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SOFTWARE-IN-THE-LOOP COMBINED MACHINE LEARNING METHOD FOR DYNAMIC RESPONSE ANALYSIS OF FOWTS

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Abstract. Wind industry is facing many challenges on how to analyze and predict the dynamic responses of floating offshore wind turbines (FOWTs). Artificial intelligence (AI) brings a new solution to overcome these challenges. A new AI technology-based method, named SADA, was proposed for the analysis of dynamic responses of FOWTs. This paper aims to introduce the methodology of SADA in detail and give a briefly demonstration of the optimization and analysis results. Firstly, SADA is introduced with the selection of the Key Disciplinary Parameters (KDPs). The AI module in SADA was built by incorporating the machine learning algorithms into a coupled aero-hydro-servo-elastic in-house program *DARwind*, with the data transmission interface of the KDPs. Secondly, SADA weights KDPs by AI algorithms' actor network and changes their values according to the training feedback of dynamic responses of Hywind Spar-type FOWT platform through comparing the *DARwind* simulation results and those of experimental data or measured data. Many other dynamic responses that cannot be measured in basin experiment or measurement could be predicted in higher accuracy with this intelligent *DARwind*. Finally, the result was shown that the platform's motions and other physical quantities can be predicted by SADA with higher accuracy. Through the analysis of the correlation between KDPs and physical quantities during the training process, a quantitative and qualitative discussion can be made on the influence of KDPs on the dynamic response of the FOWTs system. The SADA method takes advantage of AI-numerical-experimental-measured method and will be able to bring a promising solution for wind industry, to overcome the handicaps impeding accurate analysis for dynamic responses of FOWTs during design stage.

1 INTRODUCTION

As a clean and renewable energy source, wind energy is receiving more and more attention all over the world, with the improvement of wind power equipment related technologies in recent years. Wind turbines are currently one of the most popular ways to harvest the wind energy, which are divided into land-based wind turbines, offshore wind turbines and floating offshore wind turbines (FOWTs). The research and attention on FOWTs both from the academic field and the industrial field have been greatly expanded in recent years. FOWTs possess complicated dynamic responses characters and therefore require diverse analysis methods. Stewart and Muskulus [1] compared several experiments with different technology of blade simulation or aerodynamic loads. Chen et al. [2] summarized the challenges of experiments technique for FOWTs dynamic responses analysis, including mass control and blade pitch control. Early researches of the comparison of measured data and simulated responses of Hywind demonstration project can be found by Hanson et al. [3]. More verification of Hywind prototype can be found in literatures [4, 5]. Whether it is from the reliability and low cost of research and development, the efficiency of wind farm operation, or the safety of maintenance and collision [6], the FOWTs have to bear more loads that are more complicated from those in traditional fixed bottom wind turbines. The dynamic responses prediction of FOWTs involves multiple disciplines, which is a strongly nonlinear coupled physical model. It will show responses to the coupling effects, thus indicating that caution must be taken when simplifying the theories for analysis of FOWTs [7].

As for theoretical analysis method, there are many challenges in FOWTs design involving multiple disciplines. Many theories involved in the physical model include massive functions and formulas which are determined based on assumptions and empirical parameter values. In addition, some assumptions and empirical parameters are not specifically designed for FOWTs but inherited from land-based wind turbines and traditional floating offshore units. For example, some key environmental parameters such as wave parameters and viscous damping in hydrodynamics and mooring line restoring force etc. are also difficult to be issued unique values during the analysis [8]. Here, all these key parameters involving multiple disciplines are named as Key Disciplinary Parameters (KDPs). These KDPs make it a challenging task to predict dynamic responses of FOWTs using theoretical numerical analysis tools.

With the development of AI technology, the data-driven technique is gradually being recognized by researchers. Recently, machine learning techniques have been used to model the offshore applications. For example, the SVM regression model [9] was developed for the real-time short-term forecast of wave elevations and wave excitation forces for wave power generation device or floating wind turbine. However, for wind power generation devices, most of the applications are based on land-based wind turbines. There are many studies of using artificial neural networks to obtain the power curves of the wind turbine can be found in [10-12]. Some scholars have reviewed the machine learning application in wind industry in condition monitoring [13] and power forecasting [14]. Although the AI technology has greatly promoted the development of the traditional wind power industry and offshore engineering, its applications in floating wind in industry are very few. For the research on individual FOWTs combined AI technology, which are rely on model test verification and focus on the control system. For example, using supervised learning algorithm can directly predict the motion of the FOWTs platform [15].

Therefore, on purpose of proposing an efficient and functional method, an innovative hybrid AI-based method named SADA has been introduced [8]. This paper aims to introduce the methodology of SADA in more detail and give a briefly demonstration of the optimization and analysis results. The main content of SADA includes the concept establishment of KDPs, the application of machine learning and the innovation of analysis technology. The methodology of SADA will be introduced in detail including the introduction and classification of KDPs concepts, an in-house programme *DARwind* and AI technology. Furthermore, it demonstrates how this AI-based *DARwind* can be combined with experimental results to help designers to obtain more accurate forecasts of dynamic responses of FOWTs system for many critical design factors under a wide range of different sea state.

2 SADA METHODOLOGY

This section mainly introduces the methodology of SADA in detail. Specifically, it includes the concept of KDPs, an in-house programme *DARwind* and reinforcement learning applications. In addition, feature and reward engineering of SADA will also be briefly introduced in the application of reinforcement learning algorithms. Finally, the AI-numerical-experimental-innovative analysis of KDPs will be introduced as the key link in the post-processing of the SADA.

2.1 SADA concept

Introduction of the concept of the SADA method is made in this section. The SADA method is inspired by the wide application of AI technology. It can use AI technology to assist traditional theoretical calculations to further explore the very complex nonlinear coupled dynamic response in FOWTs by experimental results or measured data. Based on the framework of reinforcement learning, it does not require data with very strong labels. As the agent in numerical simulation, *DARwind* can not only effectively become intelligent through the deep neural networks, but also can conduct a full range of analysis and utilization of existing data. Figure 1 shows the framework flow chart of the entire SADA method.

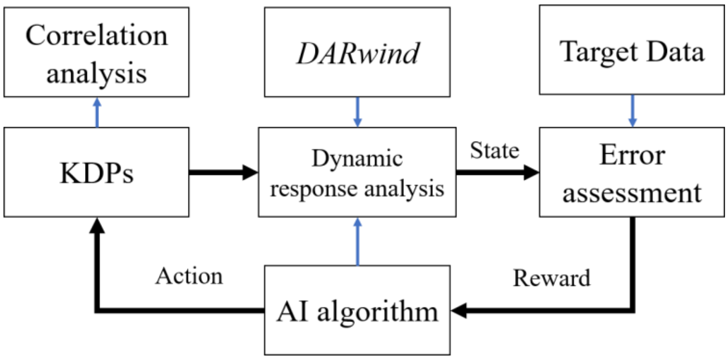

Figure 1: The overall layout of SADA.

Different from the traditional numerical calculation process, SADA makes the numerical program intelligent by weighting the KDPs and its process is shown in Figure 1. In SADA method, *DARwind* will be trained to be intelligent specially for the objective FOWT to run the dynamics response analysis with the initial critical KDPs, which is an in-house aero-hydro-servo-elastic programme. It is built for theoretically analyzing dynamic responses of FOWTs. For more information of the *DARwind* programme, please refer to the reference paper [16]. The Deep Deterministic Policy Gradient (DDPG) algorithm [17] and Gaussian random standard normal distribution is adopted in SADA to use Deep Neural Networks to estimate the optimal policy function instead of choosing the action based on a specific distribution. In general, the Venn diagram representation of the entire SADA methodology is shown in Figure 2. The specific notations and nouns combined FOWTs and Reinforcement Learning (RL) in SADA are:

- **Agent:** *DARwind*
- **State(S):** The numerical results from *DARwind*.
- **Action(A):** The act of weighting KDPs.
- **Reward(R):** The reward and punishment obtained by error assessment.

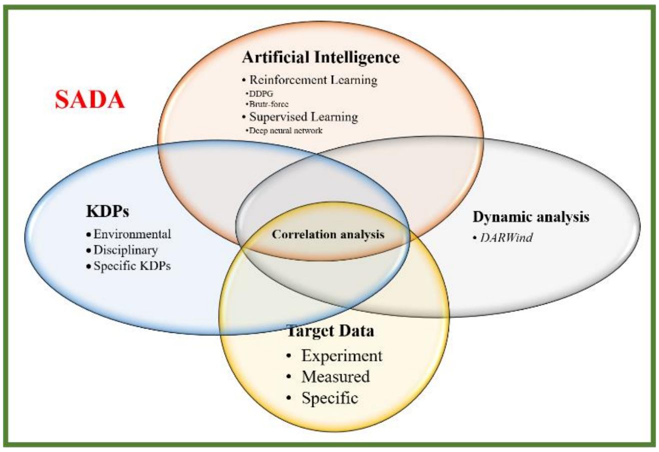

Figure 2: The Venn diagramme of SADA.

2.2 Key Disciplinary Parameters

KDPs is the first and one of the most important steps in the SADA method. So, the KDPs involved in FOWTs and their impacts will be introduced in this section. It is of great importance to select the KDPs properly, because critical KDPs will not only bring more accurate calculation results, but also be used as the data exchanging portal during the AI training process in SADA. Some KDPs involving multiple disciplines were introduced in reference [8]. Although KDPs cover a wide range of disciplines, they can be effectively classified. In general, the sources of KDPs can be divided into three categories:

- **Environmental KDPs**
- **Disciplinary KDPs**
- **Specific KDPs**

Because the scope of KDPs is very wide, some specific KDPs in the above three categories have intersection with others. Their general relationship can be shown in Figure 3. The following will briefly introduce the concepts and examples of related KDPs from these three aspects.

2.2.1 Environmental KDPs

For environmental KDPs, it mainly involves the very complex working environment of FOWTs. The wind, wave and current will be considered as the most important environmental KDPs. For wind load, wind profile is taken as an example, which can be based on analytical wind vertical distributions such as the logarithmic profiles or power law:

$$U(z)=\frac{u^*}{K}\ln\left(\frac{z}{z_0}\right) \tag{1}$$

$$U(z)=U(z_{ref})\left(\frac{z}{z_{ref}}\right)^{\alpha} \tag{2}$$

Where U is the horizontal component of the wind velocity, z is the height with respect to the ground level, u^* is the friction velocity, K is the von Karman constant, z_0 is the roughness length, α is the exponent for the power law, and the subscript ref is related to properties at a reference height. Definition of turbulence intensity can be found in [18]. The above formula has quite many empirical parameters, which have a vital influence on the power generation of wind turbines. Different changes mean that the wind turbine may need to adjust the pitch angle of the blades to maintain a constant power generation. This also means that there will be a chain reaction to the dynamic response of the entire FOWTs system, including platform motions, tower and blade deformation and fatigue, etc.

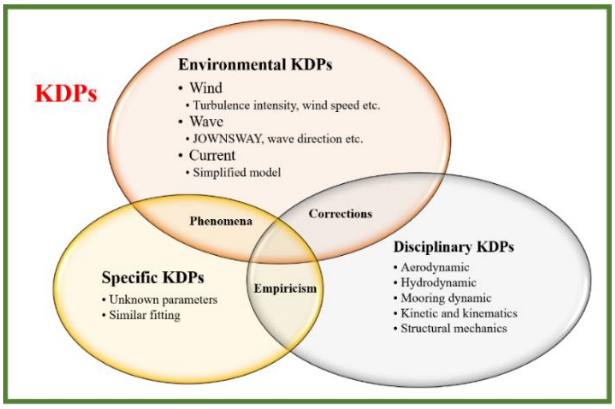

Figure 3: The Venn diagramme of KDPs.

For wave loads, designers usually use JOWNSWAP spectrum to simulate the irregular waves:

$$S(\omega)=155\frac{H_{1/3}^2}{T_1^4\omega^5}\exp\left(\frac{-944}{T_1^4\omega^4}\right)(3.3)^{\gamma}\left(\mathrm{m^2 s}\right) \tag{3}$$

$$\gamma=\exp\left[-\left(\frac{0.19\omega T_1-1}{2^{1/2}\sigma}\right)^2\right] \tag{4}$$

Where, $\sigma=0.07$, when $\omega\le 5.24/T_1$; $\sigma=0.09$, when $\omega>5.24/T_1$.

The $H_{1/3}$ is the significant wave height, which is the average of one third of the largest wave height. T_1 is the average wave period. This formula can also be replaced by other characteristic periods: $T_1=0.834T_0=1.073T_2$. T_2 is the corrected value of the average wave period T_1. T_0 is the period corresponding to the peak frequency of the same spectrum, and is also called the modal period. In the given JOWSWAP spectrum, γ can be considered as an important environmental KDPs.

The ocean current is another environmental KDPs and it can be simplified in numerical simulation. The current model varies with the depth of the power function, and the velocity at the bottom of the ocean is zero:

$$U_C(\mathrm{z}) = U_0\left(\frac{z+h}{h}\right)^c \tag{5}$$

Where, z is the vertical depth below the water surface; h is the depth of the water to the bottom; U_0 is the velocity of the water. Parameter c normally uses empirical value 1/7, but it varies for different sea states. Thus, c can be chosen as one of the environmental KDPs.

2.2.2 Disciplinary KDPs

For disciplinary KDPs, they are presented in the theoretical basis of various disciplines. They are often not only based on certain assumptions, but also depend on experimental corrections. The potential flow theory is a common method for hydrodynamic calculation, which will be used when calculating the wave induced load on a floating structure. However, the potential flow damping cannot consider the viscous effect of fluids on underwater structures. And platforms of FOWTs usually have a truss or buoy structure with a small diameter, so the calculation of viscous damping force needs to use Morison's equation correction:

$$d\boldsymbol{F}_{\boldsymbol{m}}^{\boldsymbol{V}} = -\frac{1}{2}\boldsymbol{C}_{\boldsymbol{D}}^{\boldsymbol{M}} D dz \cdot (v_w - v_s) \cdot |v_w - v_s| \tag{6}$$

$$F^V = \begin{bmatrix} \sum_{M=1}^{n} d\boldsymbol{F}_{\boldsymbol{m}}^{\boldsymbol{V}} \\ \sum_{M=1}^{n} d\boldsymbol{F}_{\boldsymbol{m}}^{\boldsymbol{V}} \cdot l_m \end{bmatrix} \tag{7}$$

Where, D is the diameter of the cylinder; v_w and v_s are the velocity component of the fluid velocity when the water mass is not disturbed and the cross-sectional slice velocity of the underwater component perpendicular to the cross-section axis; C_D^M is drag coefficient; l_m is the radius from the center point of the section to the unified coordinate system.

2.2.2 Specific KDPs

For specific KDPs, there are some experimental models or design parameters of the full-scale FOWTs that are different from the actual physical models. In addition, due to commercial confidentiality, it is impossible to obtain all the design parameters. In this case, users can only take similar physical models to replace them or design according to the maternal model. In addition, for FOWTs, there are many new physical phenomena worth exploring, and if these phenomena involve an additional force, moment or damping, they can also be considered as KDPs in specific KDPs.

2.3 AI-based *DARwind*

DARwind is an in-house aero-hydro-servo-elastic programme for the analysis and prediction of the dynamic response of FOWTs. In SADA, *DARwind* also plays the role of an agent and is combined with AI technology. Based on DDPG algorithm and Brute-force algorithm, the AI-based *DARwind* can be applied in different demands, which are:

- Suitable for analysis of a single known sea state and working condition. For example, optimize KDPs to further reduce errors in a single case.
- Suitable for analysis of known (implement in the experiment) and unknown (not implement in the experiment) sea states. For example, the optimizable working conditions are not limited to experiment.

The flow chart of AI-based method (with DDPG) is listed in Figure 4, and the main loop is the thick black solid line. In the specific process, the designers should first select the initial KDPs artificially among different classifications. On this basis, find the corresponding positions of these KDPs in dynamic response tool *DARwind*. The physical variables of the dynamic response of FOWTs calculated by *DARwind* are regarded as "state". Subsequently, the KDPs in *DARwind* are weighted by the actions output by the actor network or random distribution. For the weighted KDPs, the second dynamic response analysis and error analysis are performed again.

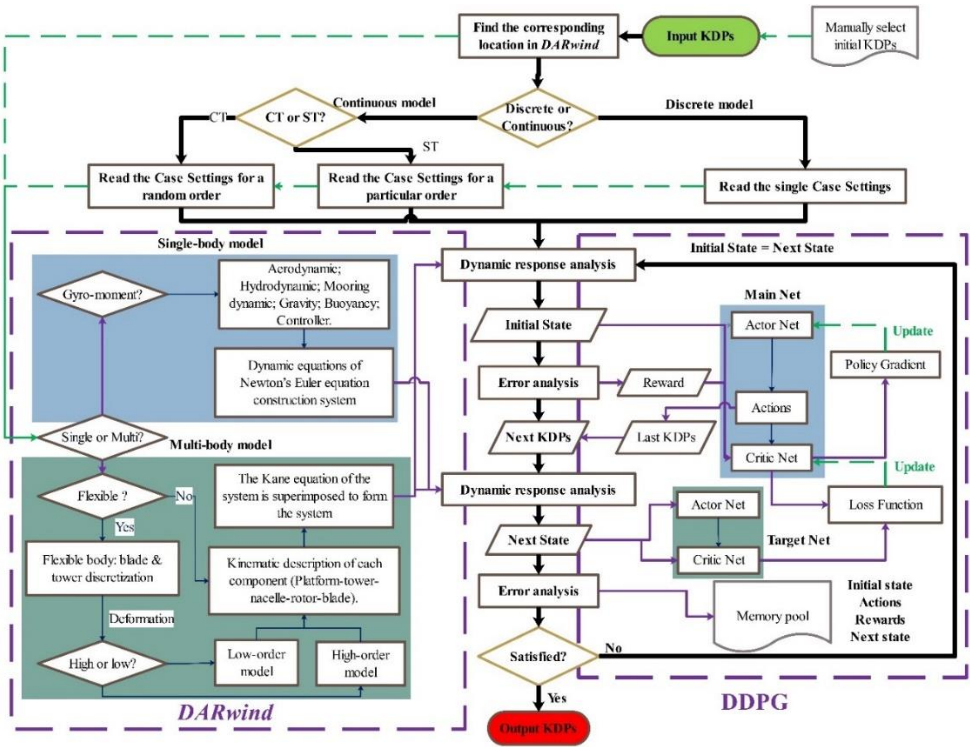

Figure 4: The flowchart of SADA.

The specific process in Figure 4 is as follows:

- Step 1. Manual selection of KDPs from disciplines.
- Step 2. Correspond each action to the KDPs and locate the position of these KDPs in *DARwind* programme.
- Step 3. Use initial KDPs to run dynamic response analysis in *DARwind* programme to obtain state.
- Step 4. KDPs in *DARwind* programme are weighted by actions by the actor network in DDPG.
- Step 5 Use weighted KDPs to run dynamic response analysis to obtain next state.
- Step 6. Use target data for error analysis and train neural networks.
- Step 7. Determine whether the error meets the requirements. If yes, output KDPs, if not, return to Step 4.
- Step 8. Use final KDPs to run dynamic response analysis in *DARwind* programme.

2.4 Reinforcement learning applications

In SADA, the framework of reinforcement learning is one of its most important cores. In this part, the application of SADA method based on reinforcement learning framework will be introduced, especially the feature engineering and reward engineering. The purpose of reinforcement learning is what action can be taken to maximize the numerical reward signal. The action here not only affects the immediate reward, but also the next state, and thus the subsequent reward. Therefore, trial and error and delayed benefits are also very significant features of reinforcement learning. As the framework of SADA, the environment is the dynamic response of the FOWTs in a specific situation. KDPs are input signals, which are provided to *DARwind* (agent) for state acquisition. There will be an error evaluation to judge the current dynamic response of FOWTs. This judgment can be a comparison of code-to-experiment, code-to-measurement, or code-to-code. A good error definition can more accurately analyze the characteristics of KDPs and it makes the optimization of SADA more efficient. For now, only the mean value is considered as the target value for each platform DOF motion. The variation of error ($Error_{\text{variation}}$) is defined as:

$$E_{\text{inital}} = \left| \frac{O_{\text{model test}} - O_{\text{inital KDPs}}}{O_{\text{model test}}} \right| \times 100\% \tag{8}$$

$$E_{\text{present}} = \left| \frac{O_{\text{model test}} - O_{\text{weighted KDPs}}}{O_{\text{model test}}} \right| \times 100\% \tag{9}$$

$$Error_{\text{variation}} = E_{\text{inital}} - E_{\text{present}} \tag{10}$$

The $O_{\text{model test}}$ is the output experimental physical quantity. The $O_{\text{initial KDPs}}$ is the numerical results by initial KDPs by *DARwind*. $O_{\text{weighted KDPs}}$ is the AI training results by weighted KDPs by *DARwind*. The $Error_{\text{variation}}$ is used to measure whether the results of SADA is better than the initial KDPs. If the $Error_{\text{variation}}$ is positive, it means that the error between experiment and numerical simulation has decreased by SADA, otherwise the error has increased.

In short, error analysis is to establish a reward mechanism to tell *DARwind* how much benefit has been obtained in this iteration. By adjusting KDPs according to the environmental feedback, this weighting process is considered as an action in reinforcement learning. Taking the code-to-experiment as an example, one case can be iterated multiple times to obtain enough memory: [State, Action, Next State, Reward]. As shown in Figure 5, with the establishment of a database, sufficient data support can be provided for the training of deep neural networks.

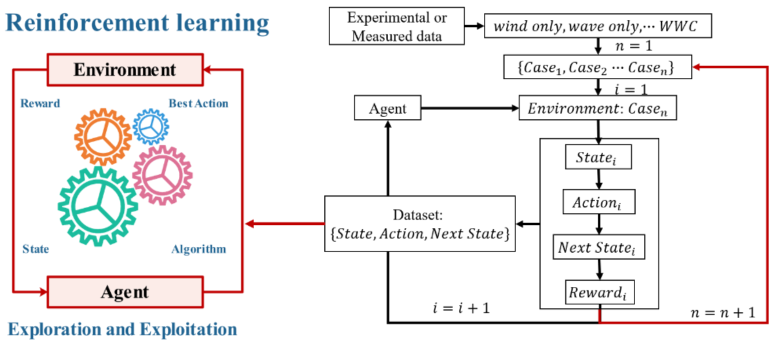

Figure 5: Data collection in SADA.

However, both experimental and actual measurement can only be obtained through sensor input. Sensors only tells partial information about the state of FOWTs. Some objects may be obscured by other physical quantities, or factors that cannot be considered in numerical analysis. In this case, a very important part of the information about the environment may not be observed intuitively. This is to consider that what the environment provides is not precise information about its state, but only observations. Therefore, in SADA, corresponding weighting parameters are designed for different target physical quantities. Take the platform motions as example, the error of some motions needs to be weighted due to the small amplitude. The specific weighting method can be shown in equation:

$$\textbf{MAPE}\left(\textit{Mean absolute percentage error}\right)=\frac{1}{m}\sum_{i=1}^{m}w_i\left|\frac{y_i-\hat{y}_i}{\hat{y}_i}\right|\times 100 \tag{11}$$

Where: m is the number of platform motions, and w_i is the weight error of each DOF motion. The y_i means the numerical results and the $\hat{y}_i$ means the experimental results.

For feature engineering and reward engineering, SADA is not only rely on detailed supervision information. The benefit signal conforms to the designer's goal to a certain extent. And these signals can more measure the progress in reaching the goal. 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, then this task may be solved well, such as finding the smallest error of a physical quantity or balancing the error among multiple physical quantities. But in some problems, the designer's goal is difficult 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 not only make the agent learn successfully and efficiently, but also can effectively feedback and guide the agent to learn during the process of interacting with the environment. For SADA, the reward engineering is not unique. For example, when the two degrees of freedom of surge and pitch are used as the target physical quantities, the reward project is based on the error of these two physical quantities. The change in the error reflects the feedback on the quality of the action. In addition to the profit target of error, the error continuity of each iteration will also be partly randomly selected in the reward engineering.

3 RESULTS AND DISCUSSIONS

In this section, some typical results are shown in term of error optimization and KDPs analysis. Specific analysis and more results can be found in the literature [8].

3.1 Error optimization

Through the optimization of SADA, the error of platform motions can be reduced, especially when applied to complex marine environments. Figure 6 shows the time history curve of surge and the gray line represents the target result. It is not difficult to see from the figure that the results after SADA optimization are more consistent with the target results, especially when the numerical model is partially simplified. The results of *DARwind* and SADA in Figure 6 are all considering the same direction of wind, waves and currents. Figure 7 shows the error change of Heave motion in the frequency domain. It can be pointed out that through the optimization of SADA, the low-frequency motion caused by the natural frequency of the system (Heave) is closer to the experimental results.

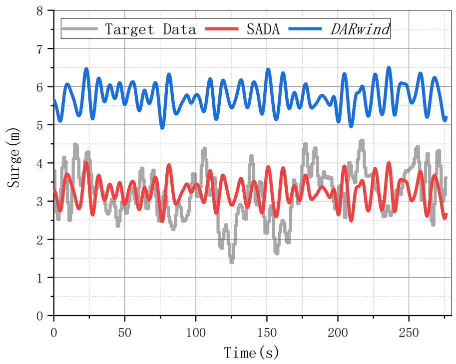

Figure 6: Time history of surge motion.

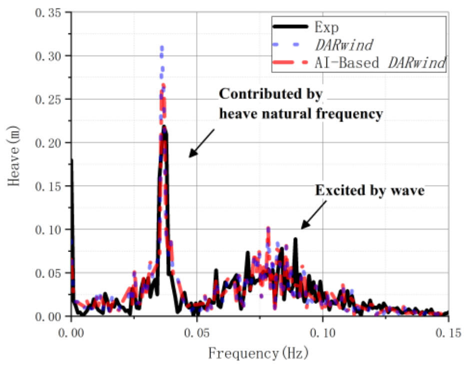

Figure 7: Frequency spectrum of heave motion.

3.2 Prediction

For some physical quantities, the prediction results of SADA can be used as reference because they are normally not available in the full-scale measurement or experiment. Therefore, it is impossible to find a method that can indirectly provide reliable data of blade tip or tower deformation. The research in this paper proved that SADA method can be a promising solution for this challenge. Take the blade tip deformation as example, Figure 8 shows the time history of the blade tip deformation by SADA and *DARwind*. Due to the large scale of FOWTs, the flexible blades are long as 60-100 meters, so the deformation of the blade tip will be very significant. The deformation of the blade in the axial direction changes greatly, which is due to the change of the normal force caused by the floater’s motion.

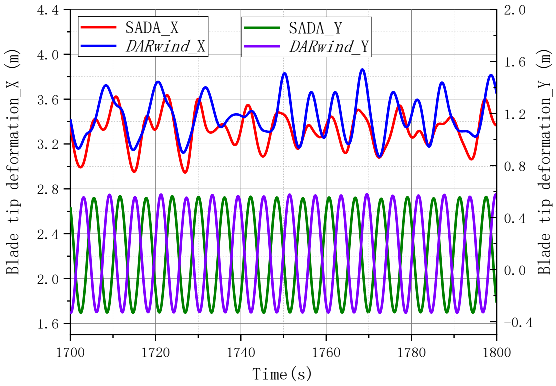

Figure 8: Time history of blade tip deformation.

3.2 KDPs analysis

SADA can use KDPs to carry out data transmission and optimize errors. Through the statistics of the changes of KDPs and the error during the training process, the correlation analysis can be used to conduct a deeper discussion of KDPs. For example, Figure 8 shows the 3D color mapping surface map between the error of the fairlead tension with current speed (V_c) and wave period (T_p). From the picture, the V_c dominates the error of the fairlead tension, while the influence of T_p is only partial, and there is no significant change in the overall trend.

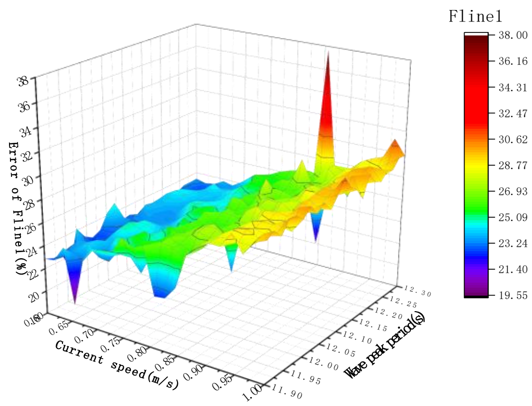

Figure 9: 3D surface map of Fline1 error, V_c and T_p.

4 CONCLUSION

There are many challenges for the dynamic responses of FOWTs in wind industry. This paper addresses a study on the methodology of an AI-based numerical-experimental technology, named SADA. SADA weights KDPs by AI algorithms' actor network and changes their values according to the training feedback of dynamic responses of FOWTs system through comparing the *DARwind* simulation results and those of experimental data or measured data. Many other dynamic responses that cannot be measured in basin experiment could be predicted in higher accuracy with this intelligent *DARwind*. Through the analysis of the KDPs, the dynamic response of FOWTs in numerical simulation can be corrected, which can also provide a reference for the verification, optimization and coupling analysis of some traditional empirical formulas or parameters as well.

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