Towards Dynamic Digital Twin for Monopile-Supported Offshore Wind Turbines

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ABSTRACT

Offshore wind turbines (OWTs) are critical in achieving the global goal of net zero greenhouse gas emissions. However, they face significant safety and reliability challenges due to harsh environmental conditions and complex evolution mechanisms of structural properties. To address these challenges, dynamic digital twin technology is proposed as a potential solution to accurately monitor structural performance and condition variations. It can contribute to real-time tracking of OWTs' performance, early detection of potential structural damages, and accurate estimation of remaining useful life.

INTRODUCTION

In recent years, offshore wind turbines (OWTs) have accounted for an increasing proportion in the total installed capacity of wind turbines due to the stability of offshore wind energy and the vast space available at sea [1]. The rapid development of OWTs also poses serious challenges [2]: the harsh environment in which OWT structures are located is subject to corrosive factors such as high salt level, high

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temperature, and high humidity that affect durability; since they are located far from land, operation and maintenance requires regular maintenance vessels, resulting in high operation and maintenance costs. Therefore, effective structural identification approach is urgently needed.

Digital twin technology is gaining more and more attention with the development of the Internet of Things, 5G, and Artificial Intelligence. It is a technology that sends real-time data from the sensors installed on a structure to an analysis center via a wireless network, and uses physics-based and data-driven methods to obtain real-time structural conditions, and to update and visualize the digital model of the structure, i.e., a "real-time mapping of the full life cycle of a physical entity in virtual space" [3]. Nevertheless, most existing studies focus on the implementation of BIM (Building Information Modelling), which cannot represent structural dynamic behaviors. Thus, this study proposes a dynamic digital twin approach to bridge this gap.

The implementation of dynamic digital twins for OWTs requires reduced order models, to improve computational efficiency [4, 5]. The existing studies of reduced-order models for OWTs mostly focus on substructures or only one form of damage to the turbine [6, 7]. Consequently, a simplified model that takes into account the overall dynamic characteristics of the OWT is needed.

The support condition significantly affects the dynamic properties of OWTs, but it is constantly changing under dynamic loads such as wind and waves [8, 9], following complex evolution mechanism. Therefore, efficient model updating is essential to represent real-time support conditions towards dynamic digital twin.

Compared to the traditional model updating methods which aim to provide frequency alignment between the numerical model and the physical structure, the dynamic digital twin should be able to achieve time domain alignment. In practice, loads strongly influence structural dynamic responses, while they are difficult to measure directly. Therefore, they need to be accurately identified and modelled [10, 11]. Among numerous existing force identification algorithms [12], Gaussian process latent force model (GPLFM) [13] stands out as it can achieve excellent time domain alignment results and greatly reduce the drift of derived unknown force.

This paper presents several key techniques for the construction of dynamic digital twin of monopile-supported OWTs, including simplified model construction, support condition identification, and load identification. The methodology is described in Section 2. The results obtained based on the proposed method are shown in Section 3. A summary and outlook are provided in Section 4.

METHODOLOGY

The process of establishing dynamic digital twin models for monopile-supported OWTs is shown in Figure 1. Firstly, a high-precision numerical model is created for dynamic analysis. Then, model order reduction methods are developed to construct the simplified finite element (FE) model. A two-stage model updating technique is utilized to achieve dynamic digital twin for OWT. In the first stage, the artificial ecosystem-based optimization algorithm is adopted to accurately identify the support condition of OWTs based on the simplified FE model. In the second stage, a simplified OWT state-space model was obtained from the simplified FE model, and the GPLFM method was used for load identification. Based on the reconstructed load and simplified model, i.e., dynamic digital twin, the structural dynamic behaviors can be efficiently simulated.

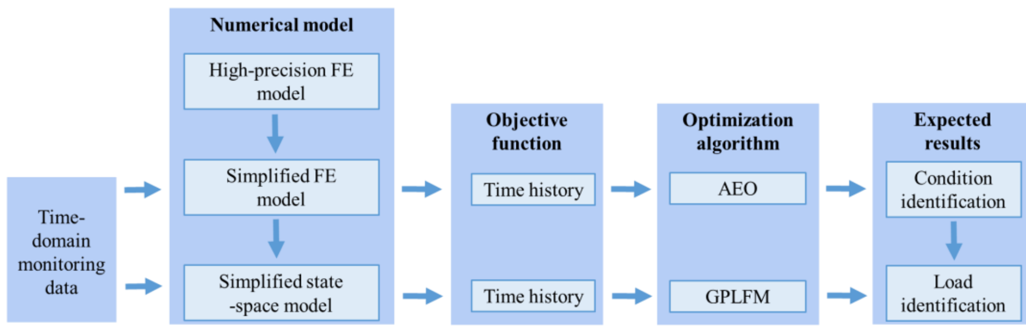


Figure 1. The proposed dynamic digital twin approach.

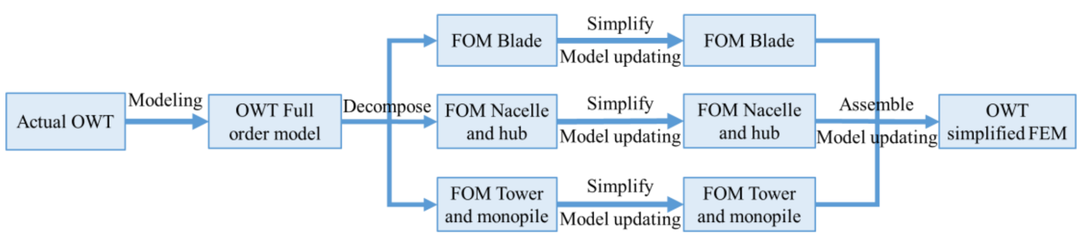


Figure 2. The process of establishing the simplified FE model for monopile-supported OWTs (reproduced from [4])

The process of the simplified FE model construction is shown in Figure 2. Firstly, a full-order FE model (FOM) is established using such high-order elements as solid and shell elements, based on an actual OWT structure. Secondly, we decompose the full-order model into three sub-structures: 1) blade, 2) nacelle and hub, and 3) tower and monopile, which is consistent with the structural composition of an OWT. These three substructure models are then simplified by using two-node beam elements, which deliver the reduce-order models of substructures. They are individually calibrated through a frequency domain model updating process. Finally, we assemble the simplified substructure models to a reduced-order model (ROM). This model is further updated to ensure simulation accuracy, which delivers the OWT simplified FE model. The detailed steps for the establishment of the simplified OWT model can be found in article [4].

Then, a time-domain model updating method is developed to identify the support condition of monopile-supported OWTs. The distributed spring-dashpots are used to simulate the interaction between the soil and monopoles, and their initial values are determined according to the p-y curves obtained from the API [14]. The parameters of the spring and dashpot are selected as the updating parameters. The extreme values of the time-domain response and their corresponding time are used to establish the objective function, which benefits the goal of time domain alignment. Artificial ecosystem-based optimization (AEO) is selected as optimization algorithm, for its superior performance in solving real-world engineering problems [15].

Finally, the GPLFM algorithm is used to estimate the unknown input force for monopile-supported OWT. Based on the state space equation transformation, the dynamics equation can be represented as a first-order differential equation and an observation equation:

$$\dot{\mathbf{x}}(t) = \mathbf{A}_c\mathbf{x}(t) + \mathbf{B}_c\mathbf{f}(t) \tag{1}$$

$$\mathbf{y}(t) = \mathbf{G}_c\mathbf{x}(t) + \mathbf{J}_c\mathbf{f}(t) \tag{2}$$

$$\mathrm{K}(\tau;\nu,\alpha,l) = \alpha^2 \frac{2^{1-\nu}}{\Gamma(\nu)}\left(\frac{\sqrt{2\nu}\tau}{l}\right)^{\nu} K_{\nu}\left(\frac{\sqrt{2\nu}\tau}{l}\right) \tag{3}$$

where $\mathbf{x}$ is the vector composed of displacement and velocity, $\mathbf{y}$ is the observed value, and $\mathbf{A}_c$, $\mathbf{B}_c$, $\mathbf{G}_c$, and $\mathbf{J}_c$ are the necessary matrices converted according to Eq. (1). The specific form can be seen in [16]. After representing the system in the form of state space equations, various force identification algorithms [12] can be used to estimate unknown input forces.

The exponential covariance function (Eq. (3)) in the Matérn family is used and set to ν = 0. The hyperparameter $\theta = [\alpha, l]$ is used to construct the covariance function in the force Gaussian model, which can be determined based on a priori knowledge by expert knowledge. More derivations of the formulas and related covariance function selections can be found in article [16].

RESULTS AND DISCUSSION

Simplified Model Construction

Numerical simulation was performed to demonstrate the accuracy of the simplified FE model. Table I shows the first 10 order modal frequencies of the full-order model

(FOM) and the simplified model. It can be found that the average deviation between the two models is less than 10%. Therefore, the simplified FE model can accurately simulate the structural dynamic behaviors of monopile-supported OWTs.

TABLE I. NATURAL FREQUENCIES OF FOM AND SIMPLIFIED MODEL. (REPRODUCED FROM [4])

Mode	FOM	Simplified model	Relative deviation (%)
1	0.170	0.174	2.429
2	0.174	0.175	0.379
3	0.511	0.524	2.636
4	0.558	0.555	-0.613
5	0.595	0.556	-6.629
6	0.653	0.623	-4.617
7	0.754	0.726	-3.666
8	0.770	0.805	4.553
9	1.047	1.151	9.936
10	1.226	1.180	-3.720

Support Condition Identification

Three distributed spring-dashpot sets have been selected based on the preliminary comparative study. The actuator is adopted to apply dynamic load on the OWT test model, and the proposed model updating method is used to identify the changes in the support condition caused by the dynamic load. The identification results are shown in Table II, we can observe: 1) the stiffness parameters increase and the damping parameters decrease, which is consistent with the change of the mode parameters; 2) the closer the mud line, the greater the change of the parameters, which is consistent with the actual situation where the top soil layer experience larger deformation and force. The results indicate that this method can identify the real-time support condition for monopile-supported OWTs.

TABLE II. VARIATIONS OF UPDATED PARAMETERS.

Position of spring-dashpot sets	Model updating 1			Model updating 2		
	S1	S2	Q1	S1	S2	Q1
Z/6	0.686	0.781	0.560	4.360	4.715	0.375
3Z/6	0.812	0.773	1.046	4.729	3.238	0.325
5Z/6	1.007	1.143	1.127	1.420	2.206	0.711

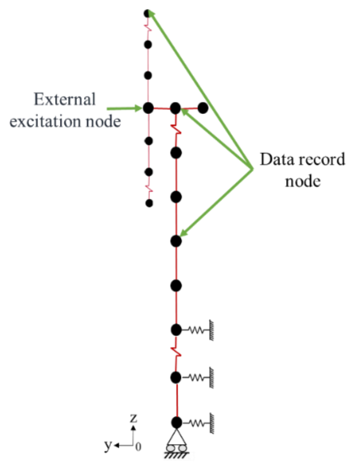


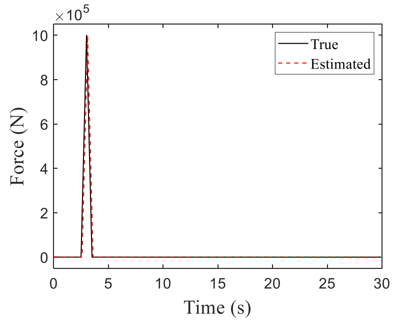
Figure 3. The external excitation and data collection location of the simplified model.

Load Identification

The simplified OWT model was selected for the load identification study in this section. The damping ratio is set to 0.03, the Rayleigh damping coefficient is calculated from the first two orders of frequency of the model, and the damping matrix is $\mathbf{C} = 0.0329\mathbf{M} + 0.0274\mathbf{K}$. As shown in Figure 3, the external excitation is located at the top of the tower and the displacement acceleration data are recorded for the middle of the tower, the top of the tower, and the top of the blade.

An impact excitation of magnitude 1×10^6 N was first applied on the top of the tower. The load was applied at $t = 2.5$ s; ramped up linearly from 0 to 1×10^6 in 0.5 s; peaked at $t = 3$ s; and then ramped down linearly from 1×10^6 to 0 in another 0.5 s. Only the acceleration in the middle of the tower was used as a known response to estimate the unknown impact load. Finally, the load was input into the system and the reconstructed responses can be obtained. The load identification and the time domain response reconstruction results, compared against the numerical simulation results, are shown in Figures 4 and 6, respectively. It can be seen that the performance of force identification and response reconstruction is very good, with a slight time lag. The reconstructed response was brought forward one time step and compared with the true value. All the normalized mean square errors (NMSE) were less than 0.01%.

Further, a random excitation between -3.5×10^5 N and 3.5×10^5 N was applied to the top of the tower. The force was estimated, and the response was reconstructed using the acceleration in the middle of the tower as the known response. The results are shown in Figures 5 and 7. Again, the fit is almost perfect except for a slight lag in the results for the force and response. Similarly, after one time step forward in the reconstruction response, the NMSE of all responses is less than 0.1%.



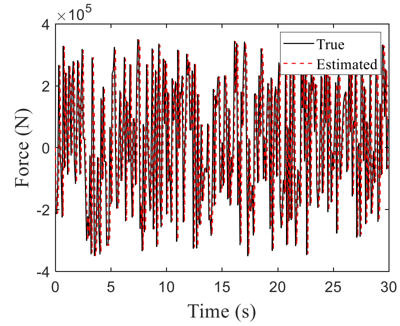


Figure 4. Estimated force of the tower.

Figure 5. Estimated force of the tower

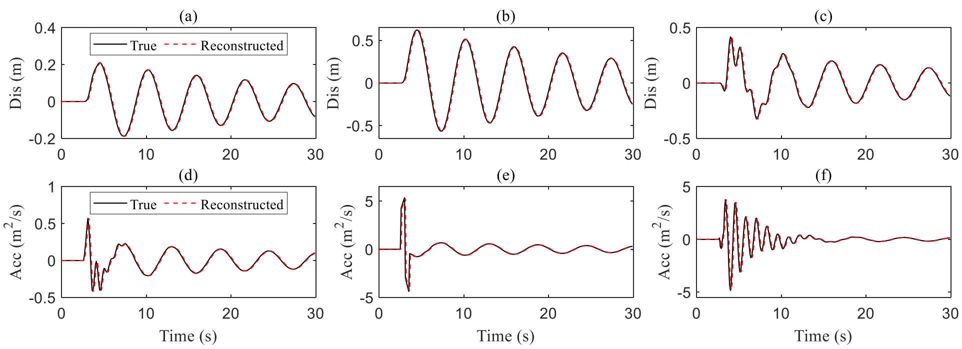


Figure 6. The response of the reconstruction. (a), (b), and (c) represent the displacements located at the middle of the tower, the top of the tower, and the top of the blade, respectively. (d), (e), and (f) represent the acceleration at the middle of the tower, the top of the tower, and the top of the blade, respectively.

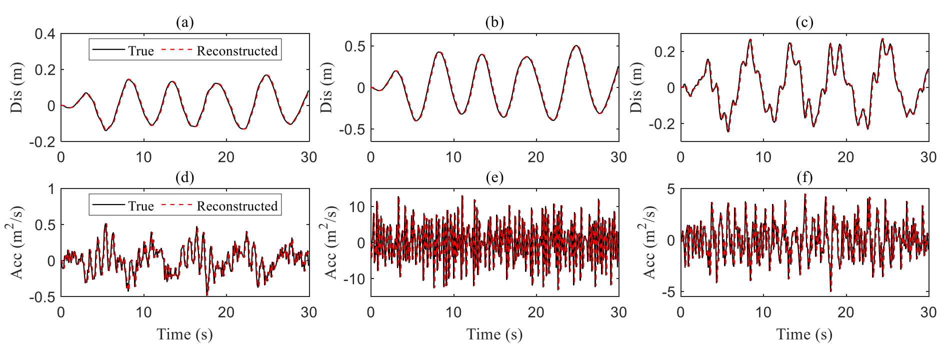


Figure 7. The response of the reconstruction. The representation of (a)-(f) is consistent with Figure 6.

CONCLUSION

This paper presents an approach to the construction of dynamic digital twin for monopile-supported OWTs. A simplified FE model was developed, which can achieve similar modeling accuracy compared with the full-order FE model. The time-domain model updating technique is used to identify support condition. The GPLFM method is used to reconstruct the loads on the structure. The approach achieved excellent time domain alignment on a numerical example, with less than 0.1% NMSE. This study may be an important step towards the construction of dynamic digital twin for monopile-supported OWTs, which offers a promising solution to the challenges of safe operation and maintenance of these structures and may ultimately enhance their economic and environmental sustainability.

REFERENCES

1. GWEC. 2021. "Global Wind Report 2021". *Global Wind Energy Council*.
2. Lian, J. Cai, O. Dong, X. Jiang, Q. Zhao, Y. 2019. "Health monitoring and safety evaluation of the offshore wind turbine structure: a review and discussion of future development,". *Sustainability*.,11(2).
3. Jiang, F. Ma, L. Broyd, T. Chen, K. 2021. "Digital twin and its implementations in the civil engineering sector," *Automat Constr*., 130(2):103838.
4. Liang, J. Kato, B. Wang, Y. 2023. "Constructing simplified models for dynamic analysis of monopile-supported offshore wind turbines," *Ocean Eng*., 271:113785.
5. Lu, K. Zhang, K. Zhang, H. Gu, X. Jin, Y. Zhao, S. Fu, C. Yang, Y. Lu, Z. 2021. "A review of model order reduction methods for large-scale structure systems," *Shock Vib*., 2021:1-19.
6. Li, H. Ding, H. 2010. "Reduction-based model updating of a scaled offshore platform structure," *J Eng Mech*., 136(2):131-42.
7. Lin, Z. Cevasco, D. Collu, M. 2020. "A methodology to develop reduced-order models to support the operation and maintenance of offshore wind turbines," *Appl Energ*., 259:114228.
8. Abdullahi, A. Bhattacharya, S. Li, C. Xiao, Y. Wang, Y. 2022. "Long term effect of operating loads on large monopile-supported offshore wind turbines in sand," *Ocean Eng*., 245:110404.
9. Xu, Y. Nikitas, G. Zhang, T. Han, Q. Chryssanthopoulos, M. Bhattacharya, S. Wang, Y. 2019. "Support condition monitoring of offshore wind turbines using model updating techniques," *Struct Health Monit*., 19(4):1017-31.
10. Liu, Y. Shepard, W. S. 2005 "Dynamic force identification based on enhanced least squares and total least-squares schemes in the frequency domain," *J Sound Vib*., 282:37-60.
11. Vanlanduit, S. Guillaume, P. Cauberghe, B. Parloo, E. De, Sitter. G. Verboven, P. 2005. "On-line identification of operational loads using exogenous inputs," *J Sound Vib*., 285:267-79.
12. Auger, F. Hilairet, M. Guerrero, J. M. Monmasson, E. Orlowska-Kowalska, T. Katsura, S. 2013. "Industrial applications of the Kalman filter: A review," *IEEE T Ind Electron*., 60(12):5458-71.
13. Alvarez, M. Luengogarcia, D. Lawrence, N. 2009. "Latent Force Models,"
14. API. 2008. "Recommended practice for planning, designing and constructing fixed offshore platforms—working stress design," *American Petroleum Institute*.
15. Zhao, W. Wang, L. Zhang, Z. 2019. "Artificial ecosystem-based optimization: a novel nature-inspired meta-heuristic algorithm," *Neural Comput Appl*., 32(13): 9383-9425.
16. Nayek, R. Chakraborty, S. Narasimhan, S. 2019. "A Gaussian process latent force model for joint input-state estimation in linear structural systems," *Mech Syst Signal Pr*., 128:497-530.