Analysis of Key Disciplinary Parameters in Floating Offshore Wind Turbines with An AI-Based SADA Method

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Abstract

Floating offshore wind turbines (FOWTs) are a promising offshore renewable energy harvesting facility but requesting multiple-disciplinary analysis for their dynamic performance predictions. However, engineering-fidelity level tools and the empirical parameters pose challenges due to the strong nonlinear coupling effects of FOWTs. A novel method, named SADA, was proposed by Chen and Hu (2021) for optimizing the design and dynamic performance prediction of FOWTs in combination with AI technology. In the SADA method, the concept of Key Disciplinary Parameters (KDPs) is also proposed, and it is of crucial importance in the SADA method. The purpose of this paper is to make an in-depth investigation of the characters of KDPs and the internal correlations between different KDPs in the dynamic performance prediction of FOWTs. Firstly, a brief description of SADA is given, and the basin experimental data are used to conduct the training process of SADA. Secondly, categories and boundary conditions of KDPs are introduced. Three types of KDPs are given, and different boundary conditions are used to analyze KDPs. The results show that the wind and current in Environmental KDPs are strongly correlated with the percentage difference of dynamic response rather than that by wave parameters. In general, the optimization results of SADA consider the specific basin environment and the coupling results between different KDPs help the designers further understand the factors that have a more significant impact on the FOWTs system in a specific domain.

Key words: floating offshore wind turbine, SADA, KDPs, machine learning, basin experiment

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1 Introduction

Floating offshore wind turbines (FOWT) are highly complex systems, accounting for the coupling between aero-hydro-servo-elastic dynamics. Owing to the high cost of the floating substructure and foundations, there is a sizeable overall cost difference (Wu et al., 2019). More precisely, the preliminary design or analysis may cause an increase in the operation and maintenance cost of the wind farm, such as gearbox failures (Li et al., 2021), leading edge erosion (Mishnaevsky et al., 2021), and accidental ship collisions (Zhang et al., 2021; Zhang and Hu, 2022). The deterioration of the mooring line over time will lead to an increase in the failure of single or multiple lines (Lugsdin, 2012; Yang et al., 2022). Regardless of the aspect, only based on reasonable and reliable R&D can it minimize exposure to technical risks and reduce the cost of FOWTs.

Although FOWT has broad development prospects, it is still a cutting-edge emerging technology. The knowledge of FOWTs involves multiple disciplines, indicating that caution must be taken when simplifying the theories for FOWTs (Amaral et al., 2021). Specifically, many theories involved in the FOWTs include massive formulas determined based on assumptions and empirical parameter values. They are not explicitly designed for FOWTs but are inherited from land-based wind turbines. For example, some traditional aerodynamic theories are shown in Table 1, including the drag coefficient \( C_d \), the axial induction factor \( \alpha \), and tangential induction factor \( \alpha' \). These classical theories cannot perfectly explain the actual aerodynamic performance of FOWTs due to the existence of many empirical parameters.

Many scholars are devoting in this research field. For example, the third phase of the Offshore Code Comparison, Collaboration, Continued, with Correlation and Uncertainty (OC6) project (IEAWind, 2021) carried out a code-to-experiment case analysis for validating the aerodynamic loading on a wind turbine rotor undergoing significant motion caused by a floating support structure by using different methods, including Blade element momentum theory (BEM), Dynamic Blade element momentum theory (DBEM), Computational fluid dynamics (CFD), etc. In general, the highly coupled nonlinear performances of FOWTs bring many challenges to the implementation of design and

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Table 1 Comparison of aerodynamic models of different wind turbines

| Model                     | Object       | Wake tangential velocity \(\Delta \Omega r\) | Blade number \(N\) | Drag coefficient \(C_d\) | Optimal wind energy utilization factor \(C_{p_{max}}\) | Optimal factor \(k\) |
|---------------------------|--------------|-----------------------------------------------|-------------------|-------------------------|-------------------------------------------------------|----------------------|
| One-dimensional           | Disc         | 0                                             | \(\infty\)        | 0                       | \(16/27\)                                             | 1/3                  |
| Induced speed relational  | Ring element | \(>0\)                                        | \(\infty\)        | 0                       | \(8\delta^2 \rho R^3 \int_0^{1}\) \((1 - \delta)\delta r^4 dr\) | \(a = 1 - 3a\)       |
| Optimal airflow inclination| Ring element | \(>0\)                                        | \(\infty\)        | 0                       | \(2\delta (1 + \delta)^2 \sin \frac{\alpha}{3} \int_0^{1} \frac{\delta^2}{\delta^3} \) | \(\phi = \frac{2\delta}{\delta^3}\) |
| Simplified BEM (\(\delta = 0\)) | Blade element | \(>0\)                                        | Limited           | 0                       | \(2\delta^2 \int_0^{1} (\delta - 1)(1 + \delta)^3 r^4 dr\) | \(-\) |
| BEM                       | Blade element | \(>0\)                                        | Limited           | 0                       | \(-\)                                                  | \(-\)                |

With artificial intelligence (AI) technology development, innovations have also appeared in offshore engineering and fluid mechanics research. Garnier et al. (2021) and Viquerat et al. (2021) gave a general description of the application of deep reinforcement learning (DRL) in fluid mechanics. Xie et al. (2022) applied DRL to the control system of the breakwater to find the best strategy for wave dissipation. Mainly, Khan et al. (2020) and Stetco et al. (2019) reviewed the applications of AI in power forecasting and environmental monitoring of wind turbines. Nevertheless, there are fewer applications of AI technology on the design and optimization of FOWTs so far.

Chen et al. (2021a) proposed an AI-based proposals innovative artificial intelligence (AI) technology-based method, named SADA (Software-in-the-Loop combined Artificial Intelligence Method for Dynamic Analysis of Floating Wind Turbines), to optimize the design and predict dynamic performances of FOWT. The concept of Key Disciplinary Parameters (KDPs) is proposed in SADA method, working as a data transmission interface between AI technology and disciplines in numerical simulation of FOWTs. Specifically, the KDPs can be divided into three categories with their unique boundary conditions in SADA:

- Environmental KDPs;
- Disciplinary KDPs;
- Specific KDPs.

The Environmental KDPs vary with different FOWTs and locations, such as gravitational acceleration, water density, air viscosity, and operational water depth, etc.

The Disciplinary KDPs constitute the largest category of KDPs. Those empirical formulas and parameter values in the fundamental theories for calculating loads, motions, and all the dynamic responses of FOWTs can be put in the disciplinary KDPs category; for example, the Prandtl’s tip loss factor, Glauert correction, the correction of the thrust and cone angle induced by the rotor. The viscous damping of floater in hydrodynamic; some KDPs involving multiple disciplines were introduced in reference (Chen et al., 2021a).

For specific KDPs, some experimental models or design parameters of the full-scale FOWTs are different from the actual physical models. Besides, some experiments used static lines or cables to replace a static thrust from a given turbine’s thrust curve or drag discs to reproduce the static wind loading (Roddier et al., 2010; Guanche et al., 2011; Wan et al., 2016). The mooring lines model is simplified, using the quasi-static catenary equation to replace the delta link of multi-lines by increasing the yaw stiffness. As for potential flow theory, there are also some empirical parameters based on previous experiments. Their values might not be accurate for FOWTs calculation, and these empirical parameters can be classified as specific KDPs.

Therefore, this paper aims to conduct an in-depth investigation of the properties of KDPs based on the SADA method. Firstly, the methodology of SADA will be introduced briefly. Secondly, some of the KDPs will be selected to optimize the dynamic performance of FOWTs by experimental data. Thirdly, the interaction between different categories of KDPs is discussed through correlation analysis. Finally, qualitative conclusions are drawn for the study of some KDPs.

2 SADA methodology

This section mainly and briefly introduces the methodology of SADA, including the KDPs concepts, DARwind program, and AI algorithm application. In addition, the KDPs used in this paper will be provided. For more details on the SADA method, please see the works of references (Chen et al., 2021a, 2021b, 2021c).

2.1 SADA method

The SADA method is a novel concept to integrate the AI technology (Artificial Neural Networks and Deep Reinforcement Learning) and DARwind (a coupled aero-hydro servo-elastic program) for optimized design and dynamic performance prediction of FOWTs. Fig. 1 shows the general flowchart of the entire SADA algorithm.

Firstly, the concept of KDPs is proposed, and it is the most crucial concept in SADA, working as a data transmission interface between AI technology and disciplines in numerical simulation of FOWTs.

Secondly, DARwind can be trained to be more intelligent and can give more accurate predictions for FOWTs by ANN
or DRL algorithms on target data (experimental or full-scale measured data). All information generated in the iterative loop will be recorded, including the change of KDPs and the corresponding percentage difference of FOWTs simulation.

Finally, this information will be integrated to carry out relevant statistical analysis to feedback the optimal selection of KDPs.

2.2 DARwind

This section briefly introduces the DARwind program, and for more specific information about DARwind, please refer to the published literature (Chen et al., 2019).

The current version of the DARwind is written in the high-level programming language FORTRAN, verified by a series of code-to-experiment comparisons to show its feasibility. The functional modules of the DARwind program can be roughly divided into Input module, Solver module and Output module, as shown in Fig. 2.

![Fig. 2. Modules of DARwind procedure.](image)

2.3 Application of AI technology

This section introduces the AI technology used in the SADA method, including the Artificial Neural Networks, Deep Reinforcement Learning, and percentage difference evaluation.

The application of DRL in SADA is the most innovative highlight. The specific notations and nouns combining FOWTs and DRL in SADA can be seen in Fig. 3.

As an agent, DARwind will take continuous action through the SIL algorithm, i.e., adjust KDPs appropriately to obtain more accurate prediction results and minimize the percentage difference of dynamic performance of FOWTs. The action here affects the immediate reward and the next state, thus the subsequent reward. The purpose of DARwind is to find what action can be taken to maximize the numerical reward signal. The roles of the deep neural networks are amplified to record [state, action, reward, next state] in different situations through the SIL algorithm. The reward here is the feedback of the evaluation of percentage difference, which are:

\[
P_{\text{initial}} = \left| \frac{O_{\text{target data}} - O_{\text{initial KDPs}}}{O_{\text{target data}}} \right| \times 100\%; \quad (1)
\]

\[
P_{\text{present}} = \left| \frac{O_{\text{target data}} - O_{\text{weighted KDPs}}}{O_{\text{target data}}} \right| \times 100\%; \quad (2)
\]

\[
P_{\text{difference}} = P_{\text{initial}} - P_{\text{present}}; \quad (3)
\]

where \(O_{\text{target data}}\) is the target data which can be the experimental results or measured data, \(O_{\text{initial KDPs}}\) is the numerical results by initial KDPs, and \(O_{\text{weighted KDPs}}\) is the numerical results by weighted KDPs. In the SADA method, the Gaussian random normal distribution can be used to randomly weight KDPs within their reasonable variation. It can also use the deep neural network to output the corresponding action according to the input state (to change the value of KDPs, for example, if the output is 0.1, then 0.1 multiplying the relevant coefficient will be added to the original value), that is, to weight the KDPs.

The percentage difference \(P_{\text{difference}}\) is used to measure whether the results of SADA is better than the initial KDPs. If \(P_{\text{difference}}\) is positive, it means that the difference between target data and numerical results has been decreased by SADA, otherwise the difference has been increased. In short, evaluation of \(P_{\text{difference}}\) is to establish a reward mechanism to tell DARwind how much benefit has been obtained in this iteration.

In addition to the \(P_{\text{difference}}\) evaluation in feature engineering and reward engineering, target data are not the only criterion. One of the challenges of setting reward engineering in SADA is that the DARwind needs to learn, approach in actions, and finally, achieve the goal that the designer hopes. If the designer’s goal is easy to distinguish, this task may be solved well, such as finding the minimum \(P_{\text{difference}}\) of a
physical quantity or balancing the $P_{\text{difference}}$ among multiple physical quantities. Nevertheless, in some problems, the designer’s goal is challenging to quantify, and it is not easy to be translated into a loss function, especially when these problems require the agent to make very skillful actions to complete complex tasks or a series of tasks.

In practice, a reasonable result signal can make the agent learn successfully and efficiently and can effectively feedback and guide the agent to learn during the process of interacting with the environment. For SADA, reward engineering is not unique. For example, when the surge and pitch are used as the target physical quantities, the reward project is based on $P_{\text{difference}}$ of these two physical quantities. The change in $P_{\text{difference}}$ reflects the feedback on the quality of the action. In addition to the profit target of $P_{\text{difference}}$, the $P_{\text{difference}}$ continuity of each iteration will also be randomly selected in the reward engineering.

2.4 Basin experiment and data collection

This section will introduce the basin experiment (target data) and the data collection in SADA.

The target data are provided by one basin experiment of FOWTs in this paper. The basin model test was carried out at Deepwater Offshore Basin in Shanghai Jiao Tong University with a model set-up corresponding to a 1:50 Froude scaling. Fig. 4 shows the experimental model and sensors of the 5MW Spar-type floater. More details on the test executions, such as the model blades fabrication, wind field tests, restoring tests of the mooring system can be found in Duan et al. (2016).

The data selected from one testing case are shown in Table 2, where wind speed ($V_w$), current speed ($V_c$), and wave parameters including significant wave height ($H_s$), wave period ($T_p$) and peak factor ($\gamma$) are given.

2.5 DPs selection and BC setting

This section introduces the selection of KDPs and their boundary condition setting. A good boundary condition can speed up the convergence of SADA as the KDPs are adjustable. In addition, it reflects the rationality of the dynamic response of FOWTs accurately. Therefore, the corresponding boundary condition would be set according to different KDPs in this paper.

The case study will be conducted to KDPs analysis based on SADA method. In this paper, 21 KDPs were selected, which can be found in Table 3. These 21 KDPs are representative of the various disciplines involved in FOWTs. There are more KDPs, but the purpose of this paper is to use SADA to explore the feasibility of KDPs analysis, so only these representative KDPs are selected.

### Table 3 Selected KDPs

| No. | Discipline | KDPs                | Symbol                  |
|-----|------------|---------------------|-------------------------|
| 1   | Wind       | $V_w$               |                         |
| 2   | Aero       | $\alpha_c$          |                         |
| 3   | Tower drag | $C_{\text{p,\text{Tower}}}$ |                   |
| 4   | Current    | $V_c$               |                         |
| 5   | Significant wave height | $H_s$               |                         |
| 6   | Peak period| $T_p$               |                         |
| 7   | Shape factor| $\gamma$         |                         |
| 8–13| Hydro      | Added linear viscous damping matrix | $C_{\text{d}}^\text{Hydro}$ |
| 14–19|           | Added linear restoring matrix | $C_{\text{s}}^\text{Hydro}$ |
| 20  | Added static force (3, 3) | $F_{\text{static}(3,3)}$ |                         |
| 21  | Platform drag | $C_{\text{w,\text{Platform}}}$ |                   |

The flowchart of KDPs selection is shown in Fig. 5. The specific decision process is as follows:

Step 1: Choose the corresponding KDPs from three categories.

Step 2: Use the concept of significant figures to set the boundary conditions according to the specific values of each KDP.

Step 3: Determine the percentage difference between the numerical results and the target data.

Step 4: Adjust the boundary conditions appropriately.

![Fig. 4. Experimental model and sensors.](image)

To better understand the changes of each KDPs and their impact on the dynamic response of the whole FOWTs system, specific boundary conditions (BCs) have been set for 21 KDPs. Table 4 shows the categories of three sets of boundary conditions, where A, B and C refer to environmental KDPs, disciplinary KDPs, and specific KDPs, respectively.

![Fig. 5. Flowchart of KDPs selection.](image)
The setting of BC1 is based on the study of environmental KDPs (wind, current, and wave). Allow the environmental KDPs to vary within a small range. The other two groups of KDPs remain unchanged. In BC2, the coupled changes of environmental KDPs and disciplinary KDPs are considered.

The database established by SADA can statistically analyze the changes of KDPs and the dynamic response of related FOWTs. Correlation analysis was used to explore the influence of KDPs on the entire FOWTs system in the coupled state, which was fed back to the selection and theoretical revision of KDPs in the first stage. Take the Spearman correlation coefficient as an example (McHugh, 2018; Xiao, 2021), for a sample with a sample size of \( n \), raw data are converted into rank data, and the correlation coefficient \( r \) is:

\[
    r = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}}. \tag{4}
\]

3 Results and discussion

In this section, the results optimized for dynamic performance prediction of FOWTs by SADA will be discussed. In addition, the analysis of KDPs will also be shown from the training process and correlation analysis.

3.1 Dynamic performance prediction

This part will show the results of dynamic performance prediction by SADA in terms of surge and pitch motion, fairlead tension, and thrust force of wind turbine.

Through SADA, the percentage difference of each physical quantity can be effectively reduced. Fig. 6 shows the variation of percentage difference in terms of 4 physical quantities. The four physical quantities are the surge and pitch motion of the FOWTs platform, the fairlead tension of the first mooring line (F1), and the axial thrust of the rotor (Thrust).

In Fig. 6, both BCs effectively improve the prediction accuracy of the four physical quantities. The optimization result of BC1 is mainly due to the change of environmental KDPs. BC2 allows for a smaller range of variation in disciplinary KDPs. Therefore, some hydrodynamic coefficients of the platform itself are optimized, such as added viscous damping matrix coefficients and added linear restoring force matrix coefficients. This also explains why the prediction of the tension of the first fairlead is more accurate.

Fig. 7 shows the corresponding amplitude changes of these four physical quantities. The amplitude changes of the surge and pitch of the platform motion after optimization can be found more intuitively. In addition, the change of wind turbine axial thrust amplitude is similar in BC1 and BC2, both reaching 18 kN. The tension of the first fairlead changes significantly.

3.2 KDPs analysis

This section will carry out correlation analysis on the relationship between the weighted KDPs and the dynamic response of FOWTs system during the loop of SADA optimization.
The correlation coefficient is Spearman, and the confidence interval is 95. By taking BC1 as an example, the correlation analysis results are shown in Table 5 (*: the correlation is significant at 0.05). A unitless measure (correlation coefficient \( r \)) is used to describe the correlation in the table. The value of \( r \) is in the range of \([-1, 1]\). The closer \( r \) is to 0, the weaker the linear relationship will be. Larger than 0 is a positive correlation; smaller than 0 is a negative correlation. The \( p \)-value is for statistical significance. When the \( p \)-value is small, the null hypothesis will be rejected, and its threshold is usually set to \( p=0.05 \). If \( p<0.05 \), the correlation coefficient is not zero.

Table 5  Spearman correlation of KDPs in BC1

|       | \( V_w \) | \( V_c \) | \( H_s \) | \( T_p \) | \( \gamma \) |
|-------|-----------|-----------|-----------|-----------|-----------|
| Surge | \( r \)   | \(-0.17^*\) | \(-0.37^*\) | \(-0.01\) | \(-0.06\) | \(0.13^*\) |
|       | \( p \)   | 0.00      | 0.00      | 0.89      | 0.20      | 0.00      |
| Pitch | \( r \)   | \(-0.91^*\) | \(-0.41^*\) | 0.03      | \(-0.06\) | 0.05      |
|       | \( p \)   | 0.00      | 0.00      | 0.49      | 0.19      | 0.26      |
| Fline1| \( r \)   | 0.22**    | 0.98*     | \(-0.04\) | 0.20**    | \(-0.00\) |
|       | \( p \)   | 0.00      | 0.00      | 0.32      | 0.00      | 0.96      |
| Thrust| \( r \)   | \(-0.95^*\) | 0.21*     | 0.00      | 0.07      | 0.03      |
|       | \( p \)   | 0.00      | 0.00      | 0.95      | 0.08      | 0.46      |

It uses a two-tailed significance test, and * in the table indicates that the correlation is significant at the 0.05 level. It is not difficult to see that \( V_w \) and \( V_c \) have a strong correlation with the four physical quantities. In this case, the percentage difference is mainly caused by these two KDPs. Among the three parameters related to waves, only surge and fairlead tension are related to \( T_p \) and \( \gamma \) respectively. This shows that the percentage differences of the four physical quantities have no relation with the wave parameters during SADA optimization. This also shows that the wave in the numerical model is more accurate, which is closer than that of the basin experiment. Therefore, following the experimental settings when simulating waves, even a small range of fluctuations will not significantly impact the overall dynamic response of the FOWTs system.

Figs. 9 and 10 show the scatter distribution diagrams of pitch and wind speed, fairlead tension, and current. The black dots in the figure are data points. The red line is its linear fit curve. The percentage difference of pitch has a robust negative correlation with wind speed, and its \( r \) is \(-0.98\). Correspondingly, \( r \) of fairlead tension and the current speed is 0.98. Furthermore, \( F1 \) has a strong positive correlation with current speed.

The percentage difference of pitch has a strong negative correlation with wind speed \((r = -0.91)\) and current velocity \((r = -0.41)\). A bubble chart is a multivariate chart that is a variation of a scatter chart. That is, three values are used to determine each data series. Data in two dimensions are mapped in a Cartesian coordinate system, replaced by \( x \) and \( y \), respectively. However, unlike scatter plots, bubble charts have categorical information for each bubble. Its area represents the value of the third data. For example, in Fig. 11, \( x \) and \( y \) represent wind speed and current speed, respectively. The bubbles are the difference changes of the normalized pitch motion. The size of its area and the corresponding color represent the difference between the pitch and the target data. The larger the area, the larger the difference. The darker the color, the smaller the difference. It is not difficult to see from Fig. 11 that the decreasing trend of bubbles along the \( x \)-axis is more significant. This also echoes the \(-0.91 \) correlation between \( V_w \) and percentage difference of pitch in Table 5.

In BC2, not only the environmental KDPs are considered, but also some disciplinary KDPs and specific KDPs are often cared about by designers, such as the added restoring force matrix coefficient and the added first-order
The first-order linear added damping $C_{ld(1,1)}^H$ significantly affects platform motion and fairlead tension, especially the correlation between percentage difference of heave, fairlead tension and $C_{ld(1,1)}^H$ reached −0.37 and −0.39, respectively. However, compared with the environmental KDPs, other KDPs have a limited impact due to their minor boundary conditions. Unlike BC1, the three-wave parameters have a more significant impact on the percentage differences of the five physical quantities.

In the case of KDPs coupling except for the environment, the relationship between thrust and wind speed is consistent with BC1. Fig. 12 shows the linear fitting results of wind speed and thrust.

The percentage difference of Heave is more sensitive, and the current speed also occupies the leading role and reaches 0.88. Fig. 13 shows the bubble map among $C_{ld(1,1)}^H$, $V_c$ and percentage difference of heave. Obviously, with a smaller current speed and a larger platform viscous damping, the percentage difference of Heave percentage difference is smaller.

When considering both $T_p$ and $C_{ld(1,1)}^H$, the side effects of damping have a more significant impact on the tension of the fairlead. It can be seen in Fig. 14 that when the current is determined, greater damping will reduce the percentage difference of the fairlead tension.

In general, the study of KDPs is very challenging due to the nonlinear coupling characteristics of the FOWTs system. For the analysis of BC1, designers can initially understand the relationship between environmental KDP and the percentage difference of dynamic response. By ignoring the simplification of the numerical model and the limitations of the theoretical analysis method, the environmental KDPs can be modified to a certain extent to meet the more realistic essential experimental environment. The correlation analysis is primarily used to determine the percentage difference of the fairlead tension.

### Table 6 Spearman correlation of KDPs in BC2 (**: the correlation is significant at 0.05)**

|        | Surge | Heave | Pitch | Finel | Thrust |
|--------|-------|-------|-------|-------|--------|
| $V_e$  | $r$   | 0.17* | 0.47* | −0.91*| 0.18*  | −0.95* |
| $p$    | 0.00  | 0.00  | 0.00  | 0.00  | 0.00   | 0.00   |
| $V_c$  | $r$   | −0.25*| 0.88* | −0.30*| 0.98*  | 0.09   |
| $p$    | 0.00  | 0.00  | 0.00  | 0.00  | 0.00   | 0.04   |
| $H_s$  | $r$   | −0.07 | 0.21* | −0.07 | 0.24*  | 0.06   |
| $p$    | 0.12  | 0.00  | 0.14  | 0.00  | 0.19   |
| $T_p$  | $r$   | −0.13*| 0.22* | −0.11*| 0.25*  | 0.00   |
| $p$    | 0.00  | 0.00  | 0.01  | 0.00  | 0.07   |

The first-order linear added damping $C_{ld(1,1)}^H$ significantly affects platform motion and fairlead tension, especially the correlation between percentage difference of heave, fairlead tension and $C_{ld(1,1)}^H$ reached −0.37 and −0.39, respectively.
relationship between the experimental values or measured values. If take the current speed as an example, it may not directly derive the specific, accurate distribution under the basin environment. However, it can be seen from the SADA iteration process that the percentage difference of dynamic response in the numerical calculation is more affected by the current than that by wave parameters. The metric to measure the size of this difference can be seen as a judgment on the importance of its correlation with the variation of the percentage difference of each physical quantity. It is supposed that the slight change of current has a significant correlation with the percentage difference change of other physical quantities. In that case, there is a particular gap between the experimental value of the basin, the numerical calculation model, and the actual design condition value.

The analysis of BC2 is more complicated because it also considers other types of KDPs. In the past, the designers could only modify these parameters based on the dynamic performance of FOWTs in the basin experimental environment to carry out static water attenuation as a reference. The SADA method provided in this article can optimize this type of KDP to a certain extent. On the one hand, the modification is based on previous basin experiment techniques. On the other hand, the optimization results consider the specific basin environment, and the coupling results between different KDPs, especially the sea environments, are not limited to static water. Therefore, based on the correlation of such KDPs, designers can further understand the factors that have a more significant impact on the FOWTs system in a specific environment. Some more exciting phenomena were also discovered, such as the correlation between the added linear viscous damping with the heave. However, the current work does not provide the correlation between KDPs quantitively.

4 Conclusions

This paper aims to conduct a deeper analysis of KDPs by the SADA method. First, a brief introduction to the concept of KDPs and KDPs involved in the field of FOWTs is given. Based on 21 KDPs, different boundary conditions are set up for them. The optimization of dynamic performance prediction of FOWTs is conducted. Finally, the correlation analysis of different KDPs during the SADA loop is performed. The results can be summarized as follows.

1. Using SADA to intelligently adjust 21 KDPs can effectively predict significant physical quantities with higher accuracy.

2. Through the analyses of the environmental KDPs, the sea environment of FOWTs in numerical simulation can be corrected and provide a set of more reliable analyses and experimental environment basis.

3. Through the analysis of different categories of KDPs, the accuracy can be further improved based on the original values and provide a reference for the coupling analysis of FOWTs.

The SADA method uses the advantages of reinforcement learning framework and software in the loop to accumulate design experience and builds a numerical simulation optimization framework from dynamic response prediction and system characteristics. The action-value network in the reinforcement learning algorithm is used for iterative loop training, and a key parameter database integrating [response-design parameters-reward and punishment] is established. In this way, data mining can be carried out in-depth and can better meet the requirements of designers. Finally, combined with experiments, a unique design evaluation method can be developed for the design of proprietary FOWTs, and statistical models such as correlation analysis and principal component analysis can be used to further analyze some uncertain phenomena to provide reliable theory support. In summary, more studies are in progress and uncertainties in various disciplines will be explored in the future.

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References

Amaral, G.A., Mello, P.C., Do Carmo, L.H.S., Alberto, I.F., Malta, E. B., Simos, A.N., Franzini, G.R., Suzuki, H. and Gonçalves, R.T., 2021. Seakeeping tests of a FOWT in wind and waves: an analysis of dynamic coupling effects and their impact on the predictions of pitch motion response, Journal of Marine Science and Engineering, 9(2), 179.

Chen, J.H., Hu, Z.Q., Liu, G.L. and Wan, D.C., 2019. Coupled aerohydro-servo-elastic methods for floating wind turbines, Renewable Energy, 130, 139–153.

Chen, P., Chen, J.H. and Hu, Z.Q., 2021a. Software-in-the-loop combined reinforcement learning method for dynamic response analysis of FOWTs, Frontiers in Marine Science, 7, 628225.

Chen, P., Jia, C.J., Ng, C. and Hu, Z.Q., 2021b. Application of SADA method on full-scale measurement data for dynamic responses prediction of Hywind floating wind turbines, Ocean Engineering, 239, 109814.

Chen, P., Song, L., Chen, J. H. and Hu, Z.Q., 2021c. Simulation annealing diagnosis algorithm method for optimized forecast of the dynamic response of floating offshore wind turbines, Journal of
Hydrodynamics, 33(2), 216–225.
Duan, F., Hu, Z.Q. and Niedzwecki, J.M., 2016. Model test investigation of a spar floating wind turbine, Marine Structures, 49, 76–96.
Garnier, P., Viquerat, J., Rabaut, J., Larcher, A., Kuhnle, A. and Hachem, E., 2021. A review on deep reinforcement learning for fluid mechanics, Computers & Fluids, 225, 104973.
Guanche, R., Vidal, C., Piedra, A. and Losada, I., 2011. IDERMAR METEO. Offshore wind assessment at high and very high water depths, OCEANS 2011 IEEE-Spain, IEEE, Santander.
IEAWind, 2021. Offshore Code Comparison Collaboration, Continuation with Correlation and Uncertainty. https://iea-wind.org/task30/.
Khan, N.M., Khan, G.M. and Matthews, P., 2020. AI based real-time signal reconstruction for wind farm with SCADA sensor failure, 16th IFIP International Conference on Artificial Intelligence Applications and Innovations, Springer, Neos Marmaras.
Li, H., Diaz, H. and Soares, C.G., 2021. A failure analysis of floating offshore wind turbines using AHP-FMEA methodology, Ocean Engineering, 234, 109261.
Lugsdin, A., 2012. Real-time monitoring of FPSO mooring lines, risers, Sea Technology, 53(7), 21–24.
McHugh, M.L., 2018. Spearman correlation coefficient, in: The SAGE Encyclopedia of Educational Research, Measurement, and Evaluation, Frey, B. B. (ed.), SAGE Publications, Inc., Thousand Oaks, pp. 1554–1558.
Mishneavsky, L., Hasager, C.B., Bak, C., Tilg, A.M., Bech, J.I., Rad, S.D. and Faeter, S., 2021. Leading edge erosion of wind turbine blades: Understanding, prevention and protection, Renewable Energy, 169, 953–969.
Rodrier, D., Cermelli, C., Aubault, A. and Weinstein, A., 2010. Wind-Float: A floating foundation for offshore wind turbines, Journal of Renewable and Sustainable Energy, 2(3), 033104.
Stetco, A., Dinmohammadi, F., Zhao, X.Y., Robu, V., Flynn, D., Barnes, M., Keane, J. and Nenadic, G., 2019. Machine learning methods for wind turbine condition monitoring: A review, Renewable Energy, 133, 620–635.
Viquerat, J., Meliga, P. and Hachem, E., 2021. A review on deep reinforcement learning for fluid mechanics: an update, arXiv preprint arXiv: 2107.12206.
Wan, L., Gao, Z., Moan, T. and Lugni, C., 2016. Experimental and numerical comparisons of hydrodynamic responses for a combined wind and wave energy converter concept under operational conditions, Renewable Energy, 93, 87–100.
Wu, X.N., Hu, Y., Li, Y., Yang, J., Duan, L., Wang, T.G., Adcock, T., Jiang, Z.Y., Gao, Z., Lin, Z.L., Borthwick, A. and Liao, S.J., 2019. Foundations of offshore wind turbines: A review, Renewable and Sustainable Energy Reviews, 104, 379–393.
Xiao, X., 2021. Introduction to Spearman Correlation Coefficient and Its Calculation Example. https://aiatechtogether.com/article/927.html.
Xie, Y.L., Zhao, X.Z. and Luo, M., 2022. An active-controlled heaving plate breakwater trained by an intelligent framework based on deep reinforcement learning, Ocean Engineering, 244, 110357.
Yang, R.Y., Chuang, T.C., Zhao, C.Y. and Johanning, L., 2022. Dynamic response of an offshore floating wind turbine at accidental limit states—mooring failure event, Applied Sciences, 12(3), 1525.
Zhang, Y.C. and Hu, Z.Q., 2022. An aero-hydro coupled method for investigating ship collision against a floating offshore wind turbine, Marine Structures, 83, 103177.
Zhang, Y.C., Hu, Z.Q., Ng, C., Jia, C.J. and Jiang, Z., 2021. Dynamic responses analysis of a 5 MW spar-type floating wind turbine under accidental ship-impact scenario, Marine Structures, 75, 102885.