

Software-In-the-Loop Method to Predict the Global Dynamic Responses of Full-scale Floating Wind Turbines by Artificial Neural Network

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ABSTRACT

The design of floating offshore wind turbines (FOWTs) need accurate predictions of full-scale global dynamic responses. Conventional basin experimental method can hardly be used directly to predict the full-scale global dynamic responses of FOWTs, due to the dissimilarity of aerodynamic load and hydrodynamic load. Besides, numerical simulation methods are not reliable enough at this moment due to the lack of full-scale data validation. Therefore, it is necessary to find an accurate, economic and efficient approach for FOWT design engineering practice. A new method, named as SILANN, is proposed in this study, which utilizing Software-in-the-Loop method with artificial neural network (ANN) approach for engineering prediction. Firstly, the methodology of combing ANN with in-house programme DARwind is introduced. Then, datasets and validation cases were selected from the results of basin experiment and DARwind in terms of 3DOFs (surge, heave and pitch motions). The predictions' results show a good performance. The difference between simulation results and those of experiment can be significantly reduced by this method. This proposed method takes advantage of the AI technology, which brings new solution for overcoming the handicap impeding direct using of traditional basin experimental technology in floating wind turbine design.

1 INTRODUCTION

Floating offshore wind turbine are very complex systems. The dynamics models of FOWTs, which account for the coupling between aerodynamics loads (turbine), hydrodynamics loads (floater), flexible structural components (turbine and floater), elasticity, blade-pitch controls, and restoring effect of the mooring lines, are needed to validate their technical and economic feasibility [1]. How to predict and validate a new or improved full-scale concept of FOWTs is also coming with rapid research progress of renewable energy industry, for their sophistication in design process [2]. Currently, there are three methods to validate the technical feasibility, which are on-site measurement, numerical simulation and basin model scale experiment [4]. A brief comparison of these three methods has been concluded in table 1.

Despite there are numerous sophisticated numerical tools arising [5], it is important to stress that the development of theories limits the traditional numerical methods on FOWT application to a certain extent [6]. For a completely new concept, the results of model testing are usually more convincing than those of numerical simulations. When the theoretical basis and calculation results of the numerical calculation can be satisfactorily matched with the experimental results, the former will be more efficient. Therefore, the ideal way is to combine model tests and numerical calculations [6]. However, due to the flexibility of superstructure, the basin model test technology for FOWTs has become greatly complicated and technically demanding.

Compared with the traditional floating structure model testing technology, there have been numerous key innovations. Many scholars selectively avoided the simulating aerodynamic issues by using the original disk [7-9] to replicate the required thrust force in a much easier way. Three scale relationships including prototype to model [10], Froude-scaled wind and tip speed ratio (TSR) [11], have been mentioned by Martin *et al.* [12]. Duan *et al.* [13, 14] conducted a 1/50th scale spar-type model tests by comparing the testing results

under different environmental conditions. As for cutting-edge technology, Bachynski *et al.* [15] and Sauder *et al.* [16] also offered a brief review of the real-time hybrid approaches testing which is adopted for FOWTs' experiments. However, all of these basin model test methods have their own drawbacks, such as increasing the wind speed to match the corresponding thrust force; time delay in the hardware-in-the-Loop (HIL), and neglecting of the gyroscopic moment etc. These simplification and scale problems have greatly limited the accuracy of prediction.

Table 1: Comparison of three different methods

Methods	Advantages	Disadvantages
Onsite measurement	More accuracy; The actual sea state;	Limit published data; Difficult to measurement; Expansive cost; High risk; Time consuming.
Numerical simulation	Faster; Cheaper; Convenient;	High fidelity of numerical model; Hard to simulate nonlinear phenomena;
Model scale experiment	Better controls & repeatable environmental conditions (nonlinear hydro-aero phenomena);	Scaling issues; High specific facilities and calibration methods required.

In recent years, with the development of computer technology, self-deep learning of artificial neural networks (ANN) has become an important topic of artificial intelligence (AI) research [17]. There are inaccurate data or complex attribute relationships that are difficult to quantify by traditional analysis methods [18]. ANN modelling is a nonlinear and multilayer mathematical techniques, which can define the relationships that may exist between (what the user chooses to be) the inputs and the outputs [19]. Although the research on the ANN in the field of wind turbines has been carried out for many years, it is basically applied to the fault analysis [20, 21] and power prediction of wind turbines [22, 23]. It brings an innovative and alternative way to use AI technology to improve the accuracy of numerical simulation in terms of global dynamic response of FOWTs.

After that, two different scaled experiments can be conducted and the scaling relationship of these two models may be found by using Software-in-the-Loop and ANN method (SILANN). SILANN will not only represented in the conditional mathematical form of "if and then" causal relationships in numerical simulation as expert systems did [24], but also contain an instance of rule-phenomena-based expressions of knowledge.

This paper demonstrated the numerical results show a good accuracy, which obtained by ANN optimization in predicting the 3DOFs' motion (surge, heave and pitch) of a spar-type FOWTs. The remaining sections of this paper are organized as follows: Section 2 and 3 describe the principle of DARwind and ANN. Section 4 describes how to establish ANN model for the DARwind. Section 5 shows the results of SILANN and error analysis. Sections 6 and 7 discuss some issues of SILANN and give conclusion respectively.

2 DARWIND

The numerical simulations of FOWT in the proposed SILANN method were conducted by an in-house programme, DARwind, which is an intergrade programme based on full coupled aero-hydro-servo-elastic methods [4]. The current version of DARwind is written using the programming language FORTRAN, giving full play to the computational efficiency advantages of the language in numerical simulation.

The functional modules of the DARwind program can be roughly divided into: Input module, Solver module and Output module according to the running process. First, the program reads the structural and environmental information and simulation parameters. Then, the FOWTs will be built from physical to mathematical model in the time domain solver. Finally, the calculation result can be obtained in the output module.

The solver is the core module of the entire program code, including hydrodynamic modules [6], Mooring modules (quasi-static approach [25]), aerodynamic modules (the blade element/momentum method (BEM) [26] and corrections [27]), servo modules [1], kinematics and kinetics modules (Kane's dynamical equations [28] in combination with the Cardan angles method [29], the hybrid coordinate dynamical method [30], the nonlinear deformations model and the adjacent array approach [31]).

These functional modules are coupled to each other during simulation. For example, the calculation of the dynamic performance mooring system depends not only on the properties of the mooring line itself, but also on hydrodynamic loads and platform motion. The ServoDyn uses a generator torque controller and a blade pitch controller. These control systems are subject to environment (wind speed), real-time blade vibration, and

platform motion response. The behaviour of the controller affects the load and other dynamic response characteristics of the system.

The modules of DARwind are shown in Figure 1 below, the details of the specific content please refer to [4]. More code-to-code comparisons between DARwind and other programmes can be found in the supporting literature [32].

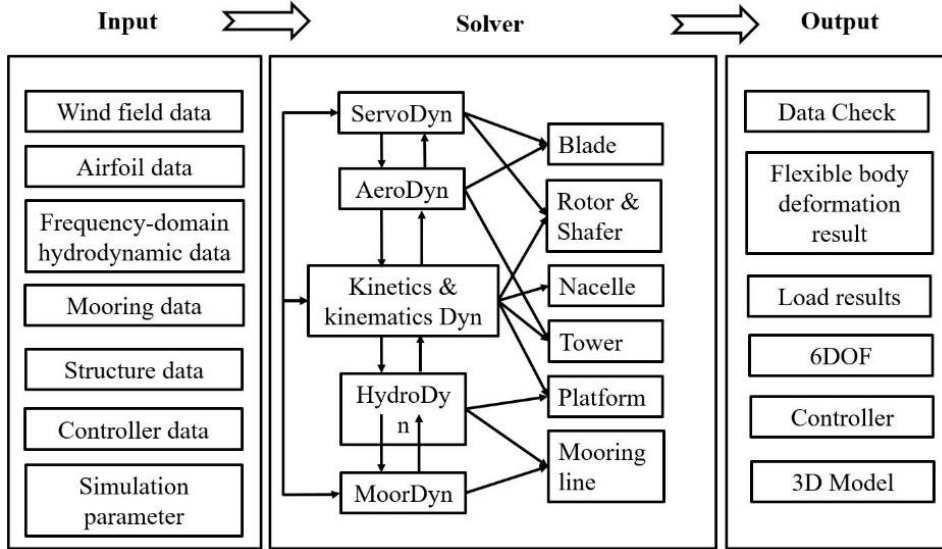


Figure 1: Structure of DARwind.

3 ANN MODELLING

3.1 Artificial Neural Network

This section aims to Briefly introduce the neural network, and the algorithms taken. It also describes the process of ANN modelling, including the experimental conditions and the choice of input data. ANN is a bionics model, which emulate a biological neural network [33]. It not only can deal with complex nonlinear problems, but also without sophisticated expertise in the field. It is an effective mining, classification and forecasting of data.

The Standard BP (back propagation) neural network is a multi-layer feedforward neural network and it is applied in this study. Its main features are signal forward transmission and error back propagation, including input layer, hidden layer and output layer [35], as shown in Figure 2. This algorithm is the core of SILANN method.

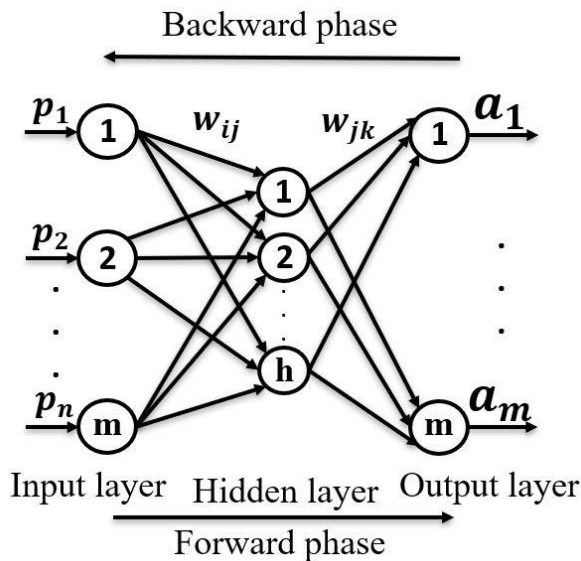


Figure 2: BP neural network topology with single hidden layer.

In the basin experiment, it is difficult to simulate the experimental conditions by existing numerical simulation, because of some simplified models. For the strong coupled dynamic response of the FOWTs, the ANN can effectively establish a multi-layer nonlinear network through the transfer function to optimize the numerical results of the experimental conditions. As for the weights and thresholds in the neural network model, it is obtained by adaptively processing the data and performing parallel processing of self-learning. Regarding the development and application of ANN, please refer to [34].

The network adjusts the weights and thresholds based on the prediction error. It also can learn and store a large number of input and output model mappings, so there is no need to pre-set the model's transfer functions and the mathematical equations. Wang provide a general procedure of BP network training [33]. A flow chart of the SILANN calculation in the code is shown in Figure 3.

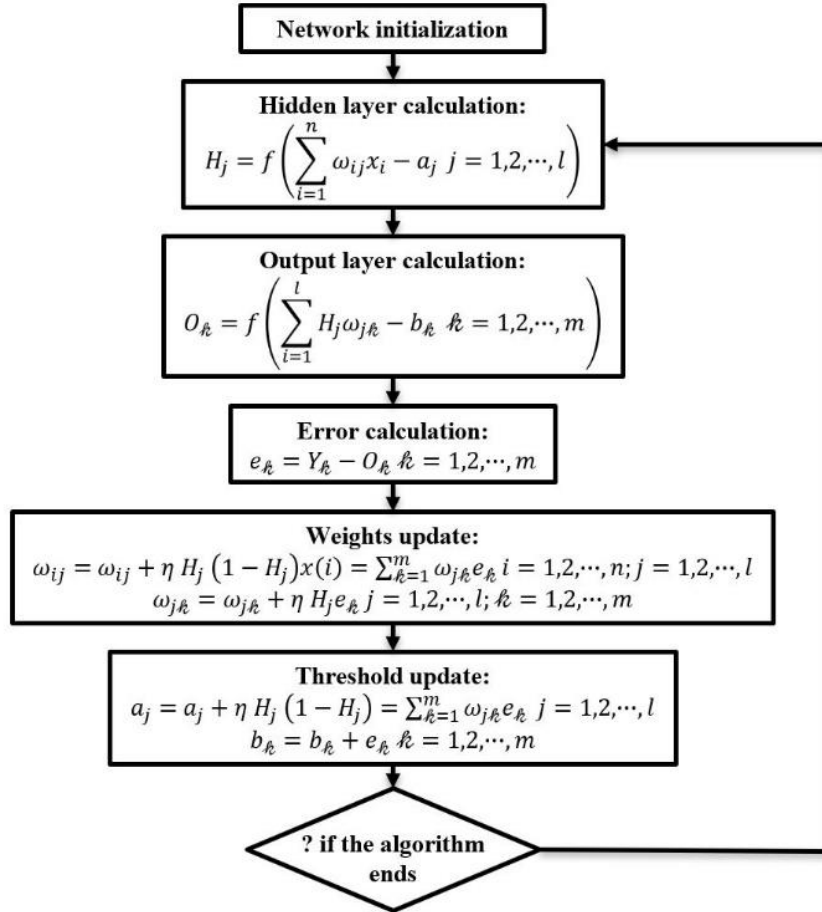


Figure 3: Flow chart of ANN calculations' steps.

3.2 Basin experiment results

The experiment was conducted at the Deepwater Offshore Basin of the Shanghai Jiao Tong University using a OC3 Hywind FOWT [11, 36], as shown in Figure 4. More details on the test executions can be found in references [13, 14].

The load cases for the following verification works are Time domain results from the experiment of OC3 Hywind model, including wind only; wind & wave; wind and wave and current, as shown in Table 2. The irregular wave cases are based on the JONSWAP wave spectrum, wherein H_s represents the significant wave height, T_p represents the spectral peak wave period, and γ represents the spectral peak parameter. The verifications mainly focus on the hydrodynamics of platform in term of 3DOF motions (Surge, Heave and Pitch).

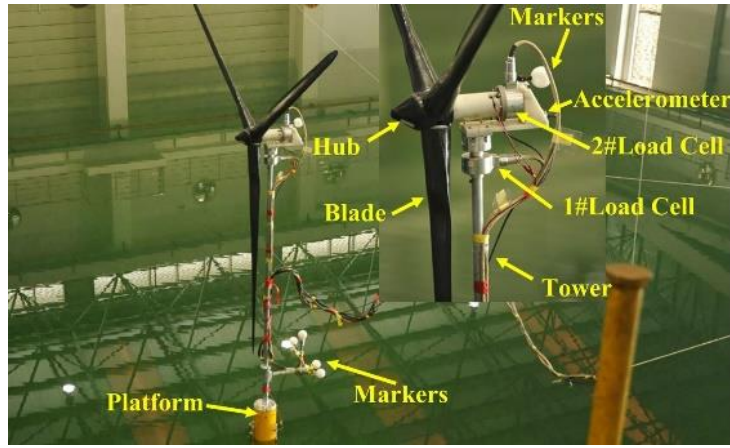


Figure 4: Experimental model and sensors.

Table 2: Test matrix.

Load Case	Wind speed (m/s)	Wave parameter			Current speed(m/s)
		H_s (m)	T_p (s)	γ	
LC1	11.4	—	—	—	—
LC2	11.4	7.1	12.1	2.2	—
LC3	11.4	7.1	12.1	2.2	0.5

3.3 BP algorithm and data selection

According to the BP neural network theory, the algorithm is implemented by MATLAB. The neural network adopts a double hidden layer structure, and the flowchart of BP algorithm as shown in Figure5. The prediction accuracy is improved compared with the single hidden layer, but the running time is increased.

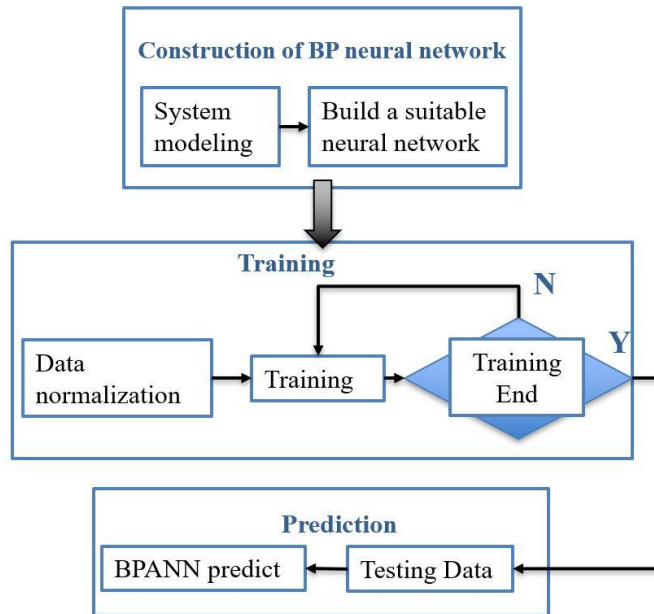


Figure 5: Algorithm flowchart of BP.

The data is the time-domain results of 3DOF motions of platform (surge, heave and pitch), which come from LC2 & LC3 with total sets of 10221 & 10121 data, respectively. The results from DARwind and experiment will be utilized as the primary data. The specific classification can be found in the Table 3. The Table 4 is a supplementary explanation of Table 3, which shows the main components of input and output data.

Table 3: ANN data selection.

Load Case	Total Sets	Training input data (DAR)	Training Output data (EXP)	Test input data (DAR)	Test output data (EXP)
LC2	10221	1-9721	1-9721	9721-10221	9721-10221
	3618s	3441s	3441s	177s	177s
LC3	10121	1-9621	1-9621	9621-10121	9621-10121
	3583s	3406s	3406s	177s	177s

Table 4: ANN data.

Load Case	Input data	Output data
LC2	Surge, Sway, Heave, Roll, Pitch, Yaw	Surge, Heave, Pitch
LC3	Surge, Sway, Heave, Roll, Pitch, Yaw	Surge, Heave, Pitch

In these two cases, the training data was selected in randomly ordered. Disrupting the data allows the input data to approximately satisfy the conditions of independent distribution. It also facilitates the convergence of the model. If it is not disturbed, it may affect the generalization ability of SLIANN, resulting in over-fitting. The remaining 500 sets of data (177s) for each condition are used as network test data. Before the training, the data is normalized, that is, all the data is converted into [0, 1]. SILANN use the Min-max normalization, as shown in Eq. (1) below. The normalization function uses the original function, mapminmax, in MATLAB:

$$x_k = \frac{(x_k - x_{min})}{(x_{max} - x_{min})} \quad (1)$$

Where x_{min} is the smallest number in the data sequence; x_{max} is the largest number in the sequence.

The purpose is to remove the different order of magnitude of the data, avoiding the large difference in the order of magnitude of the input and output data. The network prediction error is large, without the normalization.

4 VERIFICATION AND DISCUSSION

4.1 ANN prediction and Error Analysis

It can be clearly seen from the Figure 6&7 that the numerical time domain results after optimization by the ANN basically keep the same trend as the results of basin model test (MT), but some of the points are relatively inaccurate.

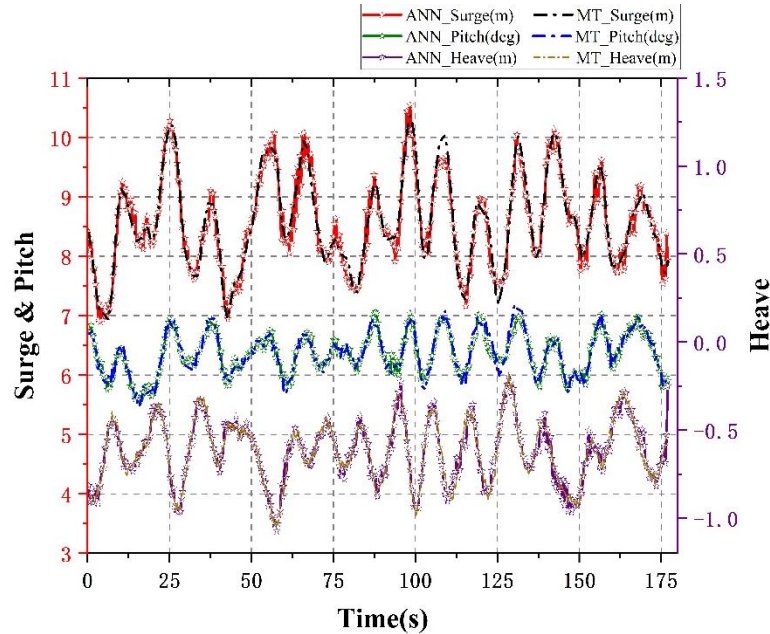


Figure 6: The prediction of ANN under LC2.

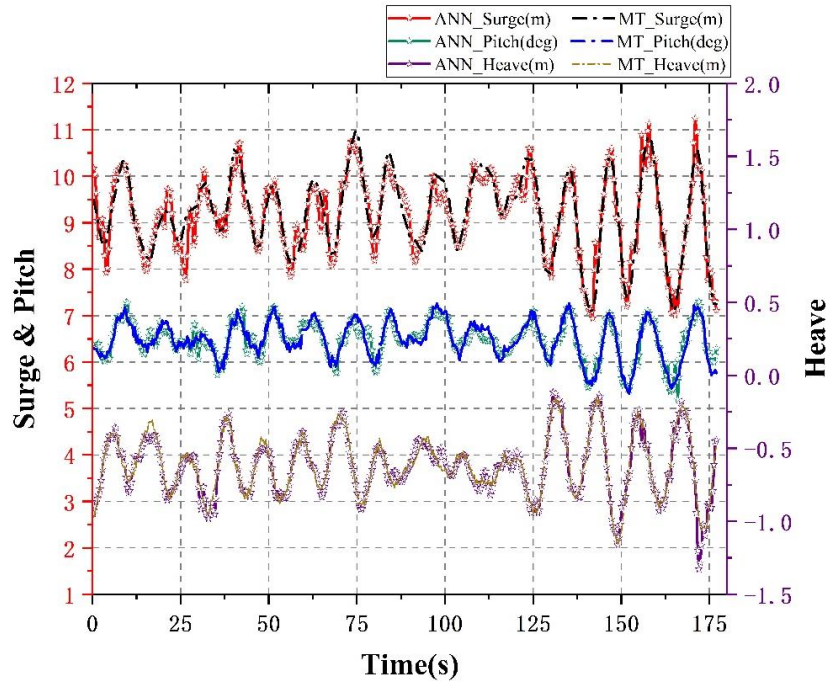


Figure 7: The prediction of ANN under LC3.

In Table 4, the maximum error occurs in LC3. The minimum value of the surge motion is 1.626m, and the maximum value of the Pitch motion is 0.22. And the error percentages are 29.862% and 328.358%, respectively. However, the magnitude of pitch motion under LC3 is very small, and it is found through a complete data time domain comparison that only a few minority prediction errors are large. In addition, from the results of the standard deviation, the maximum error is 0.873 and 0.201, respectively, which is basically the same as the experimental results of 0.862 and 0.201, and the results are similar to the average, data volatility is not strong, so it can be accepted.

Table 5. Statistical comparison

Response		Surge (m)		Heave (m)		Pitch (deg)	
		ANN	MT	ANN	MT	ANN	MT
LC2	AVG	8.559	8.581	-0.620	-0.619	6.364	6.369
	Max	10.547	10.368	-0.194	-0.184	7.060	7.204
	Min	6.892	6.928	-1.075	-1.043	5.569	5.458
	Stdev	0.770	0.789	0.175	0.175	0.344	0.363
LC3	AVG	9.172	9.209	6.486	6.485	-0.619	-0.614
	Max	11.243	10.980	7.302	7.266	0.067	-0.153
	Min	5.445	7.071	5.195	5.325	-1.327	-1.154
	Stdev	0.873	0.862	0.399	0.410	0.210	0.201

A more intuitive average comparison can be seen in Figure 8.

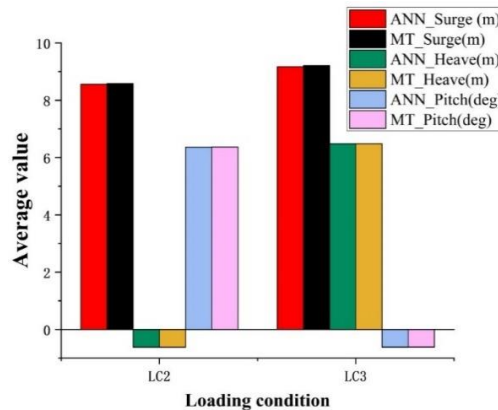


Figure 8: Comparison result with ANN and Experiment.

4.2 Error Analysis

Table 4 and Figure 9 gives a comparison of the percentage error of the average value, which allows a more intuitive comparison of the differences between the SLANN and DARwind results. It is not difficult to see that the error percentage of numerical simulation results after optimization by ANN is significantly reduced in every motion especially in Heave and Pitch.

Table 6. Average error comparison (%)

Response		Surge (m)		Heave (m)		Pitch (deg)	
		ANN	DAR	ANN	DAR	ANN	DAR
LC2	AVG	1.701	6.910	6.159	63.912	1.305	11.710
LC3	AVG	2.570	6.932	2.054	10.243	11.574	51.724

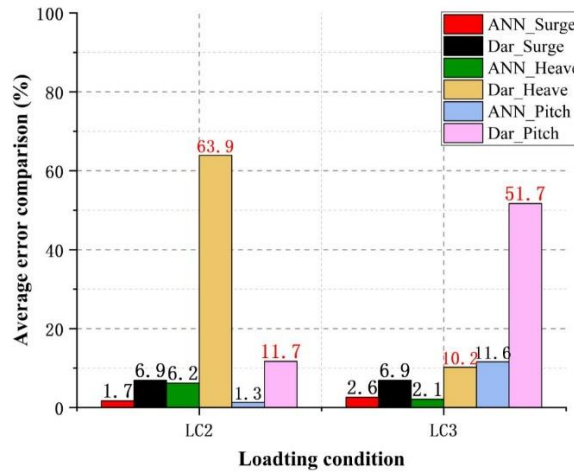


Figure 9: Average error comparison (%) with ANN and DARwind.

It should also be mentioned that although the average error of the platform Heave & Pitch motion in the DARwind calculation results is as high as 63.9% and 51.7% under LC2 and LC3, respectively, the result is still acceptable because the actual amplitude of these two motions is small. However, the results of the ANN may be further optimized, significantly reducing the error.

5 CONCLUSION

This paper presented the Software-In-the-Loop method to predict the global dynamic responses of the full-scale FOWTs by using Artificial Neural Network and then reported a series of verifications. The DARwind and ANN technique have been described briefly. The predictions of the SILANN results are acceptable, and the DARwind results are optimized to some extent, thus achieving a more accurate simulation of the actual experimental conditions.

This paper only established a normal behaviour ANN model for one output (one program has to be output 3DOF in three times). In the future, more components are needed to establish and also implement multiple outputs. Due to the wide range of fields involved and the many related parameters, principal component analysis will also be used to optimize the input training data. After all the important parameters of the basin experiment can be fully simulated, the nonlinear scale relationship existing in reality can be found by conducting two different scale models, which will also be the emphasis of the SILANN. Therefore, the prediction of the dynamic response of the full-size FOWTs is realized, which provides a new verification idea for the design and innovation of the new FOWTs.

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