to identify damage severity using mode shapes in simple beam elements. Behmanesh et al. [?] studied effects of modeling errors on damage detection findings using Bayesian model updating to detect shear frame damage. Zhang et al. [?] employed Bayesian model updating considering model uncertainties to detect and identify damage in an eight-story building. While Bayesian approaches have proven effective for addressing uncertainties in damage identification, very little work has applied this approach to offshore jacket platforms.

Given the complex structure of offshore jacket platforms, determining the most critical nodes for monitoring is challenging [?]. A sensor optimization strategy must be applied when performing Bayesian-based SHM, yet little work considers optimal sensor placement (OSP) [?] within Bayesian-based SHM frameworks.

The OSP problem is a min-max multi-objective optimization problem [?, ?] with objectives of maximizing optimization criteria while minimizing sensor deployment expense [?]. Damage identification often depends on changes in modal information such as natural frequencies and mode shapes caused by structural element damage. Accurate acquisition of structural modal responses is critical for damage identification and heavily depends on OSP. However, sensor installation in offshore jacket platforms is usually decided by experience, so OSP is not considered in most damage identification studies \cite{28–30}, leading to sensor waste or reduced accuracy of measured modal information.

OSP involves two aspects: optimization criteria and optimization algorithms. Several optimization criteria have been developed in recent years \cite{28,30-32}. Some aim to maximize measurement merits, such as Effective Independence (EI) [?], Kinetic Energy (KE) [?], and Eigenvalue Vector Product (EVP) [?]; others aim to optimize modal identification quality, such as modal assurance criterion [?], mutual information [?], and information entropy (IE) [?, ?]. However, when applying these criteria to offshore jacket platforms, the number of sensors is fixed during OSP procedures, preventing explanation of sensor number influence on each criterion and preventing balance between sensor costs and OSP quality. It is always difficult to achieve good trade-offs between reducing sensor number and maintaining high OSP quality. Hence, fixing sensor number during OSP procedures for offshore jacket platforms is impractical.

The optimization method determines OSP effectiveness and reliability. Numerous algorithms for searching optimal sensor configurations can be classified into population strategies (e.g., Genetic Algorithm (GA) [?], Ant Colony Optimization [?], Particle Swarm Optimization (PSO) [?], Wolf Algorithm [?], and Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [?]) and trajectory strategies (e.g., Simulated Annealing). Recently, the multi-objective Lichtenberg algorithm (MOLA) was proposed [?, ?] for the first time to integrate trajectory and population strategies, improving convergence and maximum spread in multi-objective optimization and generating Pareto optimal solutions considering multiple objectives. Moreover, MOLA has demonstrated better convergence and coverage in complex optimization problems in CEC 2009 and ZDT test functions than existing algorithms [?]. Investigating MOLA as an optimization algorithm in the OSP process for offshore jacket platforms is worthwhile. Since OSP quality determines both modal information accuracy and damage identification effectiveness, OSP must be considered in the damage identification process.

To address these problems, this paper proposes the first comprehensive methodology to identify damage in offshore jacket platforms while considering OSP. The OSP model considers sensor number and one of four well-known modal criteria (EFI, KE, EVP, and IE) as optimized objectives to determine sensor configurations (number and locations), striking a balance between sensor cost and modal information accuracy. The damage identification model uses Bayesian analysis to compute damage ratio from modal data and quantify uncertainties of model parameters. The proposed technique shows promise in numerical evaluation findings for offshore jacket platform damage identification.

This work is organized as follows. Section 2 provides a detailed description of the proposed damage identification framework considering optimal sensor placement. Section 3 validates the effectiveness of the proposed OSP method. Section 4 presents damage identification results and discussions, and Section 5 draws main conclusions.

2.1 Proposed Damage Identification Framework

[Figure 1: see original paper] shows the schematic of the digital twin for the jacket platform, as proposed in [?]. This DT enables various tasks including damage identification, fault diagnosis, fatigue analysis, reduction of unnecessary maintenance activities, and formulation of optimal maintenance intervals.

The DT consists of a physical model, virtual model, twin database, and service system. In the physical model, the sensor acquisition system obtains important parameters such as load, dynamic response, damage, temperature, and maps them to the virtual model. The service system calls these parameters on demand to calculate damage parameters or evaluate information, feeding results back to the virtual model for updating. Finally, the updated high-precision virtual model efficiently predicts structural damage. Damage identification is a crucial health monitoring component and essential module in the DT framework' s service system, helping detect platform damage presence and assess its impact on structural safety. Through damage identification, timely maintenance measures can reduce failure incidence, decrease maintenance costs, and increase platform reliability and safety. Therefore, determining damage position and extent in offshore jacket platforms is a crucial research topic.

[Figure 2: see original paper] illustrates the proposed damage identification framework, comprising physical and virtual models, an optimal sensor placement model, and a damage identification model, all informed by physical sensor locations. The optimal sensor placement model seeks optimum sensor configurations (number and locations), while the damage detection model ascertains damage location and severity. The two-step process is described below.

First, before MOLA solves the Pareto front, modal information needed to optimize the objective function must be calculated using the non-damage finite element model. The best possible sensor setups are then selected and implemented in the physical model. Second, modal response data in the damaged state is collected and fed into the damage identification model. The Bayesian approach then computes the Markov chain and posterior probability distribution function (PDF) of damage ratios, providing insight into damage spread across the map. Simultaneously, the most likely damage ratio values are fed back into the virtual model for updating. The optimal sensor placement model and damage identification model are explained below with their operational processes.

2.2 Optimal Sensor Placement

[Figure 3: see original paper] presents a detailed flowchart of the optimal sensor location model for obtaining the best sensor configurations. Natural frequencies, mode shapes, and other modal responses are computed in a non-damage finite element model and saved in a database. MOLA then determines and resolves the objective functions.

In the optimal sensor placement model, four well-known modal metrics construct the objective function to guarantee modal information independence and accuracy: Effective Independence (EFI), Kinetic Energy (KE), Eigenvalue Vector Product (EVP), and Information Entropy (IE). Details of these modal metrics are as follows:

For large structures, EFI [?] is a popular metric—an efficient unbiased estimator maximizing the norm of the Fisher information matrix [?]. The covariance matrix of prediction error is expressed as are the eigenvector and eigenvalue of structure, respectively.

Where the mode shape matrix of the FEM. The larger the sensor position to the independence of the structural modes [?]. , the greater contributions of the The KE metric [?] measures dynamic contribution of each FEM element to target mode shapes, calculated by Equation (2): is the kinetic energy associated with the i-th degree of freedom in the n-th is the i-th row and j-th column is the i-th coefficient in the n-th mode, where mode, element in the mass matrix, and is the j-th coefficient in the n-th mode [?].

The EVP determines optimal measurement candidates by calculating the maximum product of mode shapes at each location for N measured modes. The i-th EVP is calculated by [?] The IE is a useful tool for determining which structural tests should be performed to lessen ambiguity impact [?]. Lower information entropy indicates higher system certainty. The basic IE form is given by is the corresponding probability of the i-th realization of discrete random Where variable and log(.) is the logarithm operator.

Another OSP objective is sensor number, representing deployment cost. As sensor number increases, installation cost and processed data increase. Including sensor number as an objective explains sensor number influence on optimization criteria and eliminates dominated configurations through Pareto dominance relationships [?]. Combining sensor number with one of four modal metrics as objective functions balances sensor cost and OSP quality.

To solve conflicting objectives of maximizing obtained modal information while minimizing sensor number, MOLA [?] is first employed for offshore jacket platform optimization. MOLA is a new meta-heuristic multi-objective optimization algorithm inspired by lightning storms and Lichtenberg Figures (LF), successfully applied in crack detection and other areas. MOLA creation details are introduced in [?]. Five key parameters determine MOLA construction and operation: population (pop), number of particles (Np), creation
111()()TTTDE −−−= = DE2ininijjnnjKEM = inKEin ijMjn 1NiijjEVP== 1()log()NiiiIExPP==− iP
radius (Rc), stick coefficient (S), switching factor (M), refinement (ref), and iteration (Niter). Among them, Np creates an LF based on Diffusion Limited Aggregation theory, shown in Figure 4: see original paper. pop is the number of points computing objective functions, described by black dots in Figure 4: see original paper. Rc, Np, and S are three important LF construction

parameters: Rc associates with LF size, while the latter two control LF density. M changes the LF in optimizer input data, worth zero, one, or two. ref is an input parameter from 0 to 1. If ref=0, only the global LF acts on the optimizer every iteration. Niter generally takes values from 100 to 1000, also defined as an initial configuration parameter.

Exploration and exploitation are well-represented in MOLA results because objective function evaluation points are fired at Lichtenberg figures of varying sizes and orientations each iteration [**?**]. [Figure 4: see original paper] shows the Lichtenberg algorithm [**?**]: (a) bitmap Lichtenberg figure; (b) population distribution.

MOLA generates and compares all Pareto fronts. Sensor number and locations can be selected from all Pareto fronts. After determining optimal sensor configurations, sensors are installed on the offshore jacket platform to collect dynamic responses.

2.3 Damage Identification Model

In the damage identification model, the Markov Chain Monte Carlo (MCMC)-based Bayesian method [**?**, **?**] calculates damage ratio. The detailed model is shown in [Figure 5: see original paper], including a sample generation module that creates candidate samples through proposed distributions and a Bayesian module that quantifies parameter uncertainties. Detailed damage identification steps are introduced below.

First, element damage ratio is treated as unknown parameters, and initial samples are drawn from prior distribution. Candidate samples are then created using the suggested probability distribution function (PDF) and initial values.

Second, the FE model calculates natural frequencies and mode shapes for both initial and candidate samples. Normalized errors are used in the proposed model as follows: where respectively denote measured and predicted natural frequencies; respectively denote measured and predicted mode shapes.

[Figure 5: see original paper] shows the damage identification flowchart. Third, according to Bayesian theory [**?**, **?**, **?**] described in Equation (7), posterior PDF is calculated using observed modal data (from physical model) and calculated modal data (from FE model). All modes are assumed to have independently distributed natural frequencies and mode shapes in the previous PDF.

Posterior PDF of damage ratios is calculated by Equations (8)-(9). where A is the vector of estimated parameters, P(A) is prior distribution.

Prior distribution is assumed to be generalized and unbiased uniform distribution according to Bayesian hypothesis. B is measured information, P(B) is a normalizing constant. P(B/A) is likelihood function, and P(A/B) is posterior PDF calculated by where n is number of measured modes and C is normalizing constant. aamfff−=f 2||-1aTm =mfafm a)()/()()()/(AABBABBBBAPPPPP)P(),P()/P(==AA))(21exp(-)()/()/()/(AAAABAJCPPfPP =])1()[()(122 =−+−=niaTmimiaimfffJ A

Finally, the Metropolis-Hastings (MH) method [?] samples and approximates posterior PDF of damage ratio, and Markov chain calculates the most probable damage ratio value based on posterior PDF. Afterwards, damage location and severity are identified and fed back into the DT virtual model for updating.

3. The OSP of the Offshore Jacket Platform

To verify optimal sensor location model efficacy, a numerical case study is implemented. Modal details and offshore jacket platform background are presented in Section 3.1. Optimal sensor placement is displayed in Section 3.2.

3.1 Description of the Offshore Jacket Platform

Based on Liu et al. [?], a three-dimensional finite element model (FEM) of an offshore jacket structure is developed using MATLAB codes (see [Figure 6: see original paper]). The jacket platform is modeled using Euler-Bernoulli beam (B31) theory, comprising 36 pipe elements and 16 nodes. The model has 72 DOF (depending on counting method), with each component having 6 DOF. The offshore jacket platform has four levels with total height 9.14 meters, and side lengths of 10.97 meters, 8.53 meters, 6.10 meters, and 3.66 meters from lowest to highest level. Each pipe part has outer diameter 17.8 cm and inner diameter 16.02 cm. Jacket structure material is steel (elastic stiffness 210 GPa, mass density 7,850 kg/m^3, Poisson’ s ratio 0.3). [Figure 6: see original paper] shows the offshore jacket platform model: (a) FE model; (b) node numbers.

Objective functions in this research are built using the first six natural harmonics and mode shapes. Modal information is calculated under non-damage state, presented in and [Figure 7: see original paper].

presents natural frequencies of the offshore jacket platform. [Figure 7: see original paper] shows the first six mode shapes of the offshore jacket platform.

3.2 Optimal Sensor Placement

For sensor placement optimization, MOLA [?, ?, ?] determines optimal sensor configurations for the offshore jacket platform.

Initially, 12 candidate sensor locations (No. 2,4,5,6,7,8,9,10,11,13,14,15) are selected as shown in [Figure 6: see original paper]. These positions are structural system intersections where stress and deformation are most critical and likely to occur. Placing sensors at these locations enables accurate monitoring of critical areas, timely issue detection, and appropriate repair or reinforcement measures, ensuring safe platform operation. Sensor number and one of four well-known optimization criteria (KE, EVP, IE, and EFI) are considered as objective functions. The optimization objective is described as Where : is generated for each iteration to evaluate two objective A vector functions: sum of sensor number and objective function related to is vector of candidate sensors; simultaneously, MOLA metric J(M) generates another binary vector of same length vector to generate selected sensor. MOLA parameters are set according to and v-shaped transfer function is employed [**?**, **?**].

shows MOLA control parameter values. Parameter Value Niter

Pareto dominance relationship then selects optimal sensor placement options in objective space (shown in [Figure 8: see original paper]). Figures show that anywhere from one to all twelve possible sensors can be optimally placed according to four criteria. For KE, IE, and EFI criteria, optimal sensor number grows linearly with information gathered in jacket structure. However, EVP criterion forms convex Pareto front as sensor number increases.

As Figure 8: see original paper shows, when fewer than five sensors are used, EVP criterion value responds strongly to sensor addition, but with more than eight sensors, no notable improvement occurs. Additionally, as more instruments are added to offshore jacket platform, higher data quality is collected. ()min(());max((()))FSlengthSJMS= 121,2,⋯,,⋯TnSABAnBaaa= ==SABS

Moreover, Hypervolume metric compares different Pareto front families [**?**]. Higher Hypervolume indicates better Pareto front convergence and coverage. Average results after 10 independent runs of all indicators are shown in [Figure 9: see original paper], clearly demonstrating EVP criterion has higher Hypervolume.

[Figure 9: see original paper] shows Hypervolume values. Although four optimal sensor placement criteria find solutions, EVP is best as it presents highest Hypervolume, indicating greatest convergence and coverage. Consequently, EVP is applied to optimal sensor placement.

To demonstrate MOLA superiority, NSGA-II is also employed for comparison—widely used for multi-objective optimization in various real-world applications. Using specific crossover and mutation forms, NSGA-II produces offspring from which next generation is chosen using non-dominated sorting and crowding distance comparison [**?**]. Taking EVP metric as example, key NSGA-II algorithm parameters for offshore jacket platform are set as: population size 200, maximum generations 100, scattered crossover function, crossover probability 0.8, Gaussian mutation function, mutation probability 0.6, mutation strength 0.1. Pareto front calculated by NSGA-II is shown in [Figure 10: see original paper].

Results are similar to MOLA. EVP criterion does not change as sensor number increases beyond 8 sensors. Therefore, 8 sensors can be chosen as minimum number.

[Figure 10: see original paper] shows Pareto front with EVP criterion. presents sensor positions selected by MOLA and NSGA-II for eight sensors. Top four sensor positions are common to both algorithms. However, remaining sensor positions differ: MOLA tends to place sensors on second layer, while NSGA-II focuses on third layer. This indicates MOLA is more inclined to maximize response amplitude by placing more sensors on top of offshore jacket platform. For target EVP criterion J(M), MOLA outperforms NSGA-II. Therefore, MOLA is considered superior and its sensor configurations will be used for damage identification.

shows sensor configurations with EVP metric. Algorithm Sensor positions NSGA-II 4,5,6,7,8,9,14,15 2,4,6,7,8,10,14,15

4.1 Damage Identification

Damage is measured as proportion of stiffness loss. Change in n-th element stiffness is expressed by Equation (11): is changes in stiffness, called damage ratio (0~1), Kn is initial where stiffness of n-th element.

To quantify noise effect, random errors are added to natural frequencies and mode shapes. Measurement errors are simulated as follows [**?**]: where and are natural frequency and mode shape, respectively; is random number with zero mean and standard deviation 1; superscript n denotes noisy parameters; and represent noise level in mode shape and natural frequency, respectively.

shows simulated damage cases. Damage cases Description E3=0.8 E3=0.6, E6=0.4, E9=0.2

[Figure 11: see original paper] shows damage scenarios: (a) one damage (D1); (b) three damage (D2).

Damage is replicated by lowering element elasticity modulus. Table 4 details two damage scenarios, and Figure 11 identifies compromised jacket structure components. Modal analysis is computed using FE model, with natural frequency and mode shapes distorted by 1% noise. First six modes' modal information is used for damage diagnosis.

In damage identification process, MCMC-based Bayesian method is employed. Several MCMC-based Bayesian method parameters are set as: MH algorithm terminates after 15,000 iterations; first 5,000 iterations are non-adapting period while remaining 10,000 iterations form stable Markov chain. Most probable damage ratio value is obtained as average of 10,000 samples.

[Figure 12: see original paper] shows damage identification result for one damage: (a) Markov chain of damage ratio; (b) posterior PDF of damage ratio 3.

[Figure 13: see original paper] shows Markov chain of damage ratio for three damage scenarios (D2).

For damage scenario D1 with one damage location, Markov chain of damage ratio is shown in Figure 12: see original paper. All samples fluctuate around stable value during sampling. Damage ratio of element 3 (damage ratio 3) converges to 0.8, while other damage ratios converge to 0. As shown in Figure 12: see original paper, kernel density estimation computes Bayesian marginal PDF for damage ratio 3. Posterior marginal PDF of damage ratio 3 fits neatly into Gaussian distribution. Most probable value of damage ratio 3 is 0.8 and damage identification errors are close to zero. Consequently, damage ratio of element 3 is successfully identified.

For damage scenario D2 with three damage locations, Markov chain is calculated and shown in [Figure 13: see original paper]. Damage ratio 3 converges to 0.6; damage ratio 6 converges to 0.4; damage ratio 9 converges to 0.2, while other damage ratios converge to 0. These results indicate three different damage degrees in offshore jacket platform. Posterior PDFs of damage ratios 3, 6, and 9 are calculated and shown in [Figure 14: see original paper]. Simultaneously, 95% confidence interval is observed in [Figure 15: see original paper]. Results demonstrate Bayesian method has great potential for damage identification as it allows quantification of uncertainty related to identified variables.

[Figure 14: see original paper] shows posterior PDF of damage ratio: (a) damage ratio 3; (b) damage ratio 6; (c) damage ratio 9.

[Figure 15: see original paper] shows posterior PDF of damage ratio with 95% confidence interval.

Most probable values and identified errors of damage ratios are calculated and shown in . To demonstrate OSP superiority, modal information collected by all candidate sensor locations is also used for damage identification, with results shown in . Identification results are very close in both situations, but OSP provides higher calculation efficiency and reduced sensor cost. All results demonstrate proposed damage identification framework not only identifies single damage but also handles multiple damage situations effectively for platform damage identification.

shows identification result of damage ratio. Variables Damage ratio 3 Damage ratio 6 Damage ratio 9 Number of sensors Optimal sensor layout (error) 0.599 (0.17%) 0.401 (0.25%) 0.198 (1.00%) Candidate sensor location (error) 0.599 (0.17%) 0.400 (0%) 0.199 (0.50%)

4.2 The Influence of Measurement Noise

Modal information measurements are highly sensitive to noise. The proposed damage identification framework requires further study of noise impact.

As illustration, consider two damage conditions with damage ratios for elements 3 and 9 set at 0.8 and 0.5, respectively. Modal properties are calculated numerically, then white Gaussian noise is added to mimic measurement uncertainty according to Equations (12) and (13). Random variation is introduced to modal data at 1%, 5%, 10%, and 15% values. Five simulation iterations—functional equivalent of five experiments—are run with added noise to collect sufficient information for damage identification. Impact of noise on proposed damage identification framework is examined by comparing natural frequencies with varying noise levels ([Figure 16: see original paper]).

[Figure 16: see original paper] shows natural frequency with different noise levels: (a) first order; (b) third order.

MCMC-based Bayesian method then calculates damage ratio with different noise levels. Corresponding posterior marginal PDFs are presented in [Figure 17: see original paper], revealing all PDFs follow Gaussian distributions. However, as noise level increases, posterior PDF peaks deviate from true values.

[Figure 17: see original paper] shows posterior marginal PDF with different noise levels: (a) damage ratio 3; (b) damage ratio 9.

Identification error of damage ratios under different noise levels is shown in [Figure 18: see original paper]. As expected, errors gradually increase with higher measurement noise levels. Maximum error of 2% is observed for damage ratio 9 when noise level is 15%, which remains acceptable for damage identification process. These results demonstrate robustness and applicability of proposed damage identification framework for offshore jacket platforms.

[Figure 18: see original paper] shows error of damage identification with different noise levels.

---

5. Conclusions

To ensure precise health monitoring of offshore jacket platforms, a novel damage identification framework is created in this research. The framework combines optimal sensor placement model with damage detection model to pinpoint exact damage location and severity. MOLA achieves balance between sensor quantity and quality, solving bi-objective issues inherent in optimal sensor placement model. To efficiently and accurately compute damage ratio and quantify model parameter uncertainties, damage identification model uses MCMC-based Bayesian method. Case study proves over 97% damage identification accuracy within 15% noise level and reduced sensor cost, validating proposed framework efficacy. Future work includes incorporating damage detection model into offshore jacket platform DT framework to create comprehensive health monitoring system based on identified damage ratio for virtual model updating. The proposed damage identification framework provides technical assistance for creating DT framework for offshore jacket platform health monitoring.

Acknowledgements

The research leading to these results has received funding from the Norwegian Financial Mechanism 2014-2021 under Project Contract No 2020/37/K/ST8/02748.

References

[1] Global wind energy council, The Global Wind Energy Development Report 2022, (2022).

[2] L. Wang, A. Kolios, X. Liu, D. Venetsanos, R. Cai, Reliability of offshore wind turbine support structures: A state-of-the-art review, Renewable and Sustainable Energy Reviews. 161 (2022) 112250. https://doi.org/10.1016/j.rser.2022.112250.

[3] M. Li, A. Kefal, E. Oterkus, S. Oterkus, Structural health monitoring of an offshore wind turbine tower using iFEM methodology, Ocean Engineering. 204 (2020) 107291. https://doi.org/10.1016/j.oceaneng.2020.107291.

[4] M. Yazdi, F. Khan, R. Abbassi, N. Quddus, H. Castaneda-Lopez, A review of risk-based decision-making models for microbiologically influenced corrosion (MIC) in offshore pipelines, Reliability Engineering & System Safety. https://doi.org/10.1016/j.ress.2022.108474. (2022)

[5] M. Wang, C. Wang, A. Hnydiuk-Stefan, S. Feng, I. Atilla, Z. Li, Recent progress on reliability analysis of offshore wind turbine support structures considering digital twin solutions, Ocean Engineering. 232 (2021) 109168. https://doi.org/10.1016/j.oceaneng.2021.109168.

[6] Y. Zhang, J.C. Ji, Z. Ren, Q. Ni, F. Gu, K. Feng, K. Yu, J. Ge, Z. Lei, Z. Liu, Digital twin-driven partial domain adaptation network for intelligent fault diagnosis of rolling bearing, Reliability Engineering System Safety. (2023) https://doi.org/10.1016/j.ress.2023.109186.

[7] W. Kim, G. Lee, H. Son, H. Choi, B.D. Youn, Estimation of fatigue crack initiation and growth in engineering product development using a digital twin approach, Reliability Engineering & System Safety. 226 (2022) 108721. https://doi.org/10.1016/j.ress.2022.108721.

[8] E. VanDerHorn, Towards a digital twin approach for vessel-specific fatigue damage monitoring and prognosis, (2022) 15.

[9] R. Goraj, Digital twin of the rotor-shaft of a lightweight electric motor during aerobatics loads, AEAT. 92 (2020) 1319–1326. https://doi.org/10.1108/AEAT-11-2019-0231.

[10] M. Wang, B. Jin, G. Liu, Z. Li, The moving vibration source perception using bionic lateral line system and data-driven method, Ocean Engineering. 247 (2022) 110463. https://doi.org/10.1016/j.oceaneng.2021.110463.

[11] M. Wang, S. Feng, A. Incecik, G. Królczyk, Z. Li, Structural fatigue life prediction considering model uncertainties through a novel digital twin-driven approach, Computer Methods in Applied Mechanics and Engineering. (2022) https://doi.org/10.1016/j.cma.2021.114512.

[12] X. Bao, T. Fan, C. Shi, G. Yang, One-dimensional convolutional neural network for damage detection of jacket-type offshore platforms, Ocean Engineering. 219 (2021) 108293. https://doi.org/10.1016/j.oceaneng.2020.108293.

[13] Xiao, Y., Shao, H., Han, S., Huo, Z., Wan. J. 2022. Novel joint transfer network for unsupervised bearing fault diagnosis from simulation domain to experimental domain. IEEE-Mechatronics, Transactions 27(6): https://doi.org/10.1016/j.marstruc.2015.10.003.

[14] F. Mauro, D. Vassalos, D. Paterson, Critical damages identification in a multi-level damage stability assessment framework for passenger ships, Reliability Engineering & System Safety. 228 (2022) 108802. https://doi.org/10.1016/j.ress.2022.108802.

[15] E.M. Coraça, J.V. Ferreira, E.G.O. Nóbrega, An unsupervised structural health monitoring framework based on Variational Autoencoders and Hidden Markov Models, Reliability Engineering & System Safety. 231 (2023) 109025. https://doi.org/10.1016/j.ress.2022.109025.

[16] A. Fathi, A. Esfandiari, M. Fadavie, A. Mojtahedi, Damage detection in an offshore platform using incomplete noisy FRF data by a novel Bayesian model updating method, Ocean Engineering. 217 (2020) 108023. https://doi.org/10.1016/j.oceaneng.2020.108023.

[17] J.M. Nichols, E.Z. Moore, K.D. Murphy, Bayesian identification of a cracked plate using a population-based Markov Chain Monte Carlo method, Computers & Structures. 89 (2011) 1323–1332. https://doi.org/10.1016/j.compstruc.2011.03.013.

[18] S. Bansal, S.H. Cheung, On the Bayesian sensor placement for two-stage structural model updating and its validation, Mechanical Systems and Signal Processing. 169 (2022) 108578. https://doi.org/10.1016/j.ymssp.2021.108578.

[19] Y. Huang, J.L. Beck, H. Li, Hierarchical sparse Bayesian learning for structural damage detection: Theory, computation and application, Structural Safety. 64 (2017) 37–53. https://doi.org/10.1016/j.strusafe.2016.09.001.

[20] T. Yin, Q.-H. Jiang, K.-V. Yuen, Vibration-based damage detection for structural connections using incomplete modal data by Bayesian approach and model reduction technique, Engineering Structures. 132 (2017) 260–277. https://doi.org/10.1016/j.engstruct.2016.11.035.

[21] Q. Huang, P. Gardoni, S. Hurlebaus, A probabilistic damage detection approach using nondestructive vibration-based testing, Structural Safety. (2012) https://doi.org/10.1016/j.strusafe.2012.01.004.

[22] I. Behmanesh, B. Moaveni, Probabilistic identification of simulated damage

on the Dowling Hall footbridge through Bayesian finite element model updating: probabilistic damage identification of the dowling hall footbridge, Struct. Control Health Monit. 22 (2015) 463–483. https://doi.org/10.1002/stc.1684.

[23] Z. Zhang, C. Sun, B. Guo, Transfer-learning guided Bayesian model updating for damage identification considering modeling uncertainty, Mechanical Systems and Signal Processing. 166 (2022) 108426. https://doi.org/10.1016/j.ymssp.2021.108426.

[24] A. Mehrjoo, M. Song, B. Moaveni, C. Papadimitriou, E. Hines, Optimal sensor placement for parameter estimation and virtual sensing of strains on an offshore wind turbine considering sensor installation cost, Mechanical Systems and Signal Processing. 169 (2022) 108787. https://doi.org/10.1016/j.ymssp.2021.108787.

[25] H. Zainol Abidin, N. Md. Din, N.A. Mohamed Radzi, Z.I. Rizman, A Review on Sensor Node Placement Techniques in Wireless Sensor Networks, International Journal on Advanced Science, Engineering Information Technology. (2017) https://doi.org/10.18517/ijaseit.7.1.1514.

[26] Z. Xu, Y. Guo, J. Homer Saleh, Multi-objective optimization for sensor placement: An integrated combinatorial approach with reduced order model and Gaussian process, Measurement. 187 (2022) 110370. https://doi.org/10.1016/j.measurement.2021.110370.

[27] H. Farahmand, X. Liu, S. Dong, A. Mostafavi, J. Gao, A Network Observability Framework for Sensor Placement in Flood Control Networks to Improve Flood Situational Awareness and Risk Management, Reliability Engineering & System Safety. 221 (2022) 108366. https://doi.org/10.1016/j.ress.2022.108366.

[28] Y. Yang, M. Chadha, Z. Hu, M.D. Todd, An optimal sensor placement design framework for structural health monitoring using Bayes risk, Mechanical Systems and Signal Processing. 168 (2022) 108618. https://doi.org/10.1016/j.ymssp.2021.108618.

[29] J.L.J. Pereira, M.B. Francisco, L.A. de Oliveira, J.A.S. Chaves, S.S. Cunha Jr, G.F. Gomes, Multi-objective sensor placement optimization of helicopter rotor blade based on Feature Selection, Mechanical Systems and Signal Processing. 180 (2022) 109466. https://doi.org/10.1016/j.ymssp.2022.109466.

[30] A. Mehrjoo, M. Song, B. Moaveni, C. Papadimitriou, E. Hines, Optimal sensor placement for parameter estimation and virtual sensing of strains on an offshore wind turbine considering sensor installation cost, Mechanical Systems and Signal Processing. 169 (2022) 108787. https://doi.org/10.1016/j.ymssp.2021.108787.

[31] V. Nieminen, J. Sopanen, Optimal sensor placement of triaxial accelerometers for modal expansion, Mechanical Systems and Signal Processing. 184 (2023) 109581. https://doi.org/10.1016/j.ymssp.2022.109581.

[32] X. Kong, B. Cai, Y. Liu, H. Zhu, Y. Liu, H. Shao, C. Yang, H. Li, T. Mo, Optimal sensor placement methodology of hydraulic control system for fault diagnosis, Mechanical Systems and Signal Processing. 174 (2022) 109069. https://doi.org/10.1016/j.ymssp.2022.109069.

[33] D.C. Kammer, Sensor placement for on-orbit modal identification and correlation of large space structures, Journal of Guidance, Control, and Dynamics. 14 (1991) 251–259. https://doi.org/10.2514/3.20635.

[34] G. Heo, M.L. Wang, D. Satpathi, Optimal transducer placement for health monitoring of long span bridge, Soil Dynamics and Earthquake Engineering. 16 (1997) 495–502. https://doi.org/10.1016/S0267-7261(97)00010-9.

[35] R.J. Barthorpe, K. Worden, Sensor Placement Optimization, in: Encyclopedia of Structural Health Monitoring, 2009. https://doi.org/10.1002/9780470061626.shm086.

[36] H. Jin, J. Xia, Y. Wang, Optimal sensor placement for space modal identification of crane structures based on an improved harmony search algorithm, Journal of Zhejiang University-SCIENCE A. 16 (2015) 464–477. https://doi.org/10.1631/jzus.A1400363.

[37] P. Bhattacharyya, J. Beck, Exploiting convexification for Bayesian optimal sensor placement by maximization of mutual information, Structural Control and Health Monitoring. 27 (2020) e2605. https://doi.org/10.1002/stc.2605.

[38] K.-V. Yuen, S.-C. Kuok, Efficient Bayesian sensor placement algorithm for structural identification: a general approach for multi-type sensory systems, Earthquake Engineering & Structural Dynamics. 44 (2015) 757–774. https://doi.org/10.1002/eqe.2486.

[39] T. Yin, K.-V. Yuen, H.-F. Lam, H. Zhu, Entropy-Based Optimal Sensor Placement for Model Identification of Periodic Structures Endowed with Bolted Joints, Computer-Aided Civil and Infrastructure Engineering. 32 (2017) 1007–1024. https://doi.org/10.1111/mice.12309.

[40] G.F. Gomes, F.A. de Almeida, P. da Silva Lopes Alexandrino, S.S. da Cunha, B.S. de Sousa, A.C. Ancelotti, A multiobjective sensor placement optimization for SHM systems considering Fisher information matrix and mode shape interpolation, Engineering with Computers. 35 (2019) 519–535. https://doi.org/10.1007/s00366-018-0613-7.

[41] M. Mishra, S.K. Barman, D. Maity, D.K. Maiti, Ant lion optimisation algorithm for structural damage detection using vibration data, J Civil Struct Health Monit. 9 (2019) 117–136. https://doi.org/10.1007/s13349-018-0318-z.

[42] Z. Chen, L. Yu, A new structural damage detection strategy of hybrid PSO with Monte Carlo simulations and experimental verifications, Measurement. 122 (2018) 658–669. https://doi.org/10.1016/j.measurement.2018.01.068.

[43] T.-H. Yi, G.-D. Zhou, H.-N. Li, C.-W. Wang, Optimal placement of triaxial sensors for modal identification using hierarchic wolf algorithm: Optimal place-

ment of triaxial sensors using HWA, Struct. Control Health Monit. 24 (2017) e1958. https://doi.org/10.1002/stc.1958.

[44] J.-F. Lin, Y.-L. Xu, S.-S. Law, Structural damage detection-oriented multi-type sensor placement with multi-objective optimization, Journal of Sound and Vibration. 422 (2018) 568–589. https://doi.org/10.1016/j.jsv.2018.01.047.

[45] J. Luiz Junho Pereira, G. Antônio Oliver, M. Brendon Francisco, S. Simões Cunha Jr, G. Ferreira Gomes, Multi-objective lichtenberg algorithm: A hybrid physics-based meta-heuristic for solving engineering problems, Expert Systems with Applications. 187 (2022) 115939. https://doi.org/10.1016/j.eswa.2021.115939.

[46] J.L.J. Pereira, M.B. Francisco, C.A. Diniz, G. Antônio Oliver, S.S. Cunha, G.F. Gomes, Lichtenberg algorithm: A novel hybrid physics-based meta-heuristic for global optimization, Expert Systems with Applications. (2021) https://doi.org/10.1016/j.eswa.2020.114522.

[47] C. Yang, An adaptive sensor placement algorithm for structural health monitoring based on multi-objective iterative optimization using weight factor updating, Mechanical Systems and Signal Processing. 151 (2021) 107363. https://doi.org/10.1016/j.ymssp.2020.107363.

[48] J.L.J. Pereira, M.B. Francisco, C.A. Diniz, G. Antônio Oliver, S.S. Cunha, G.F. Gomes, Lichtenberg algorithm: A novel hybrid physics-based meta-heuristic for global optimization, Expert Systems with Applications. (2021) https://doi.org/10.1016/j.eswa.2020.114522.

[49] H.-F. Lam, J.-H. Yang, S.-K. Au, Markov chain Monte Carlo-based Bayesian method for structural model updating and damage detection, Struct Control Health Monit. 25 (2018) e2140. https://doi.org/10.1002/stc.2140.

[50] M.-C. Chen, W. Fang, C. Yang, L. Xie, Bayesian prediction and probabilistic model of fatigue cracks in steel structures, Engineering Failure Analysis. 103 (2019) 335–346. https://doi.org/10.1016/j.engfailanal.2019.04.061.

[51] S. Mustafa, Y. Matsumoto, Bayesian Model Updating and Its Limitations for Detecting Local Damage of an Existing Truss Bridge, J. Bridge Eng. 22 (2017) 04017019. https://doi.org/10.1061/(ASCE)BE.1943-5592.0001044.

[52] M. Wang, J. Leng, S. Feng, Z. Li, A. Incecik, Precisely modeling offshore jacket structures considering model parameters uncertainty using Bayesian updating, Ocean Engineering. 258 (2022) 111410. https://doi.org/10.1016/j.oceaneng.2022.111410.

[53] K. Liu, R.-J. Yan, C. Guedes Soares, Damage identification in offshore jacket structures based on modal flexibility, Ocean Engineering. (2018) https://doi.org/10.1016/j.oceaneng.2018.10.014.

[54] K.K. Ghosh, R. Guha, S.K. Bera, N. Kumar, R. Sarkar, S-shaped versus V-shaped transfer functions for binary Manta ray foraging optimization in feature

selection problem, Neural Computing and Applications. 33 (2021) 11027–11041. https://doi.org/10.1007/s00521-020-

[55] S. Mirjalili, A. Lewis, S-shaped versus V-shaped transfer functions for binary Particle Swarm Optimization, Swarm and Evolutionary Computation. (2013) https://doi.org/10.1016/j.swevo.2012.09.002.

[56] C. Yang, Y. Xia, A novel two-step strategy of non-probabilistic multi-objective optimization for load-dependent sensor placement with interval uncertainties, Mechanical Systems and Signal Processing. 176 (2022) 109173. https://doi.org/10.1016/j.ymssp.2022.109173.

[57] K. Liu, R.-J. Yan, C. Guedes Soares, Damage identification in offshore jacket structures based on modal flexibility, Ocean Engineering. (2018) https://doi.org/10.1016/j.oceaneng.2018.10.014.

Note: Figure translations are in progress. See original paper for figures.