

1 **Short-term Motion Prediction of floating offshore wind turbine Based**
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4 **on Muti-input LSTM Neural Network**
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39 **Abstract:** The motion response of an offshore floating wind turbine (FOWT) platform is
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41 closely related to the control operation regarding the safety of a wind turbine. It is affected by
42 various factors such as sea state environments and mooring systems. In practice, how to predict
43 the motion response of the wind turbine platform in the short term has always been a concern
44 of engineering practice. At present, the development of deep learning technology has brought
45 some potential solutions to this problem. In this paper, a Multi-Input Long-Short Term Memory
46 (MI-LSTM) neural network method is proposed to predict the short-term motion response of a
47 floating offshore wind turbine platform. Specifically, the numerical simulation of the 5MW
48 Braceless platform is carried out under different environmental conditions, and the data of
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24 platform motion response, wave elevation, and mooring force are selected as input variables.
25 Then the training and test groups are established after post-processing data. Subsequently, a
26 Single-Input LSTM (SI-LSTM) model and a Multi-Input LSTM (MI-LSTM) model are
27 established to learn the input data. After comparing the overall accuracy of the results, it is
28 found that the additional mooring force and wave elevation positively affects the platform
29 response prediction results. From the aspects of discreteness and overall accuracy, it is verified
30 that the established MI-LSTM model is also applicable, considering the influence of second-
31 order hydrodynamics. Lastly, compared with the prediction results obtained by the multi-input
32 one-dimensional convolutional neural network (MI1D-CNN), the advantages of the two
33 different models are expounded from the perspectives of training time and accuracy, which
34 provides ideas for the optimization of the FOWT motion response prediction model. This study
35 sheds insights on the short-term motion response forecast and platform positioning of a FOWT.
36 Short-term forecasts of a FOWT can be achieved under various sea conditions by combining
37 the global positioning system.

38 **Keywords:** Floating offshore wind turbine; deep learning; response prediction; multi-input
39 LSTM model; second-order hydrodynamic

40 1. Introduction

41 With the rapid development of the global economy, energy has become a critical factor in
42 determining social and economic development. To meet the Net Zero target by utilizing
43 sustainable energy, the vigorous growth of renewable energy has become an essential part of
44 the development strategy worldwide. Due to its high energy conversion ability, offshore wind
45 power has been gradually installed in various countries recently. Different foundations of
46 floating offshore wind turbines have been proposed, including spar, tension leg platform (TLP)
47 shape, semi-submersible, and barge [1]-[2]. Substantial research has been carried out in terms
48 of hydrodynamics, mooring systems, stability, performance, and survivability of a FOWT [3]-

49 [6].

50 Compared with the onshore wind turbine structure, a FOWT encounters a more complex
51 ocean environment. The motion response of a FOWT occurs at six degrees of freedom (6DOF)
52 and leads to significant challenges in design and assessment [7]. Therefore, it is of great
53 significance to propose an accurate prediction method for the motion response of the FOWT to
54 guide the design and assess structural safety. In the deep learning model, motion response
55 prediction is generally based on the historical data of motion response and many other results
56 from numerical and experimental measurements. In general, deep learning technology is
57 applied to predict the motion response of structures in the next few seconds [8]. According to
58 the length of the forecast time, motion response prediction can be categorized as short-term and
59 safe-period motion prediction. Short-term prediction plays a vital role in improving dynamic
60 positioning control performance, and it provides early warning in extreme sea conditions to
61 reduce platform damage to a certain extent. A short-term forecast's prediction advanced time
62 (PAT) is generally a few seconds, and it requires high forecast accuracy [9].

63 In recent years, the application of deep learning technology in offshore structures has
64 gradually expanded. The research is mainly carried out by the convolutional neural network
65 (CNN) and the recurrent neural network (RNN) methods [10]-[18]. Wang et al. [11] proposed
66 the Low-frequency adds wave-frequency responses (LAWR) method to predict the mooring
67 line tension of a semi-submersible platform. Combined with the LSTM method, accurate results
68 are obtained for predicting mooring line tension under different cases. Pena et al. [15] proposed
69 the Wave-Generative Adversarial Network (Wave-GAN) technology, combined with CNN
70 convolutional neural network and CFD method, to predict the load of nonlinear waves on fixed
71 structural columns. Pena et al. [15] concluded the maximum error between the Wave-GAN
72 predicted value and CFD simulated value of 1.5%-2% by adjusting several parameters, and the
73 mean absolute error (MAE) of the test group is about 0.014. Lian et al. [16] constructed the

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74 digital twin of mesh clothing and established the deep neural network (DNN) to predict whether
75 the mesh clothing is damaged. The average accuracy of the final identification model is 94.3%.
76 Bjørni et al. [17] predicted the mooring line tension in the next 30 s by taking the platform
77 motion response in the first 60 s as input and constructed a three-layer deep neural network with
78 bias term. It is concluded that the average error of anchor chain tension is 0.46% through cross-
79 sectional comparisons. According to the combined prediction method of the Extreme Learning
80 Machine (ELM), the Empirical Mode Decomposition (EMD), and LSTM neural network,
81 Zhang et al. [18] proved that the combined prediction method presented higher prediction
82 accuracy than the single LSTM model and ELM-LSTM model. However, when considering the
83 influence of environmental factors and mooring force, there is limited research on predicting
84 the motion response of a FOWT. At the same time, in practice, it needs to assess the motion
85 response of a FOWT under the influence of various complex factors and consider the impact of
86 second-order hydrodynamic force. Moreover, the amount of research on the motion response
87 prediction of a FOWT under the effect of the second-order hydrodynamic force is also limited.

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88 To investigate the short-term motion prediction of a FOWT, the MI-LSTM Neural
89 Network model is used. This paper is organized as follows: Section 2 introduces the basic
90 principles of the RNN. The architecture and differences between the established SI-LSTM
91 model and the MI-LSTM model are explained in detail. The hyperparameters of the model and
92 the selection of the training and test groups are also given in this section. Then, in Section 3,
93 the structure size of the 5 MW Braceless platform model is shown. A detailed comparison is
94 made between the prediction results of the SI-LSTM and MI-LSTM models under different
95 environmental conditions in Section 4. This proves the positive excitation of the increased input
96 factor numbers on the prediction results and illustrates the advantages and benefits of the MI-
97 LSTM model. In Section 5, the applicability of the proposed model is demonstrated when the
98 second-order hydrodynamic force is considered. Given that there are few comparisons between

99 the RNN model and CNN model regarding time domain problems, in Section 6, by comparing
100 the prediction results of the proposed model with the multi-input one-dimensional
101 convolutional neural network (MI1D-CNN) model, the advantages of the two models are
102 illustrated from the perspectives of overall accuracy and training time. Finally, the conclusions
103 and recommendations are made to the future optimization of the platform response prediction
104 model.

2. Long-Short Term Memory (LSTM) Neural Network

2.1. Recurrent Neural Network (RNN)

107 Recurrent neural network (RNN) is gradually emerging in the interdisciplinary field as a
108 typical representative of deep learning technology. RNN takes time series data as input and
109 performs recursion in the evolution direction of the sequence, where all nodes (cyclic units) are
110 linked in a chain [19]. RNN has memorization, parameter sharing, and turning completeness
111 [20]-[22], so it has clear advantages in learning the nonlinear features in sequences. RNNs are
112 widely used in natural language processing, such as speech recognition, language modeling,
113 and time series prediction. RNN performs outstandingly in solving scheduling problems, and
114 motion response prediction is the typical time domain problem. Therefore, in this paper, RNN
115 is selected for model architecture.

116 Since the motion of the platform at time t is affected by the motion at the previous time
117 $t - 1$, meanwhile, the motion at current time t will also have an impact at forward time $t + 1$,
118 platform motion response is a continuous process with time dependence. Considering this
119 characteristic, the traditional deep neural network (DNN) cannot convey information precisely
120 in the time sequence, but the RNN is developed to overcome this problem. Training input data
121 from a FOWT system to predict the motion response in the next few seconds can be viewed as
122 an adaptive function mapping. The input is the previous time series information of different
123 input factors, and the output is the motion response in the future. Hence, the trained deep

124 learning model can achieve prediction in a short time.

125 The timeline expansion of the RNN is shown in **Figure 1**, where x is the network input
 126 layer, s is the network node hiding layer, and o is the network node output layer. After the
 127 network receives the input x_t at time t , the value of the hidden layer is s_t and the output
 128 value is o_t . The value of s_t depends not only on x_t , but also on s_{t-1} . In other words, s
 129 inherits the information from each node.

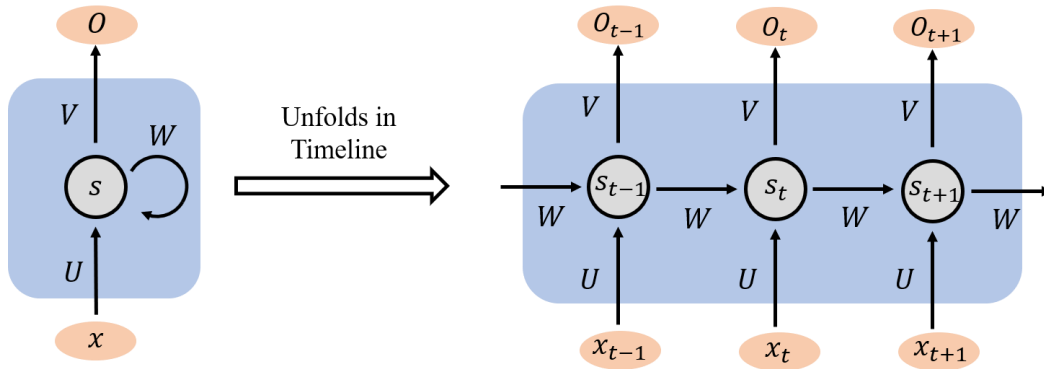


Figure 1. An unfolded RNN network

The calculation method of the RNN network is shown in Equations 1-2:

$$o_t = \mathbf{g}(\mathbf{V} \cdot s_t) \quad (1)$$

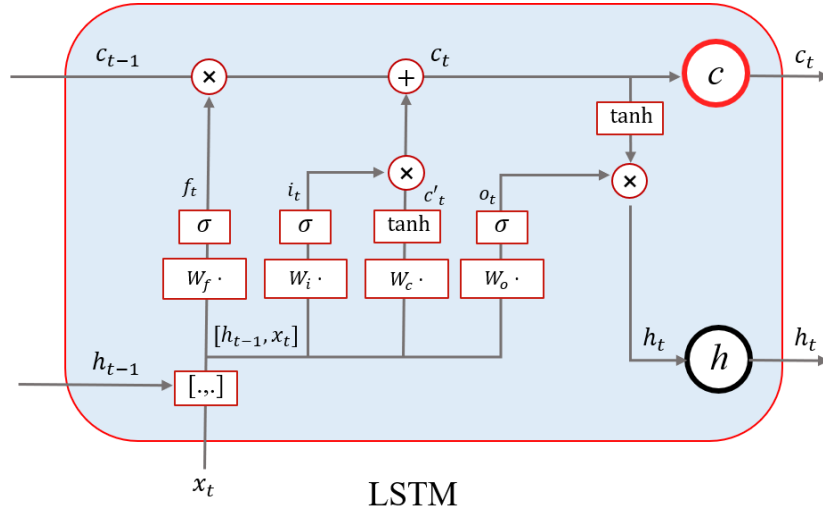
$$s_t = \mathbf{f}(\mathbf{U} \cdot x_t + \mathbf{W} \cdot s_{t-1}) \quad (2)$$

135 where \mathbf{V} is the weight matrix of the output layer, \mathbf{g} is the activation function for the output layer,
 136 \mathbf{U} is the weight matrix of the input layer x , \mathbf{W} is the weight matrix of the last value, which is
 137 the input of this time, and \mathbf{f} is the activation function for the hidden layer. Common activation
 138 functions, such as sigmoid, tanh, Rectified Linear Unit (ReLU), and linear activation function,
 139 can be selected according to data characteristics and experimental effects. The sigmoid
 140 activation function is generally selected for hidden layer activation function \mathbf{f} , while the linear
 141 activation function is generally chosen for output layer activation function \mathbf{g} . Equation 1 is the
 142 calculation formula of the output layer. The output layer is fully connected, indicating every
 143 node in the output layer is connected to every node in the hidden layer. Equation 2 is the

144 calculation formula of the hidden layer.

145 2.2. Long-Short Term Memory (LSTM) Network

146 LSTM is first proposed by Hochreiter and Schmidhuber [22]. Compared with traditional
 147 RNN, the LSTM network has improved the gradient explosion and gradient extinction. It has
 148 been one of the most popular RNN models and is widely applied in many fields, such as speech
 149 recognition, image description, and natural language processing. The internal structure of the
 150 LSTM node is shown in **Figure 2** [24].



151
152 **Figure 2.** LSTM node unit internal structure

153 At time t , the LSTM network has three inputs: current time input value x_t , LSTM output
 154 value h_{t-1} at the last time, and the unit state c_{t-1} at the previous time. The output of LSTM
 155 has two parts: the output value of LSTM at the current time h_t , and the unit state at the current
 156 time c_t . x , h , and c are vectors. In addition, LSTM uses the concept of a Gate to control the
 157 state of the unit [24]. Gate is a full connection layer which controls information transmission
 158 between input and output. Its input is a vector of time series information, and its output is a
 159 vector of real numbers between 0 and 1. The gate can be expressed as:

$$160 \quad G(x) = \sigma(W \cdot x + \mathbf{b}) \quad (3)$$

161 where W is the weight matrix of the gate, \mathbf{b} is the bias term, and σ is the generally sigmoid

162 activation function.

163 The output vector of the gate is multiplied by the element and the vector is controlled to
164 achieve the gate effect. The gated output is a vector of real numbers between 0 and 1. When the
165 gated output is 0, any vectors multiplied by the output will get the 0 vectors, indicating that no
166 information can pass through. When the gated output is 1, no changes are applied by multiplying,
167 indicating that any information can pass through. Because σ has a range of (0,1), the gate is
168 an intermediate state.

169 LSTM relies on two gates to control the content of the cell state: (1) one is the forget gate
170 that determines the amount of the cell state c_{t-1} at the last moment. c_{t-1} is used to retain the
171 current moment c_t ; (2) one is the input gate that determines the amount of the current network
172 input x_t , which is saved to the unit state c_t . Meanwhile, LSTM uses an output gate to control
173 the amount of unit state c_t that is generated from the current output value h_t . The governing
174 equations of each gate are given as follows:

$$f_t = \sigma(\mathbf{W}_f \cdot [h_{t-1}, x_t] + \mathbf{b}_f) \quad (4)$$

$$i_t = \sigma(\mathbf{W}_i \cdot [h_{t-1}, x_t] + \mathbf{b}_i) \quad (5)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tanh(\mathbf{W}_c \cdot [h_{t-1}, x_t] + \mathbf{b}_c) \quad (6)$$

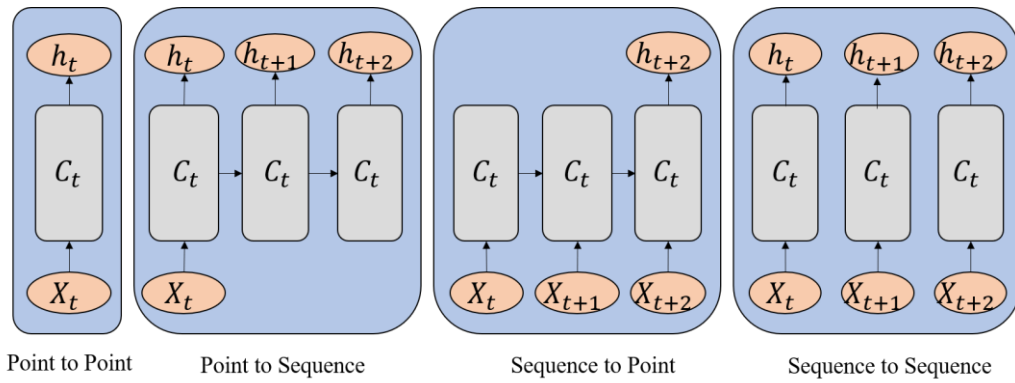
$$o_t = \sigma(\mathbf{W}_o \cdot [h_{t-1}, x_t] + \mathbf{b}_o) \quad (7)$$

$$h_t = o_t \cdot \tanh(c_t) \quad (8)$$

180 where f_t is the forgetting gate equation, \mathbf{W}_f is the weight matrix of the forgetting gate,
181 $[h_{t-1}, x_t]$ is joining two vectors into a longer vector, \mathbf{b}_f is the biased term of the forgetting gate,
182 i_t is the input gate equation, \mathbf{W}_i is the weight matrix of the input gate, \mathbf{b}_i is the offset term
183 of the input gate, c_t is the current moment element state equation, o_t is the output gate control
184 equation, h_t is the final output equation determined by the output gate and unit state.

185 Existing LSTM network prediction modes mainly fall into the following four types [25]:
186 point-to-point, point-to-sequence, sequence-to-point, and sequence-to-sequence, shown in

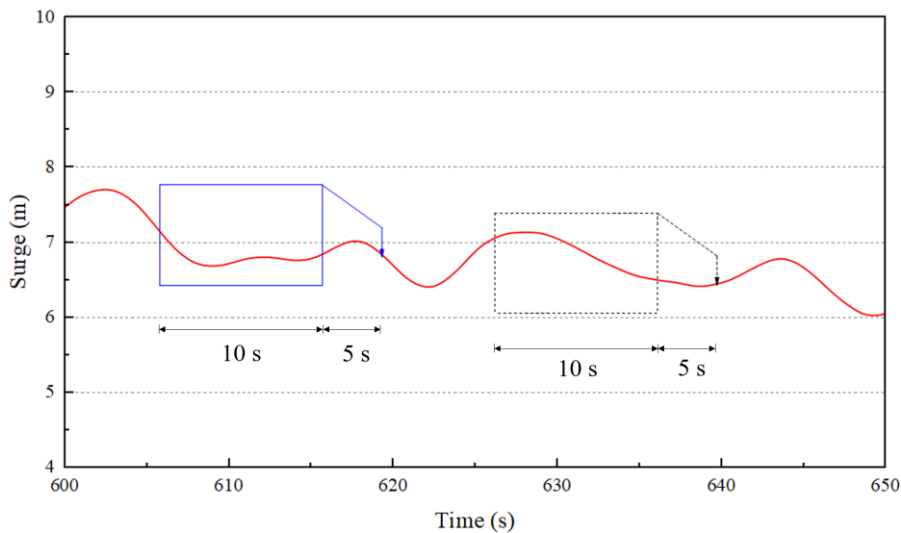
187 **Figure 3:**



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189 **Figure 3. LSTM network prediction modes**

190 The LSTM network in this paper is set up by using sequence-to-point mode for a prediction
 191 model, which uses forecasting point response from previous time series after the selected data
 192 input mode is adopted in the form of the sliding window. Each window length has 200 time
 193 points and the 10 s surge motion. The sliding window form is shown in **Figure 4**, where the
 194 mapping relationship between the data input and output is presented when the forecast time is
 195 5 s. Therefore, the response at $t + 5$ is predicted based on the response from $t-10$ to t .



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197 **Figure 4. Sliding windows for data input and output**

198 **2.3. LSTM Model Structure**

199 The LSTM network model established in this paper has three hidden layers and one fully

connected output layer, shown in **Figure 5**. The data sampling frequency is 20 Hz. The input time step of the LSTM network contains 200 time series points with a motion response of 10s. The batch size is set to 256 sample sets, which are also the input for training and updating internal parameters. The number of neurons is set to 200. These two parameters are hyperparameters and can be adjusted according to the performance of the actual test.

Input layer: input time series with a window of 200 data points, representing the motion response of 10s. The input dimension of the single-input model is 1, and that of the multi-input model is 3.

Hidden layer: The hidden layer has 200 nodes.

Output layer: The output layer is dense, the activation function is Linear, and the output result is the motion response at the target time.

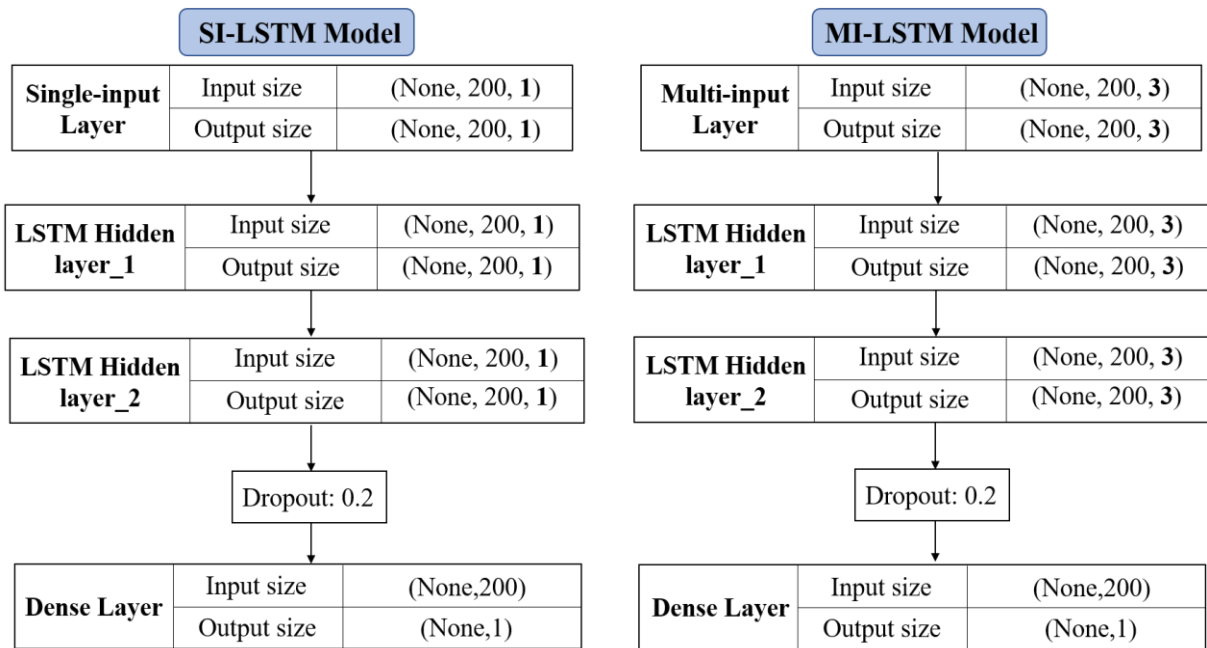


Figure 5. LSTM network model structure and data transfer format

The Adam algorithm is configured for the LSTM network [27]. Adam algorithm is an advanced Stochastic Gradient Descent (SGD) algorithm, which introduces an adaptive learning rate for each parameter. The adaptive learning method and the Momentum method are combined. The learning rate is dynamically adjusted by the first and second moment estimation

of the gradient. The gradient descent process is relatively stable and suitable for most non-convex optimization problems in large data sets and high-dimensional space.

Simultaneously, the Dropout layer is added after the input layer and the hidden layer to prevent overfitting [28], and the Dropout_1 and Dropout_2 are set to 0.2. Overfitting may occur due to a large number of unknown network parameters or training times. The principle of dropout is that during the neural network training, some neurons are randomly discarded and not used for training at this round to avoid overfitting and accelerate loss convergence.

In this paper, the LSTM neural network is constructed, and the input data consists of three parts, including time series of previous motion response, mooring force, and wave elevation. And the current motion response is set as the output data. The process of using the LSTM neural network model to predict the motion response is shown in **Figure 6**. The process of predicting motion response by LSTM neural network.

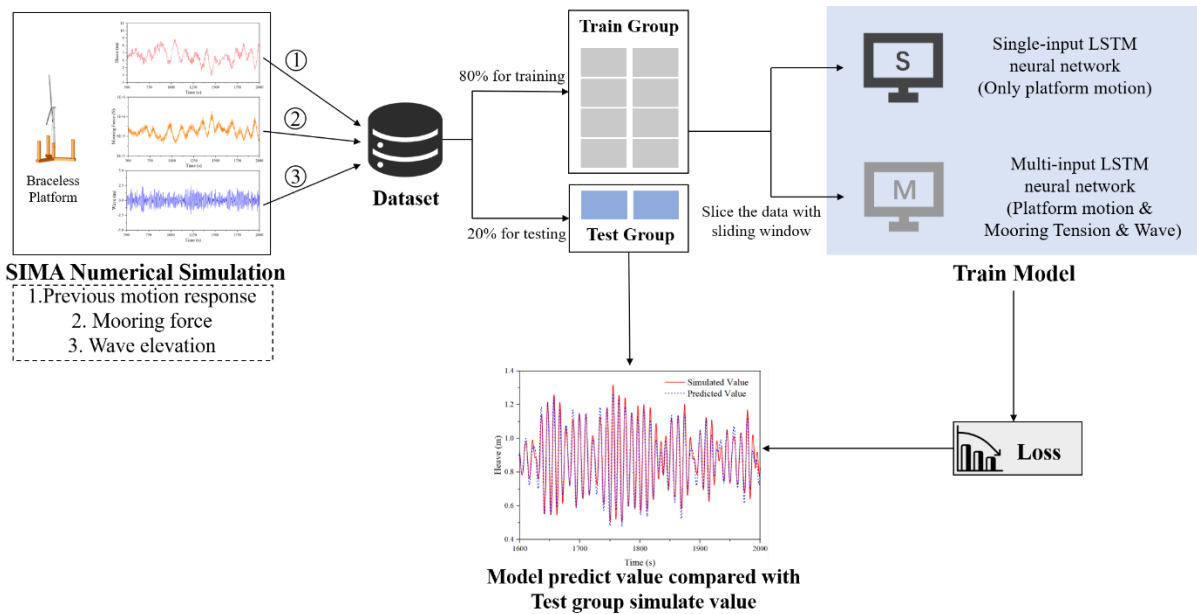


Figure 6. The process of predicting motion response by LSTM neural network

3. Braceless Platform model

The 5 MW Braceless model is established by SIMA, and the time domain response is

234 obtained by numerical simulation. SIMA is developed for the analysis of flexible marine riser
 235 systems, but it is also suited for any slender structures, such as mooring lines, and umbilicals,
 236 and for steel pipelines and conventional risers. The data used in training in this paper came from
 237 the FOWT model of a 5 MW Braceless semi-submersible platform in the water depth of 100 m.
 238 The Braceless platform consists of one central column, three side columns, and three pontoons,
 239 shown in **Figure 7**.

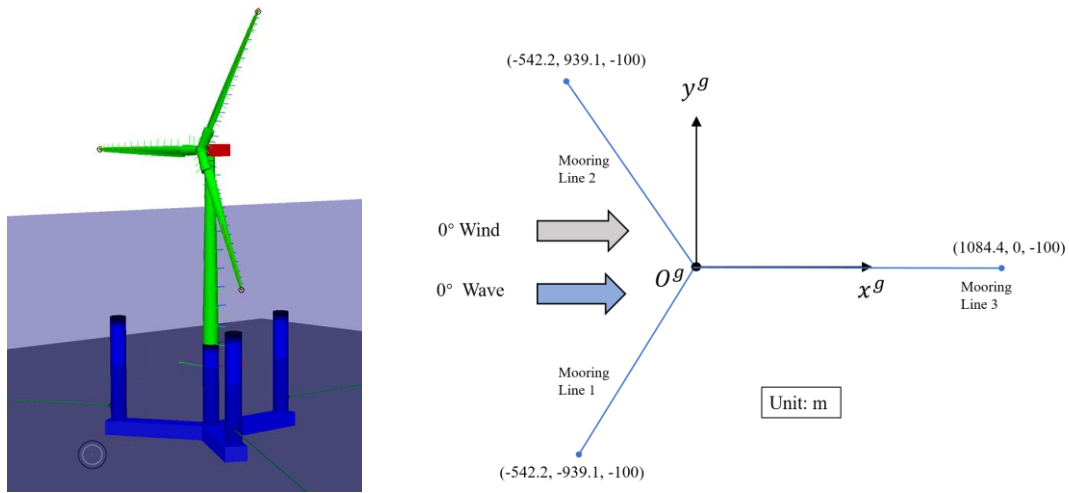


Figure 7. Schematic of 5-MW Braceless platform

243 Three side columns are evenly distributed around the central column at 120° . They are
 244 connected to the bottom of the central column by a floating buoy to form a Braceless semi-
 245 submersible platform. The three-point mooring system is adopted, and the anchor chain is set
 246 at the bottom of the side column. 0° wave-wind misalignment is considered in the simulation.
 247 The main parameters of the Braceless platform are shown in **Table 1**. Parameters of the 5 MW
 248 Braceless Platform.

249 In the following cases, the water depth is 100 m. The average wind speed V_t , effective
 250 wave height H_S , and spectrum peak period T_p at the selected cabin height are listed in **Table**
 251 **2**. Environment matrix (JONSWAP). The significant wave height and spectrum peak period are
 252 in 50 years return period. The two-parameter JONSWAP spectrum is used to describe random

253 ocean waves. The Kaimal wind speed spectrum is used to describe the offshore wind conditions.

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Table 1. Parameters of the 5 MW Braceless Platform

Parameter	Value
Central column diameter (m)	6.5
Side column diameter (m)	6.5
Buoy height (m)	6
Buoy bottom width (m)	9
Buoy short radius (m)	41
Buoy long radius (m)	45.5
Depth of the draft (m)	30
Displacement (t)	10555
Steel weight (t)	1804
Equivalent thickness (m)	0.03

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Table 2. Environment matrix (JONSWAP)

Case	Vt (m/s)	Turbulence intensity (%)	Hs (m)	Tp (s)
EC 1	9.8	10.1	2.9	9.98
EC 2	14.8	15	4.5	11.81
EC 3	16	13	5.3	12.81

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4. Single-input and Multi-input

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4.1. Data Partitioning and Error Measurement

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260 The sampling frequency of the Braceless platform simulation test is 20 Hz. The total
261 sampling length of motion response (surge, pitch, and sway) is 2000 s. The collected time series

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262 contains 40000 data points. In the training model, the first 32000 points of response data are
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2 263 the training groups and the last 8000 points of response data are the test groups. Three test cases
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4 264 (EC1, EC2, and EC3) are selected, and each test case contained 2000 s surge, pitch, and sway
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7 265 motion data.

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9 266 The training group data is used to train and obtain the neural network model. The
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12 267 relationship between training Epochs and Loss is observed through the Loss function. Then the
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14 268 test group data is imported into the trained neural network model to verify the accuracy and
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17 269 performance of the trained model.

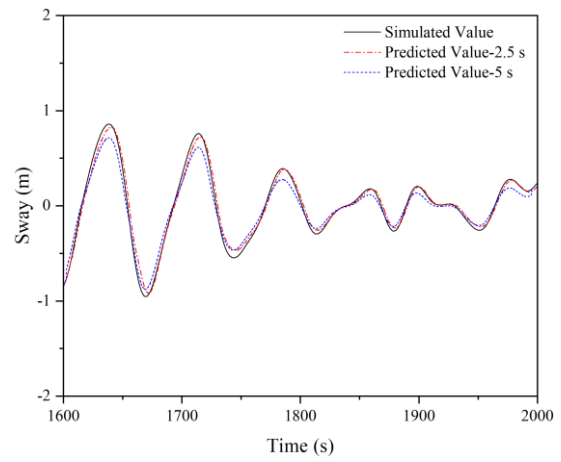
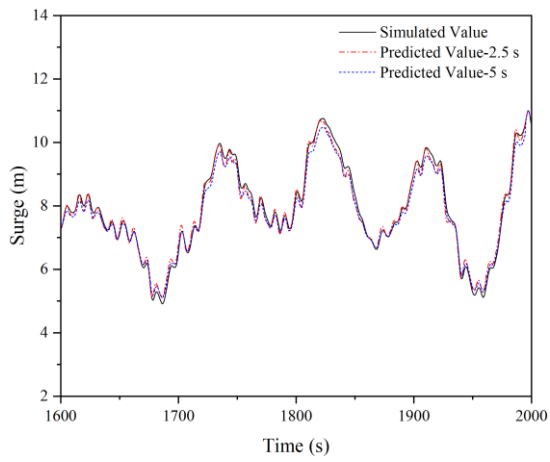
18
19 270 The Loss function adopted in this paper is the Mean Squared Error (MSE), which is the
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22 271 averaged squared difference between the predicted value and the measured value as shown in
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24 272 Equation 9:

$$27 273 \quad \quad \quad MSE = \frac{\sum (y'_t - y_t)^2}{n} \quad (9)$$

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29 274 where y'_t is the predicted value of the motion response at time t , y_t is the measured value
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32 275 of the motion response at time t , and n is the total number of predicted values 8000 in this
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34 276 study.

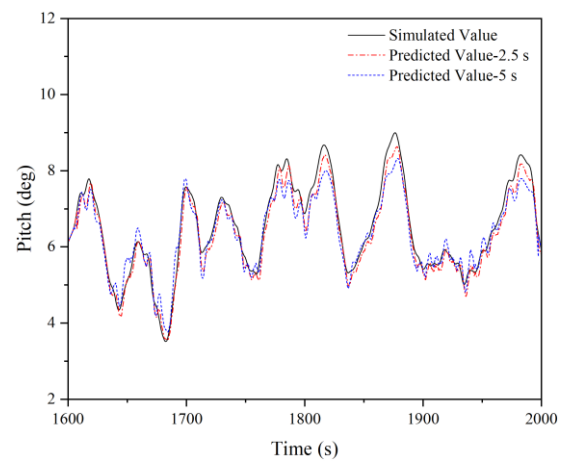
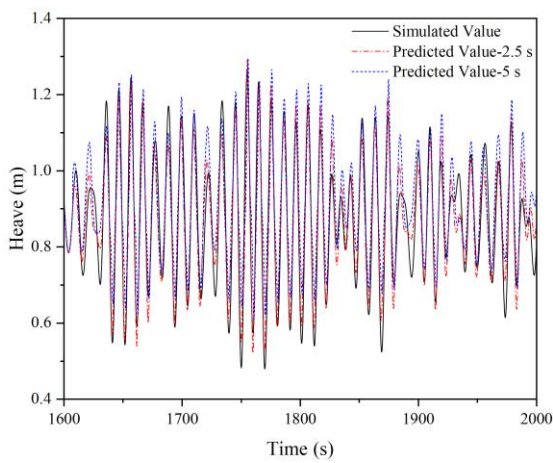
35 36 37 38 277 4.2. Single-input Predicted Results

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41 278 Single-input LSTM (SI-LSTM) model is used to train the motion response data in the
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44 279 training group in terms of the heave, surge, sway, and pitch. The training input of the model is
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46 280 only based on the previous motions. The output of the model is compared and analyzed with
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49 281 the data of the test group. The predicted advance time is set as 2.5 s and 5 s respectively. The
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51 282 actual and predicted values are shown in **Figures 8-10**.



(a)

(b)

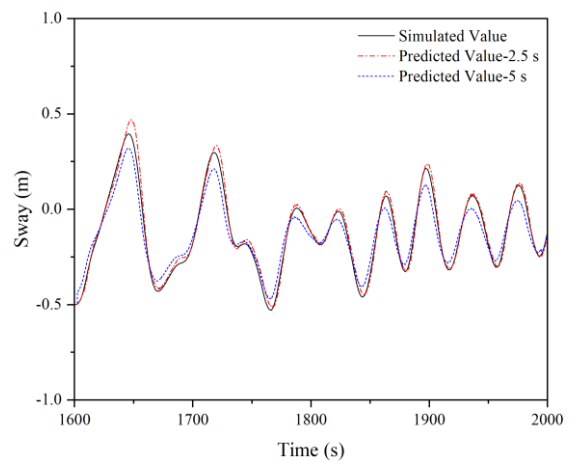
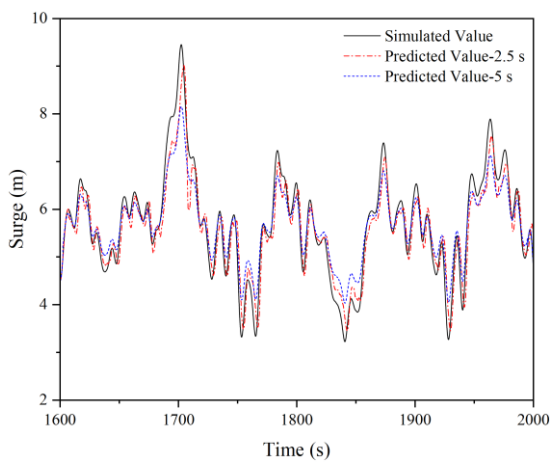


(c)

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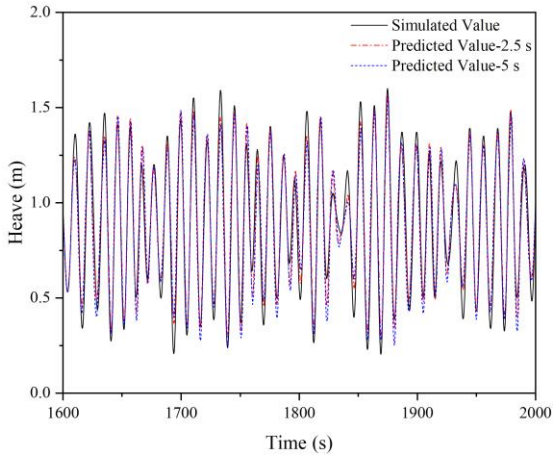
Figure 8. Simulated and predicted values of EC 1 at 2.5 s and 5 s :

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

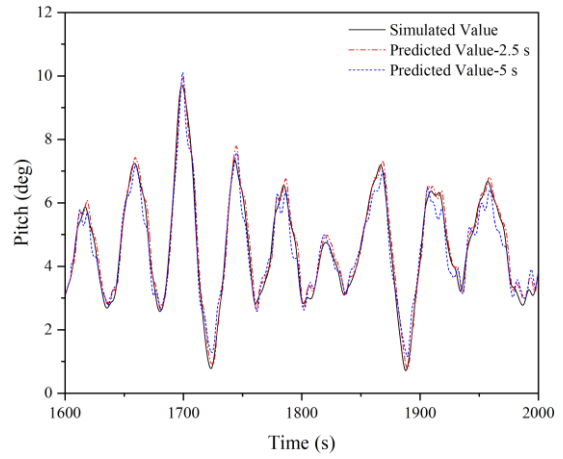


(a)

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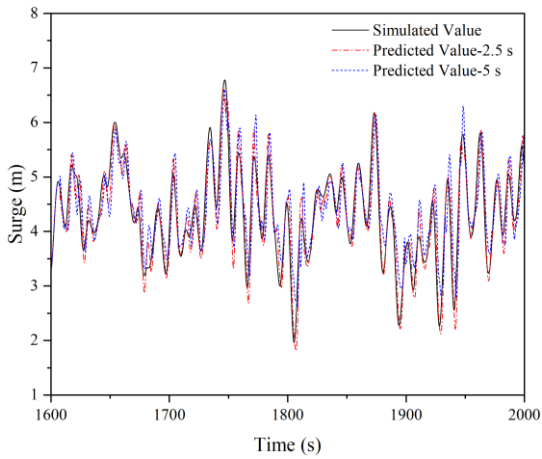
(c)



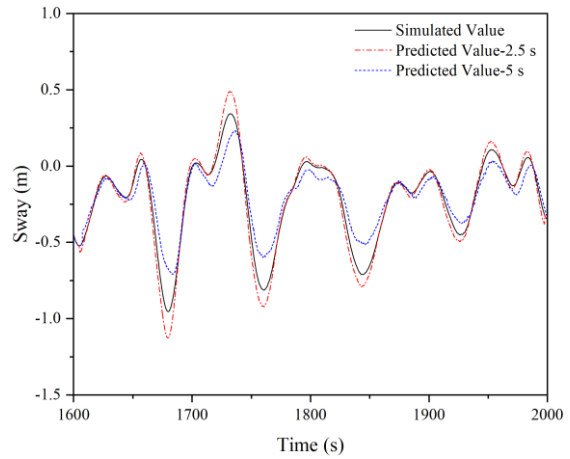
(d)

Figure 9. Simulated and predicted values of EC 2 at 2.5 s and 5 s:

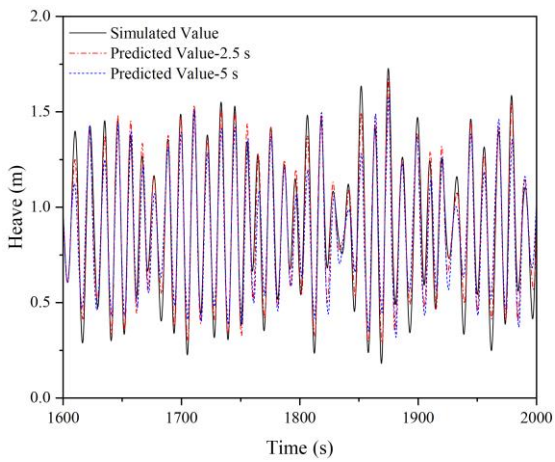
(a) Surge; (b) Sway; (c) Heave; (d) Pitch



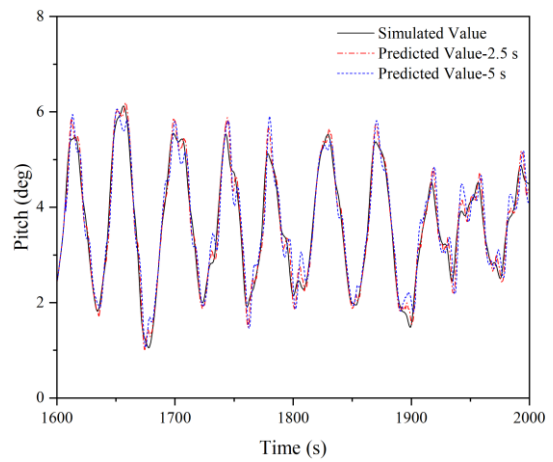
(a)



(b)



(c)



(d)

299 **Figure 10.** Simulated and predicted values of EC 3 at 2.5 s and 5 s:

300 (a) Surge; (b) Sway; (c) Heave; (d) Pitch

301 It can be seen from **Figures 8-10** that when the previous motion response is used as the
302 single input, the predicted value at PAT of 2.5 s is closer to the simulated value. Due to the large
303 amplitude of motion in the surge, the predicted results in **Figure 8(a)** agree well with the
304 simulation results, apart from the minor discrepancy at the peak of the surge in **Figures 9-10(a)**.
305 Due to the small amplitude in sway, the predicted results under the two PATs generally agree
306 with simulated results compared to the agreement between predicted and simulated surge.
307 Similarly, there is also a minor discrepancy at the peak. The amplitude of heave motion is the
308 smallest among the three motions, but it contains higher frequency components. The predicted
309 heave motion in three test cases in **Figure 8-10** presents better agreement with simulated results
310 at PAT of 2.5 s, but a minor discrepancy can be noted at the peak and trough at PAT of 5 s. The
311 peak value of pitch in **Figures 8-10(d)** is also large, but there is higher-order fluctuation at the
312 peak and trough due to the nonlinear motion induced by wind and waves. Single-input LSTM
313 model learned the nonlinear features from the training data group, so the predicted value agrees
314 well with the simulated results.

315 In summary, compared with the simulated values, the predicted values in all motions have
316 very minor discrepancies at peak and trough, but a fairly good agreement has been presented.
317 The discrepancy at peak and trough can be attributed to the limited input factors to train the
318 neural network. To unravel this, the multi-input network structure is investigated in detail in
319 Section 4.3.

320 4.3. Muti-input Predicted Results

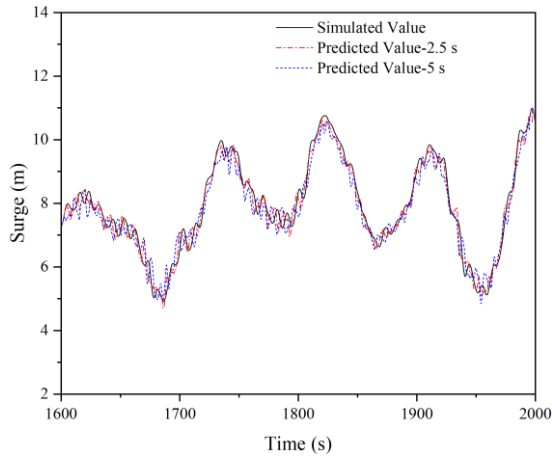
321 A multi-input model is trained to explore the effects of multiple factors as input conditions
322 on the predicted results. Unlike the single-input model, the training input of the multi-input
323 LSTM (MI-LSTM) model is based on the previous motions, mooring forces, and wave

324 elevation. The output of the model is compared and analyzed with the data of the test group.

325 The predicted advance time is set as 2.5 s and 5 s respectively. The test and predicted results

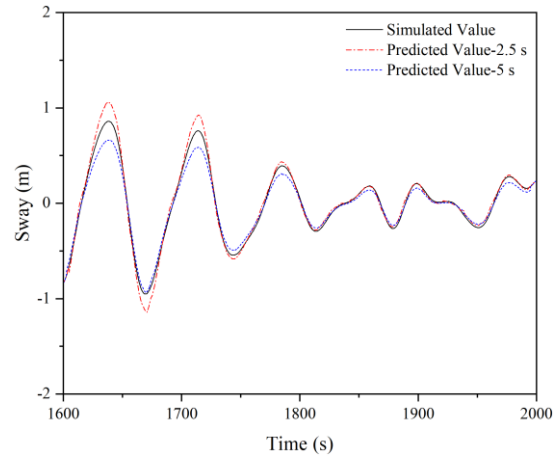
326 are shown in **Figures 11-13**.

327



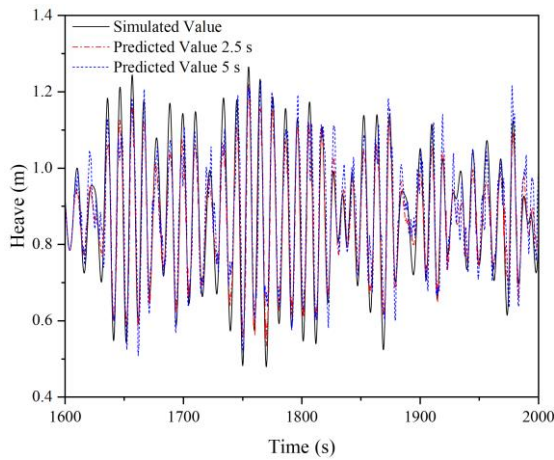
328

(a)



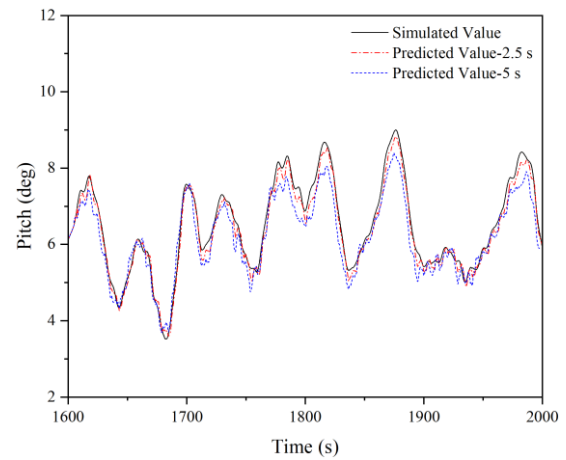
329

(b)



330

(c)



331

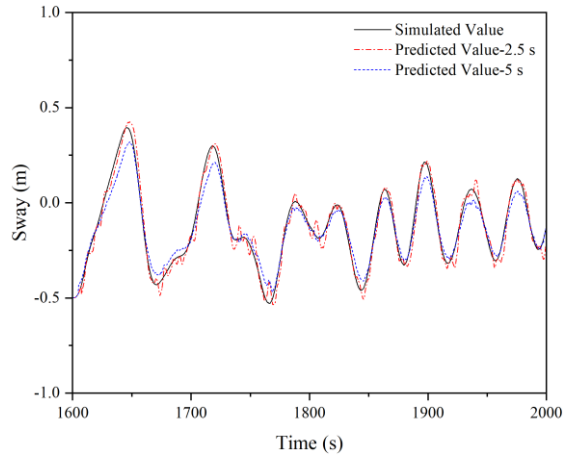
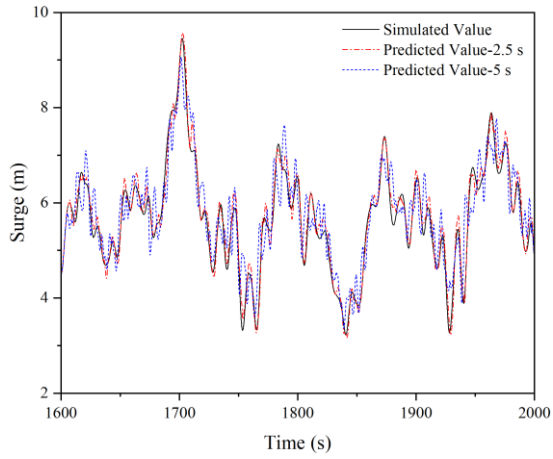
(d)

Figure 11. Simulated and predicted values of EC 1 at 2.5 s and 5 s:

332

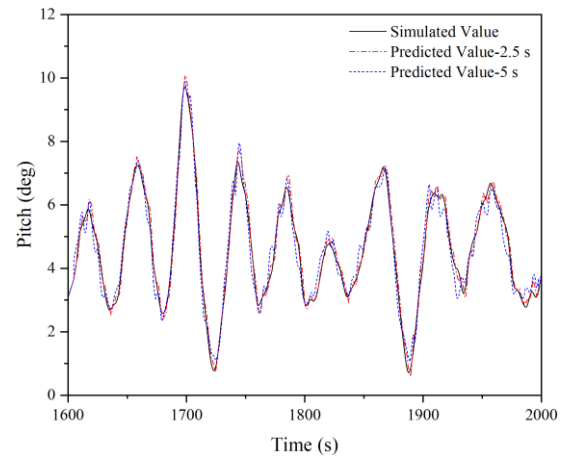
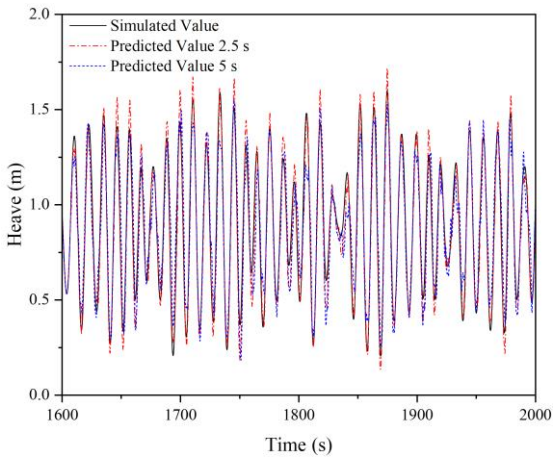
333

(a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)

(b)

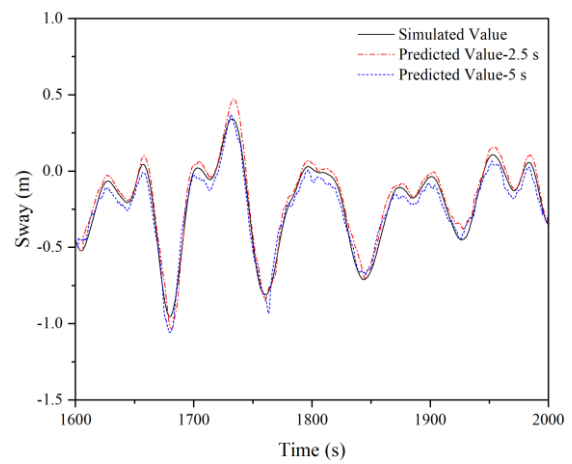
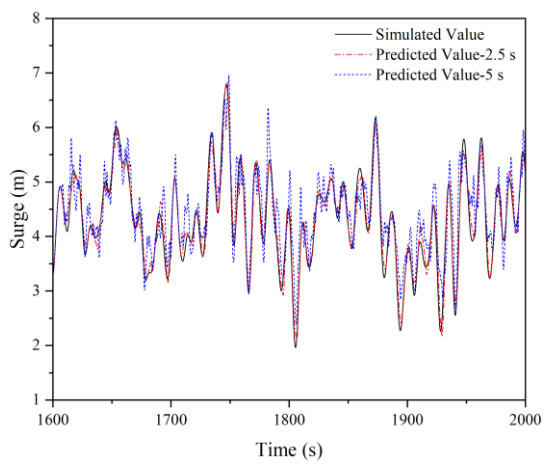


(c)

(d)

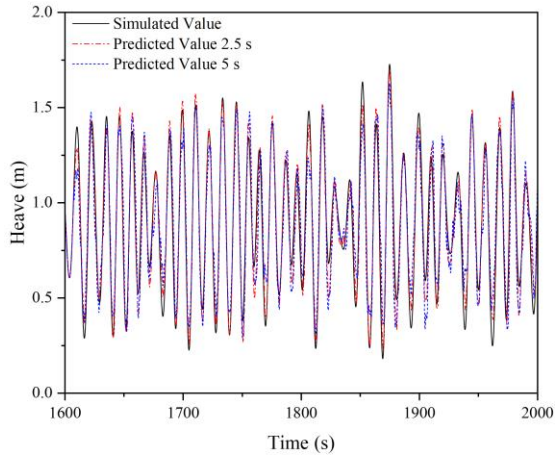
Figure 12. Simulated and predicted values of EC 2 at 2.5 s and 5 s:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

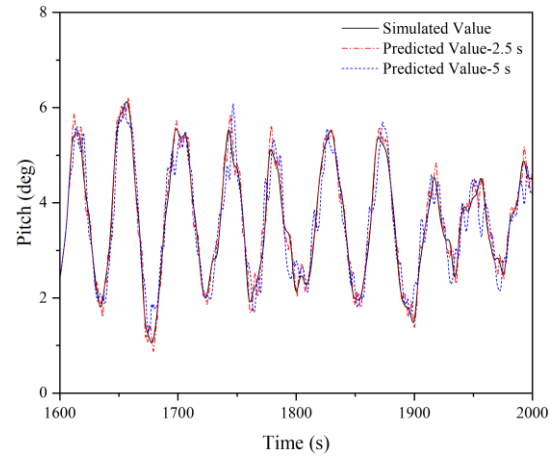


(a)

(b)



(c)



(d)

Figure 13. Simulated and predicted values of EC 3 at 2.5 s and 5 s:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

When the model input factors become multiple, i.e., adding mooring force and wave elevation, a better agreement between the predicted value and the simulated value is obtained compared with the single input case. Improved agreement of surge prediction at peak in **Figure 12(a)** is presented compared to **Figure 9(a)**. But in the case of multiple inputs, the fluctuations can also be noticed from the predicted surge. Sway and heave are not significantly improved due to their less sensitivity to mooring force. With the additional input factors, the accuracy of the predicted pitch has been improved significantly as pitch motion is sensitive to mooring forces, comparing **Figures 9(d)** and **12(d)**. It can be found that in the period 1900s-2000s, the discrepancy of the single-input model can be found, while the multi-input model presented better performance with additional input data sets. Similar to the pitch, better agreements have been achieved for the predicted surge.

In a word, after adding the additional input factors to train the multi-input model, better performance in predicting the FOWT motion response has been demonstrated. However, the saw-tooth effect of the MI-LSTM model is more obvious, caused by the deep learning of the additional input information. The saw tooth effect is further analyzed after analyzing the scatterplot of discrete situations in Section 4.4.

362 4.4 Error Analysis

1
2
3 363 In this study, the number of Epochs is set to 50 rounds. It is shown in **Figure 14** the trend
4
5 364 of the Loss function changing with the Epochs is generated and recorded during the training. It
6
7 365 can be noted that with the increment of Epochs, Loss decrease rapidly in the beginning. Then
8
9
10 366 after the rapid decrease stage, Loss finally tended to be stable. After the Epochs reaches 50,
11
12 367 Loss remains unchanged. It can be concluded that the network training effect will not be further
13
14
15 368 improved after 50 rounds and a neural network model with good accuracy is generated. The
16
17 369 model has completed learning about the relationship between the input and output data.

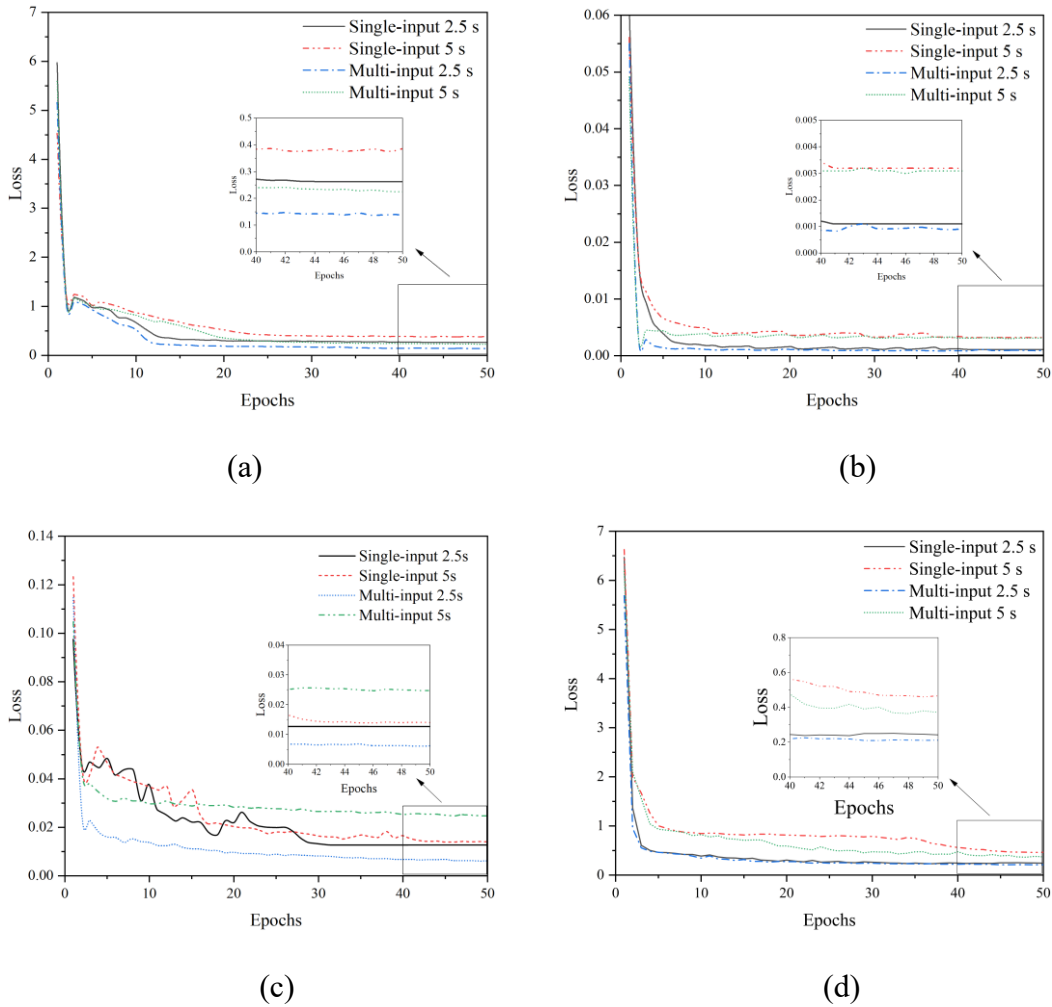
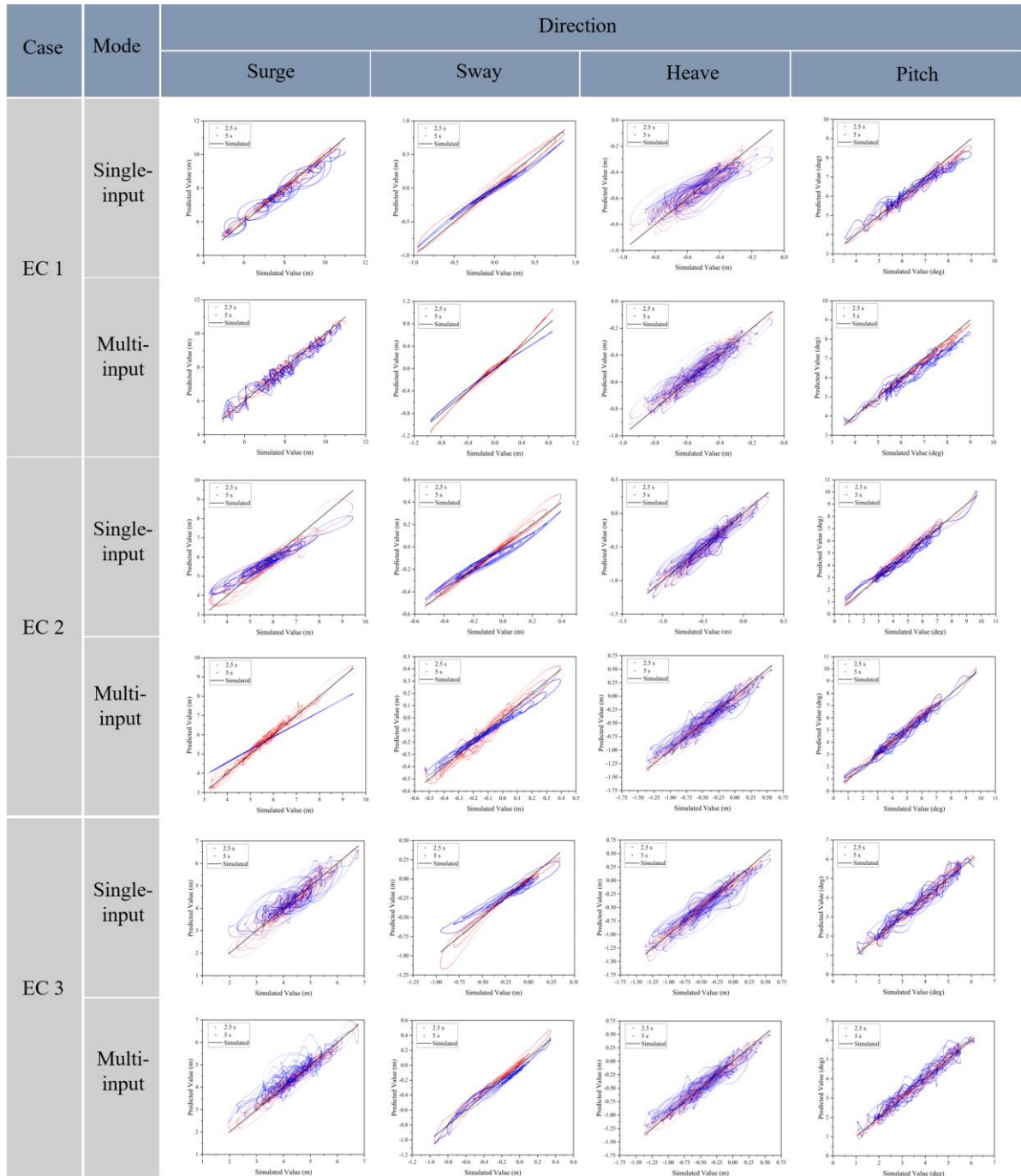


Figure 14. The curve of Loss affected by Epochs for different directions:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

At the same time, the Loss of the MI-LSTM model is found to be lower than that of the

377 SI-LSTM model both in 2.5 s and 5 s. It can be considered that the learning ability of the model
 378 is improved after additional factors are added to the training. The predicted results are shown
 379 in Sections 4.2 and 4.3 and compared with simulation data. It is difficult to observe their overall
 380 discretization, so a scatter plot of the prediction results in different input modes is plotted in
 381 this Section, as shown in **Figure 15**.



382
 383 **Figure 15.** The discrete scatter plot of prediction results with two models

384 According to **Figure 15**, comparing the SI-LSTM model with the MI-LSTM model under
 385 the different cases, it can be found that after adding two additional input factors, the discrete
 386 situation of the MI-LSTM model prediction results is significantly smaller than that of the SI-
 387 LSTM model prediction results. This phenomenon is more evident in the sway and heave of
 388 EC1, surge and sway of EC2, and sway and heave of EC3. The use of the MI-LSTM model is
 389 beneficial in reducing the discrete nature of predicted results.

390 In addition to the impact of discrete situations, the overall accuracy of the MI-LSTM
 391 model and the single-input model is also important. The individual statistics for predicting the
 392 final result of the FOWT motion response using both models are listed in Table 3. The overall
 393 accuracy of both models is presented in Figure 16.

Table 3. The accuracy of each statistic under the different input model

Mode	Statistics	EC 1				EC 2				EC 3			
		Heave	Pitch	Surge	Sway	Heave	Pitch	Surge	Sway	Heave	Pitch	Surge	Sway
Single- input 2.5 s	Max	73.2%	95.9%	99.9%	96.7%	96.2%	92.6%	95.3%	81.2%	84.3%	98.8%	97.8%	81.0%
	Min	92.3%	99.0%	96.2%	96.2%	93.4%	92.4%	93.0%	97.1%	96.8%	96.2%	92.4%	76.9%
	Average	99.7%	97.2%	99.8%	88.6%	95.6%	92.4%	98.5%	90.6%	96.9%	93.3%	96.5%	94.9%
	STD	87.5%	93.7%	94.3%	94.0%	97.7%	98.9%	83.7%	90.6%	96.0%	92.1%	93.5%	97.7%
	Overall	88.2%	96.4%	97.6%	93.9%	95.7%	94.1%	92.6%	89.9%	93.5%	95.1%	95.0%	87.6%
Multi- input 2.5 s	Max	73.2%	98.0%	97.6%	97.1%	97.4%	96.1%	96.8%	92.5%	95.8%	98.5%	99.4%	82.9%
	Min	96.0%	97.8%	95.8%	89.6%	93.3%	93.9%	98.2%	98.7%	98.3%	93.5%	96.6%	91.9%
	Average	97.5%	98.2%	99.4%	88.6%	96.0%	98.5%	98.9%	96.6%	99.2%	98.2%	99.0%	92.4%
	STD	97.3%	95.3%	96.8%	97.9%	97.8%	98.8%	95.6%	95.5%	96.6%	98.1%	94.9%	96.6%
	Overall	91.0%	97.3%	97.4%	93.3%	96.1%	96.8%	97.4%	95.8%	97.5%	97.1%	97.5%	91.0%
Single- input 5 s	Max	73.2%	92.5%	98.7%	83.2%	82.9%	95.9%	86.1%	81.1%	69.7%	88.9%	97.4%	67.9%
	Min	89.3%	93.0%	96.7%	92.2%	91.4%	80.1%	74.9%	94.4%	90.8%	89.5%	67.2%	74.3%
	Average	98.9%	97.7%	97.8%	75.0%	93.0%	89.0%	89.8%	91.7%	92.3%	93.5%	98.3%	92.9%
	STD	75.6%	81.5%	88.3%	82.6%	93.3%	89.8%	76.2%	78.7%	90.4%	87.3%	85.3%	70.2%
	Overall	84.3%	91.2%	95.4%	83.3%	90.1%	88.7%	81.8%	86.5%	85.8%	89.8%	87.1%	76.3%
Multi- input 5 s	Max	73.2%	93.3%	98.1%	76.8%	82.5%	98.2%	87.8%	80.8%	85.3%	89.1%	97.4%	82.1%
	Min	91.3%	95.1%	98.5%	98.4%	96.0%	76.5%	85.7%	94.4%	91.0%	94.3%	78.4%	89.0%
	Average	97.7%	95.5%	98.6%	83.7%	96.9%	89.8%	88.4%	91.9%	98.0%	97.5%	96.4%	89.3%
	STD	89.7%	86.2%	91.3%	85.3%	97.0%	98.0%	90.8%	81.0%	88.8%	91.6%	87.2%	93.2%
	Overall	88.0%	92.5%	96.7%	86.1%	93.1%	90.6%	88.2%	87.0%	90.8%	93.1%	89.8%	88.4%

Based on Table 3 and Figure 16, the results at PAT of 2.5 s present better agreements than at PAT of 5 s. After adopting the MI-LSTM model, the accuracy of the prediction results in pitch and heave has been significantly improved. With the increment of PAT, the period between input and output becomes larger, so the time correlation between the two decreases and the uncertainty increases. The upper limit of learning ability decreases as the correlation between input and output information decreases. Therefore, the accuracy at PAT of 5 s is lower than that of 2.5 s.

At the same time, the overall prediction result of the MI-LSTM model is better than the SI-LSTM model. The additional input factors increase the dimension of information, which enables the MI-LSTM model to explore more relationships between different input factors and the motion response of the target output. MI-LSTM model also adds more details to the final prediction results, improving the overall accuracy of the prediction results. In other words, there is a positive correlation between mooring force, wave elevation, and the motion response of the platform.

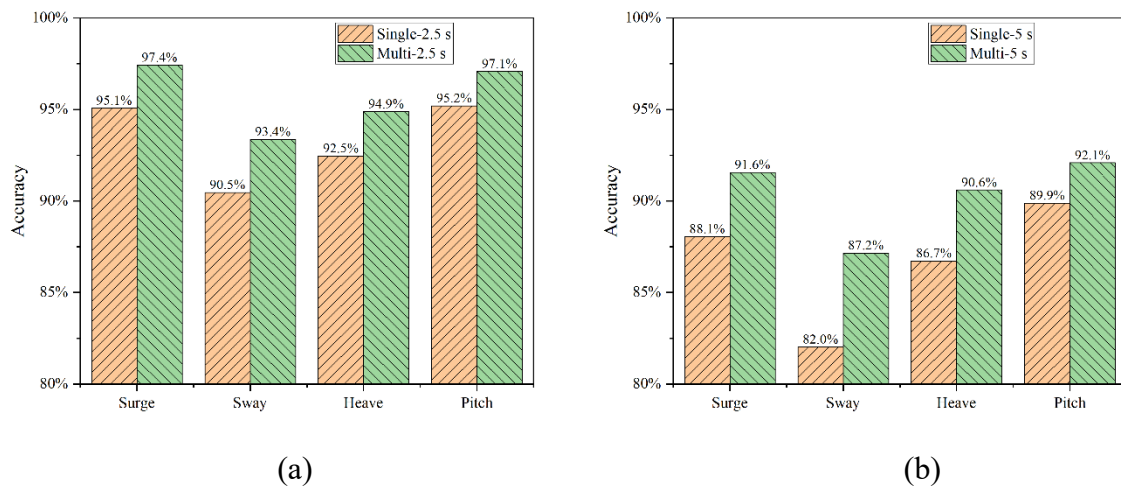
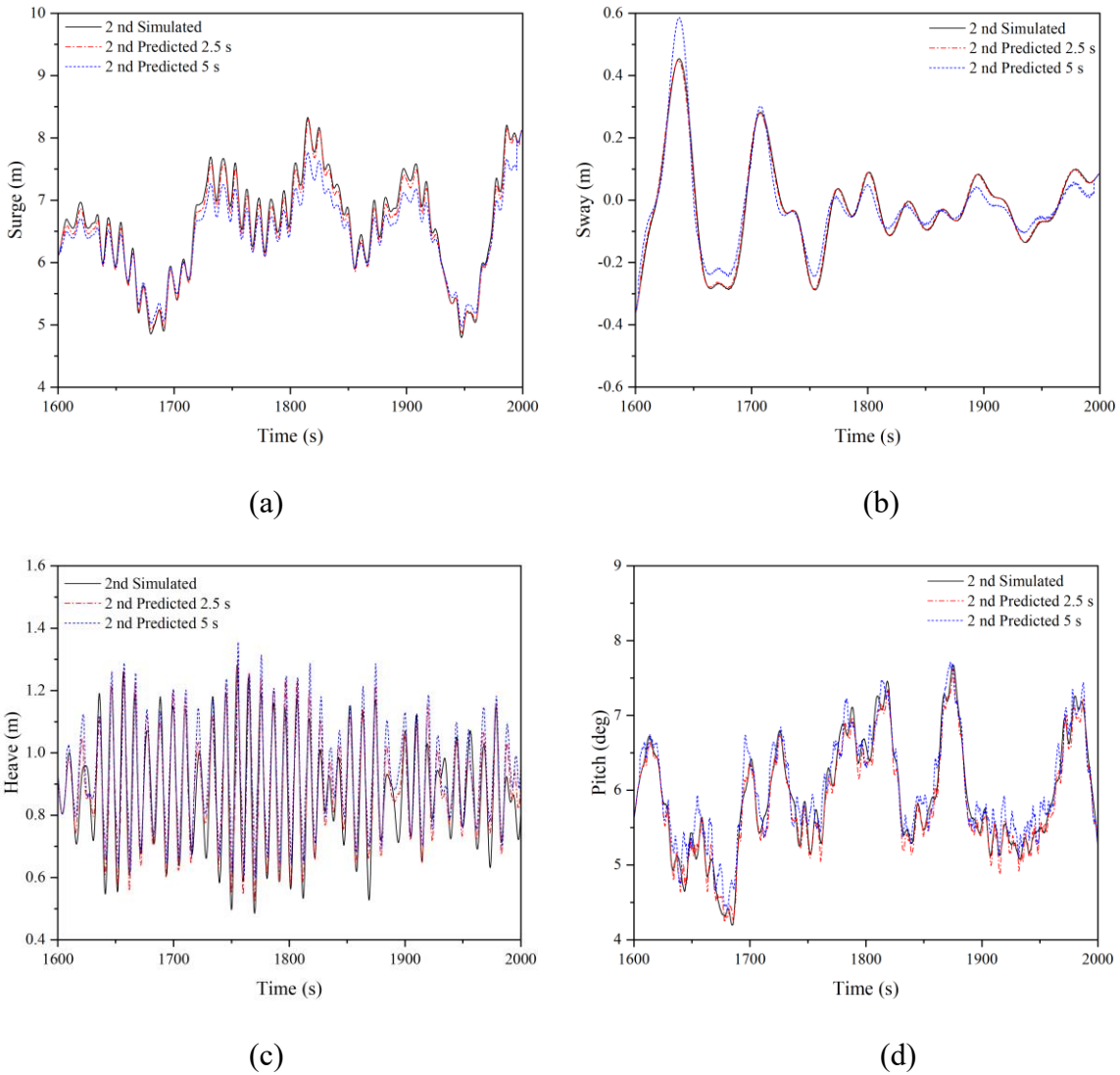


Figure 16. Overall accuracy under different PATs: (a) 2.5 s; (b) 5 s

414 **5. Second-order Hydrodynamic Effects**

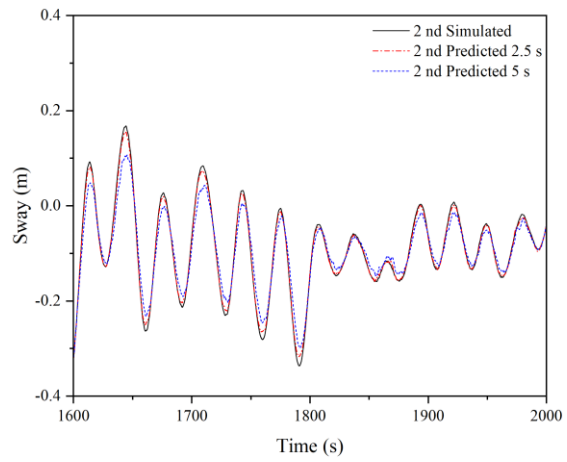
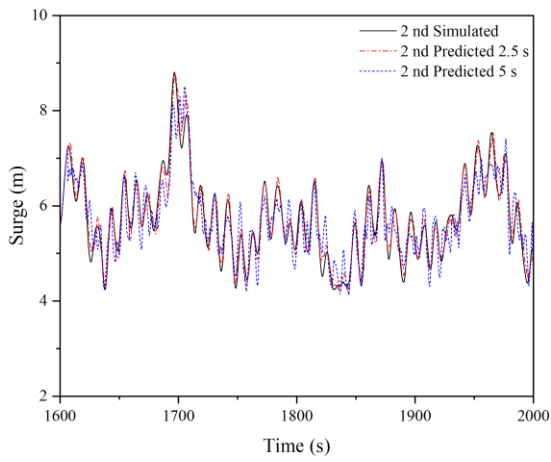
415 **5.1 Prediction results under the influence of second-order hydrodynamic effects**

416 The influence of second-order hydrodynamics is significant for the load prediction of a
417 FOWT [30]. EC1-EC3 are again simulated considering second-order hydrodynamic effects, the
418 simulation data is imported into the MI-LSTM model for training. The prediction results under
419 the second-order hydrodynamic force are obtained after the training, shown in **Figures 17-19**.



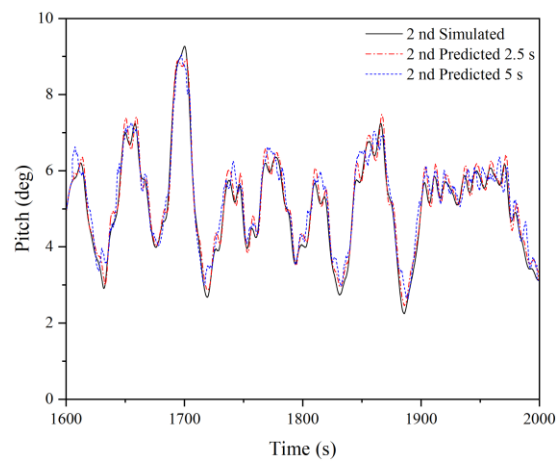
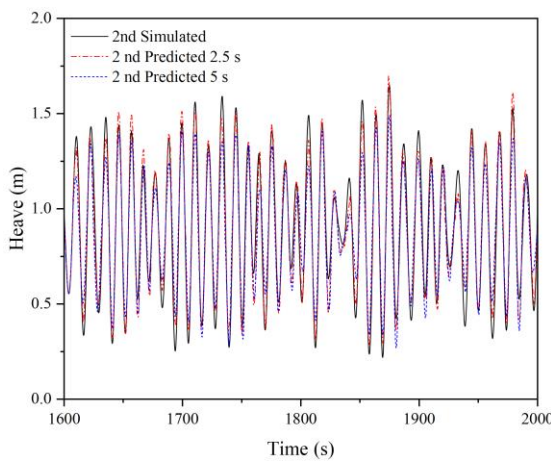
422 **Figure 17. Simulated and predicted values of EC 1 at 2.5 s and 5 s:**

423 (a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)

(b)

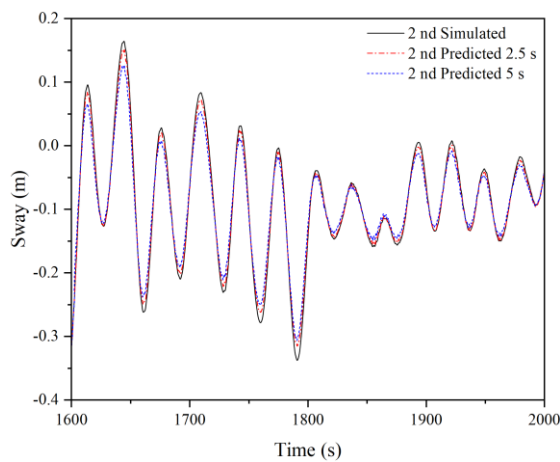
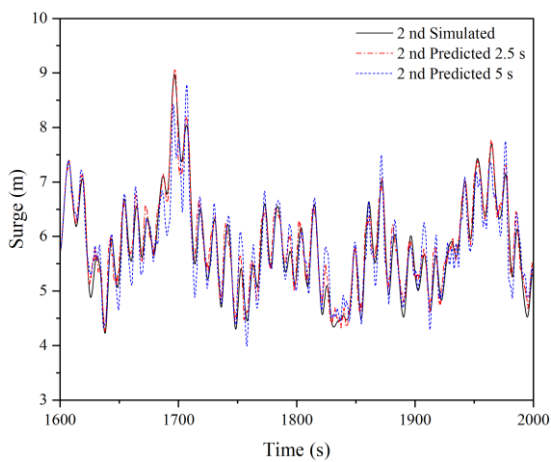


(c)

(d)

Figure 18. Simulated and predicted values of EC 2 at 2.5 s and 5 s:

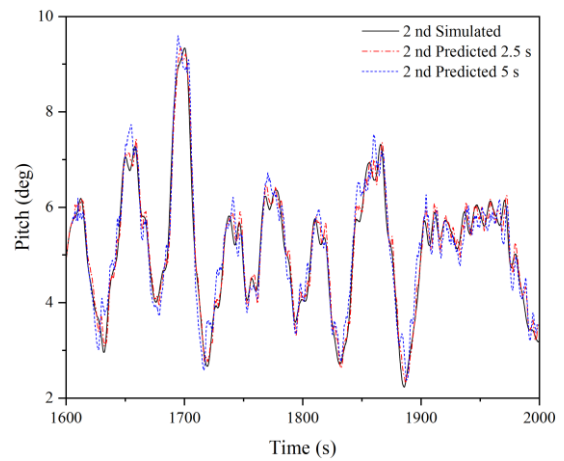
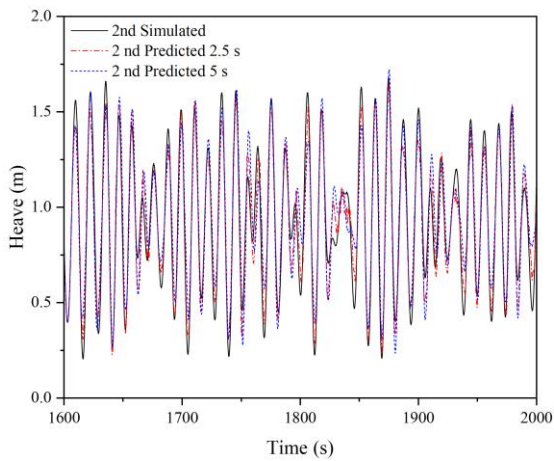
(a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)

(b)

434



(c)

(d)

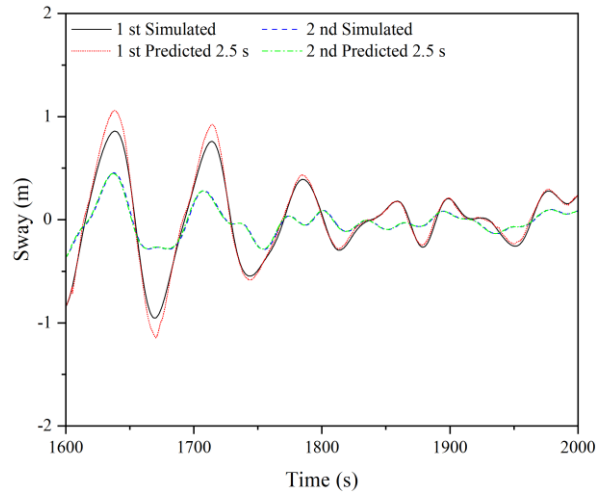
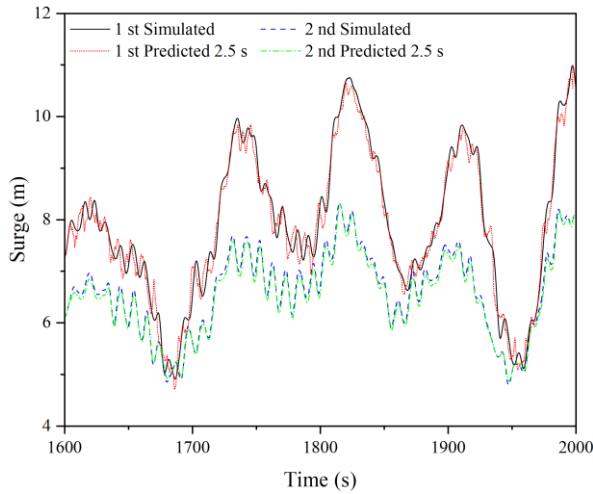
Figure 19. Simulated and predicted values of EC 3 at 2.5 s and 5 s:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

Figures 17-19 show that the peak fitting in all directions at 5 s is weaker than that of 2.5 s, similar to the case when the platform model is affected by first-order hydrodynamic forces. Compared with the first-order hydrodynamic influence, the prediction results under the second-order hydrodynamics show smaller fluctuations in both surge and pitch. On the other hand, the predicted value of sway is smooth, and there is no slight fluctuation. The error of prediction results in heave mainly occurs in peaks and troughs, but it is not obvious. The statistical accuracy in each direction, as well as the overall accuracy, is further analyzed in Section 5.2.

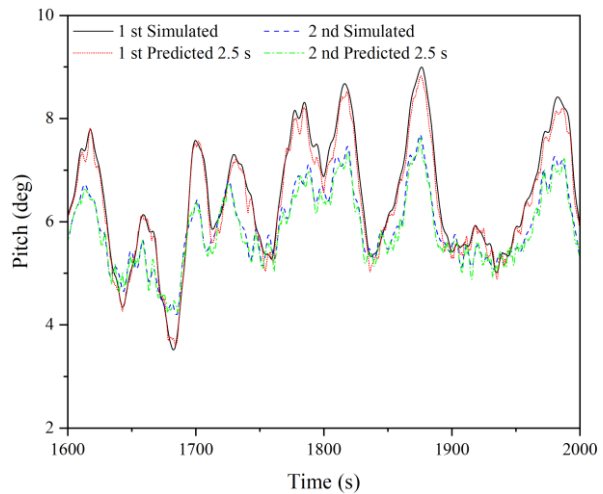
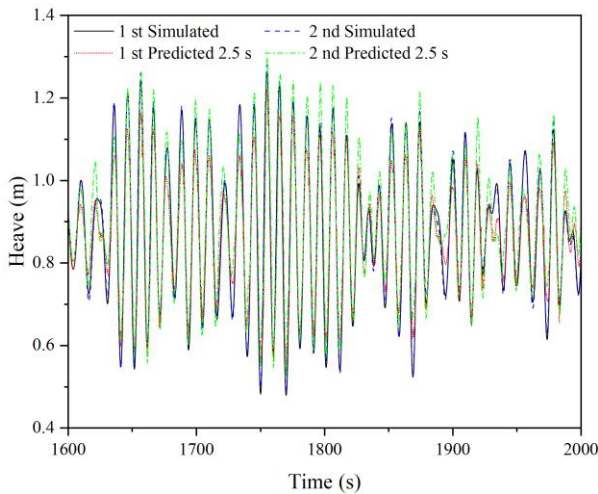
5.2. Error Analysis

To compare the short-term prediction effect of the MI-LSTM model in both first-order hydrodynamics and second-order hydrodynamics cases, the results of the PAT of 2.5 s under EC 1 are selected for comparison, shown in **Figure 20**.



(a)

(b)



(c)

(d)

Figure 20. Comparison of 1st-order and 2nd-order hydrodynamic prediction results:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

According to **Figure 20**, it is observed that the motion response exhibits a stronger nonlinear characteristic under the influence of second-order hydrodynamic forces. This phenomenon is particularly evident in the surge, pitch, and sway directions, where more nonlinear fluctuations appear at the extremes of the kinematic response in all three directions. The effect of second-order hydrodynamic forces did not have much influence in the heave direction.

463 At the same time, in the surge, sway and pitch directions, there are significant deviations
 464 in the predicted values at the extremes of the motion response for the first-order hydrodynamics
 465 case. While in the second-order hydrodynamics case, the MI-LSTM model has better prediction
 466 at both peak and trough values. In the heave direction, the motion response of the platform in
 467 the two cases does not differ much and does not have the nonlinear characteristics in the other
 468 three directions. Therefore, the prediction effect of the MI-LSTM model in the heave direction
 469 under the influence of second-order hydrodynamics is not significantly improved.

470 Under the influence of second-order hydrodynamics, this section also analyzes the
 471 individual statistics of the prediction results and calculates the overall accuracy of each
 472 direction of motion response, shown in **Table 4**.

Table 4. The accuracy of each statistic under the influence of second-order hydrodynamics

Mode	Statistics	EC 1				EC 2				EC 3			
		Heave	Pitch	Surge	Sway	Heave	Pitch	Surge	Sway	Heave	Pitch	Surge	Sway
Multi- input 2.5 s	Max	96.5%	99.4%	99.6%	98.7%	92.6%	96.3%	99.5%	92.2%	98.0%	98.9%	98.8%	91.8%
	Min	88.5%	99.2%	98.5%	99.1%	90.9%	90.7%	99.2%	97.0%	90.2%	96.2%	99.1%	94.9%
	Average	98.8%	98.8%	98.9%	96.5%	98.0%	97.6%	99.7%	99.0%	99.9%	99.0%	98.9%	99.2%
	STD	89.9%	96.2%	96.1%	98.6%	95.8%	96.5%	99.6%	94.6%	98.6%	99.2%	96.7%	92.8%
	Overall	93.4%	98.4%	98.3%	98.2%	94.3%	95.3%	99.5%	95.7%	96.7%	98.3%	98.4%	94.7%
Multi- input 5 s	Max	87.0%	99.5%	97.6%	71.0%	97.1%	97.5%	96.6%	63.4%	94.2%	97.2%	97.8%	77.1%
	Min	94.3%	95.5%	96.5%	97.5%	89.5%	82.5%	97.4%	97.0%	94.3%	93.4%	94.4%	94.9%
	Average	98.6%	98.1%	97.3%	80.7%	94.6%	96.5%	99.3%	98.2%	94.5%	98.8%	99.6%	99.0%
	STD	87.9%	92.3%	91.4%	98.1%	93.1%	92.5%	90.9%	80.4%	92.6%	98.0%	91.3%	84.1%
	Overall	92.0%	96.3%	95.7%	86.8%	93.6%	92.3%	96.0%	84.8%	93.9%	96.9%	95.8%	88.8%

474
 475 According to the results given in **Table 4**, it can be seen that the accuracy of the predicted
 476 results in all directions under the influence of second-order hydrodynamics is still at a high
 477 level, overall accuracy exceeds 90% at PAT of 2.5 s and 85% at PAT of 5 s. This phenomenon
 478 verifies the conclusions of Section 4 and confirms that an increase in PAT leads to a decrease
 479 in prediction accuracy.

480 The overall accuracy of the 4 degrees of freedom directions calculated from **Table 4** is

shown in **Figure 21**. At PAT of 2.5 s, the difference in prediction accuracy between the second-order hydrodynamics and the first-order hydrodynamics is more obvious in surge and sway. At PAT of 5 s, in the direction of surge, heave, and pitch, the prediction accuracy in the second-order hydrodynamics case is about 3% higher than that in the first-order hydrodynamics.

By comparing with the results in the first-order hydrodynamics in Section 4, it can be found that the MI-LSTM model in the second-order hydrodynamics case not only has a good ability to learn multi-factor relationships and platform response prediction but also has a higher prediction accuracy than the first-order hydrodynamics case.

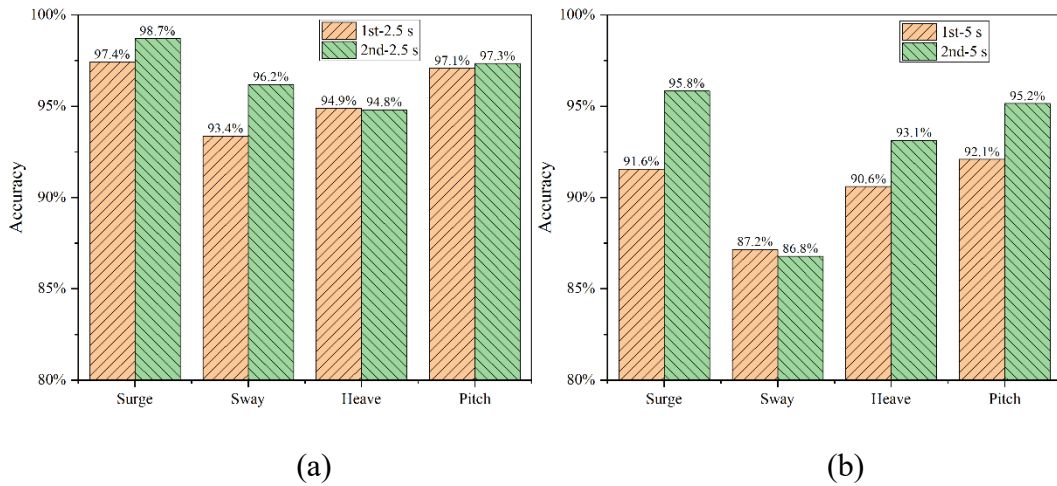


Figure 21. Overall accuracy under different PATs: (a) 2.5 s; (b) 5 s

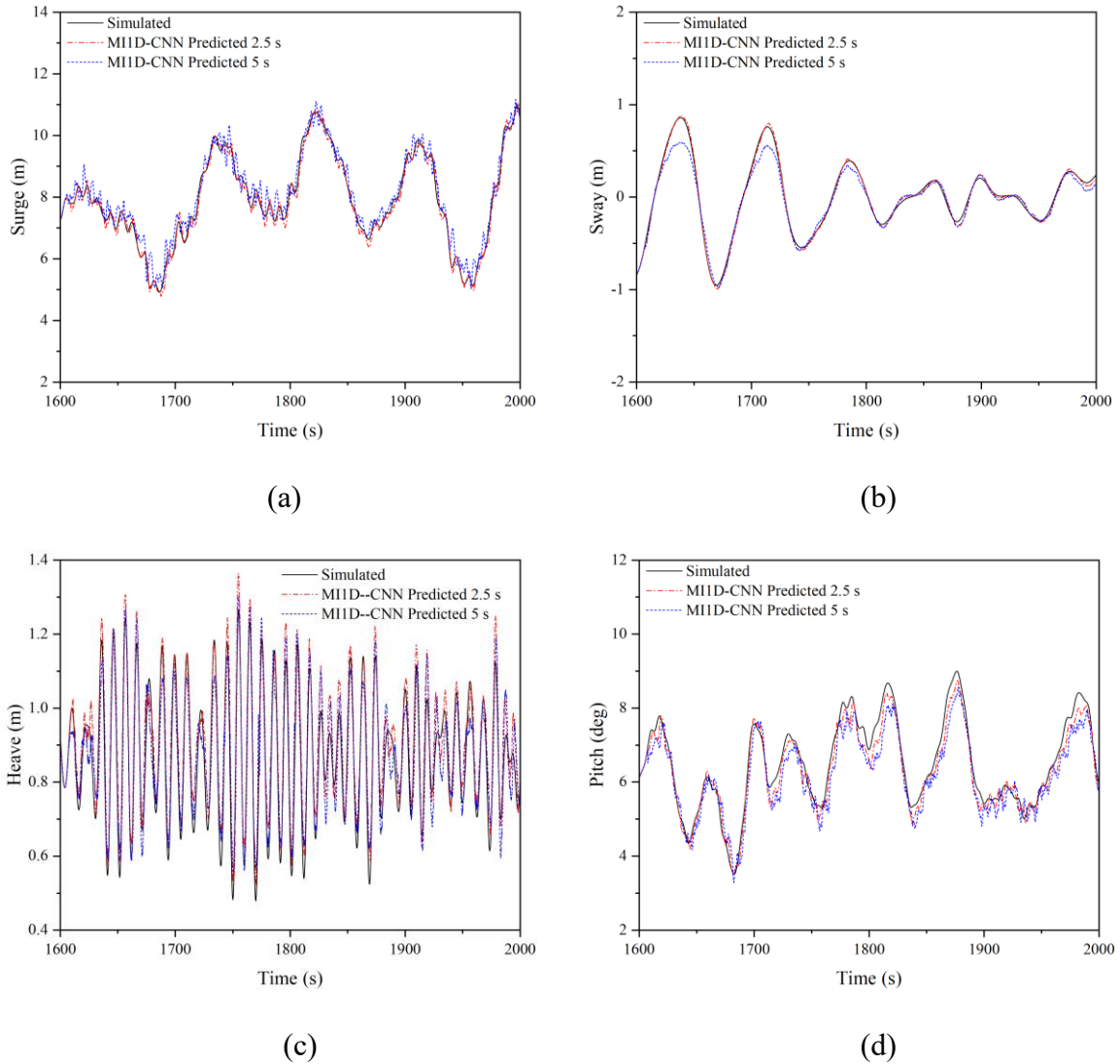
6. Comparison with the MI1D-CNN model

6.1 Predicted results with MI1D-CNN model

Currently, the mainstream deep learning methods mainly include the CNN method and the RNN method, and the MI-LSTM model established in Section 4 belongs to the RNN method. CNN methods are mostly used in image recognition and text recognition. As a representative method to deal with time series problems in CNN, a one-dimensional convolutional neural network (1D-CNN) has a certain effect on short-term prediction by adding a pooling layer.

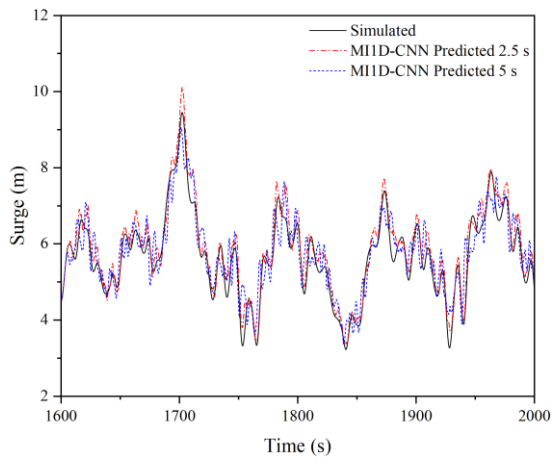
In this section, a multi-input one-dimensional convolutional neural network (MI1D-CNN)

501 is built to compare the CNN method with the LSTM method for the motion response prediction
1
2 502 problem, using the same training data as in Section 4. The training of the MI1D-CNN model is
3
4 503 completed, and the results obtained from the multi-input LSTM model are compared in Section
5
6 504 6.2 in terms of training time and overall accuracy. The prediction results obtained by the MI1D-
7
8
9 505 CNN model are shown in **Figures 22-24**.

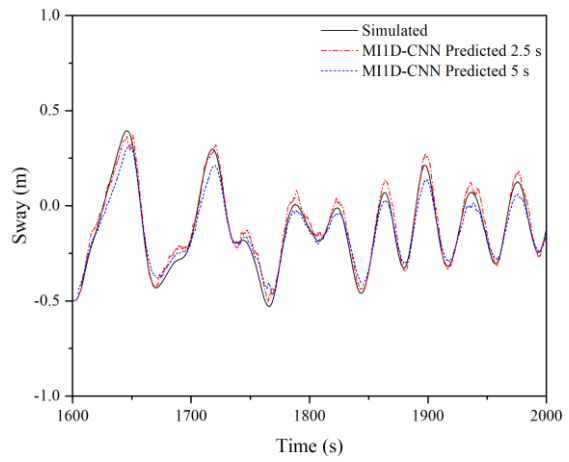


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510 **Figure 22.** Simulated and predicted values of EC 1 at 2.5 s and 5 s:

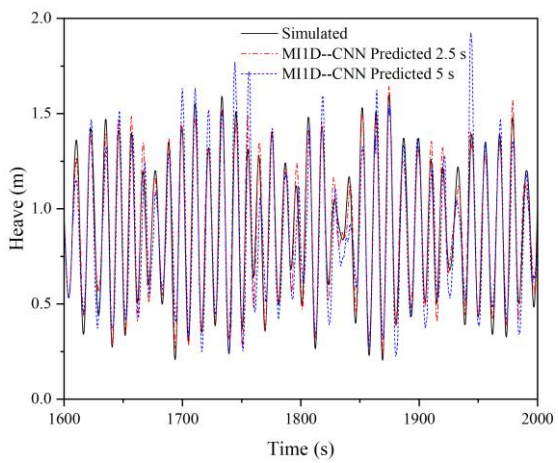
511 (a) Surge; (b) Sway; (c) Heave; (d) Pitch



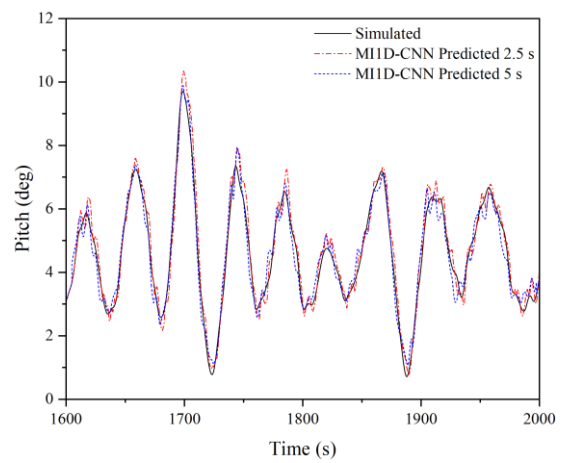
(a)



(b)



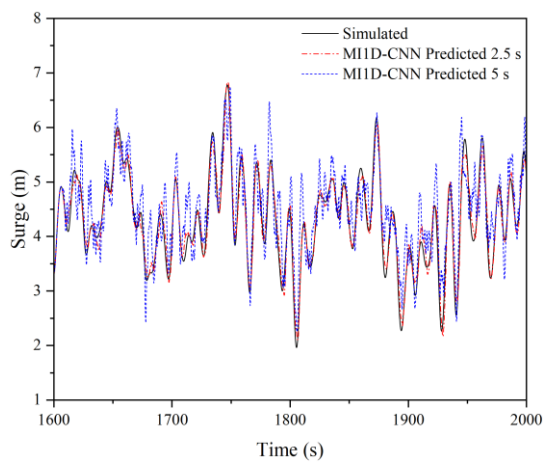
(c)



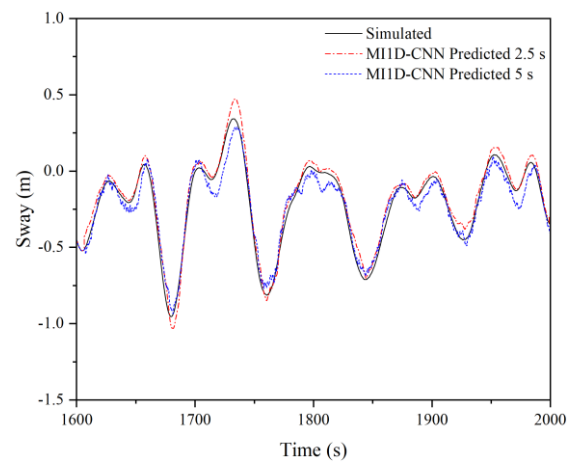
(d)

Figure 23. Simulated and predicted values of EC 2 at 2.5 s and 5 s:

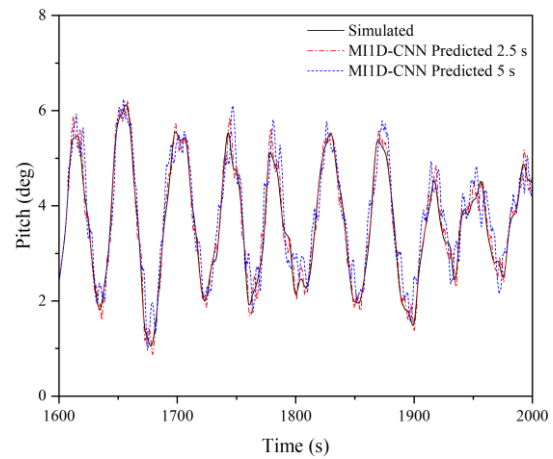
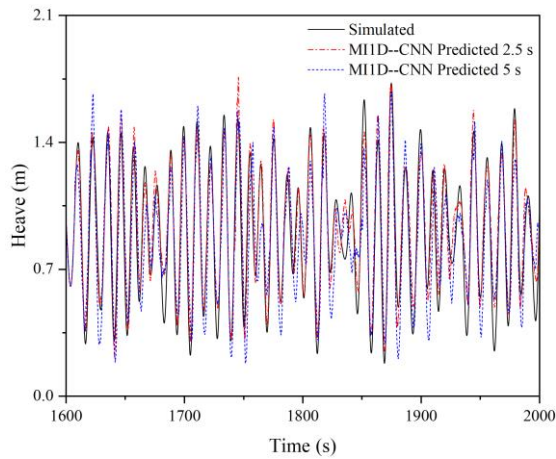
(a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)



(b)



(c)

(d)

Figure 24. Simulated and predicted values of EC 3 at 2.5 s and 5 s :

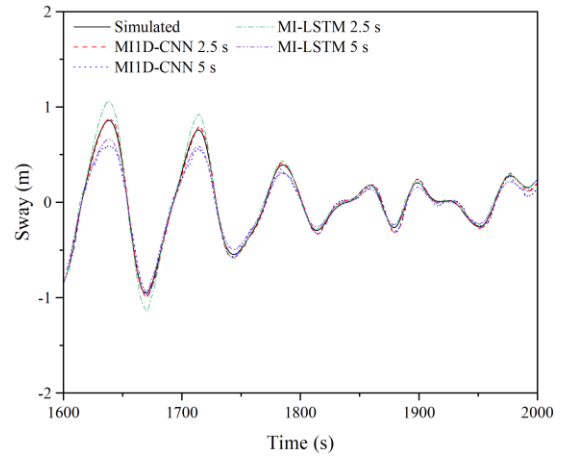
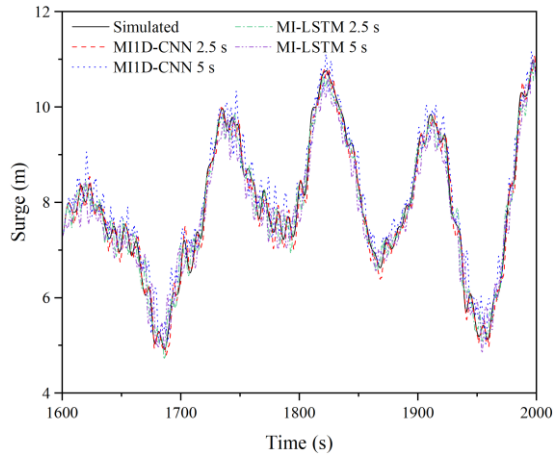
(a) Surge; (b) Sway; (c) Heave; (d) Pitch

According to **Figures 22-24**, and compared with **Figures 11-13** in Section 4.3, it can be found that the motion response predicted by the MI1D-CNN model produces a large number of serrations in surge and pitch of each environmental condition, especially at PAT of 2.5 s. At the same time, the prediction result at PAT of 5 s in sway does not fit well with the simulation results. To further compare the results of the MI-LSTM model with the MI1D-CNN model, it is further explained from the aspects of training time and overall accuracy in Section 6.2.

6.2 Comparison with Multi-input LSTM Model

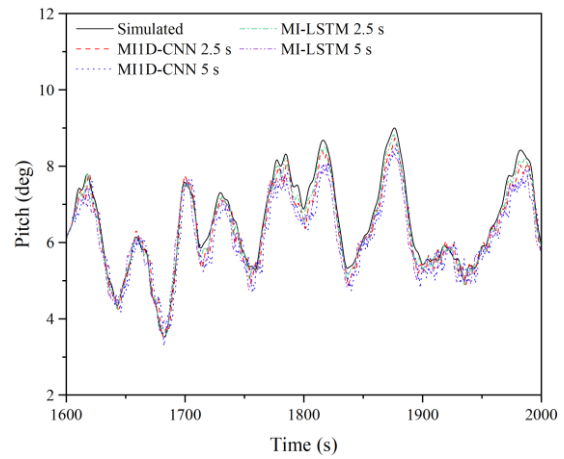
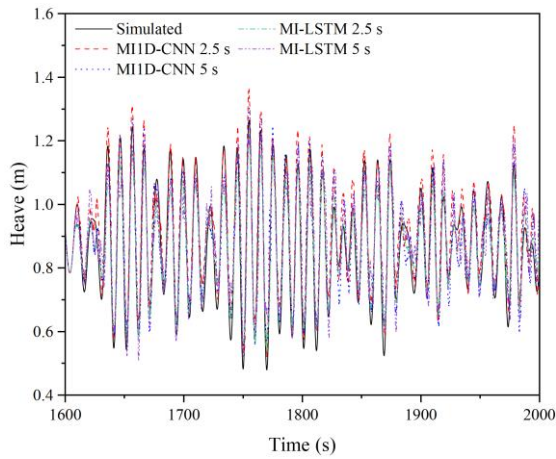
To further observe the imitative effect between the predicted values obtained by the two models and the simulated values, EC1 is selected and the results are summarized as shown in

Figure 25.



(a)

(b)



(c)

(d)

Figure 25. The results of the MI1D-CNN model and the MI-LSTM model are compared:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

According to **Figure 25**, from the overall imitative effect of the time series curve, the prediction results of both models fit well with the simulation results at PAT of 2.5 s. However, at PAT of 5 s, the result of the MI1D-CNN model is slightly inferior to the MI-LSTM model result, and when the PAT is at 5 s, the predicted value of the former has a large fluctuation. This volatility does not exist in the simulation value, particularly in **Figures 25(a)** and **(d)**. The time series of the platform response has a certain smoothness in sway, so both models' imitative effects are good. While the time series of the platform response itself is more volatile in heave, the imitative effects of the peak are not as good as in other directions.

To find out the difference between the MI1D-CNN model and the MI-LSTM model, the overall accuracy of the MI1D-CNN model is calculated by combining each operating condition. Then compare the overall accuracy of the MI1D-CNN model with the MI-LSTM model proposed in Section 4 and the result is shown in **Figure 26**.

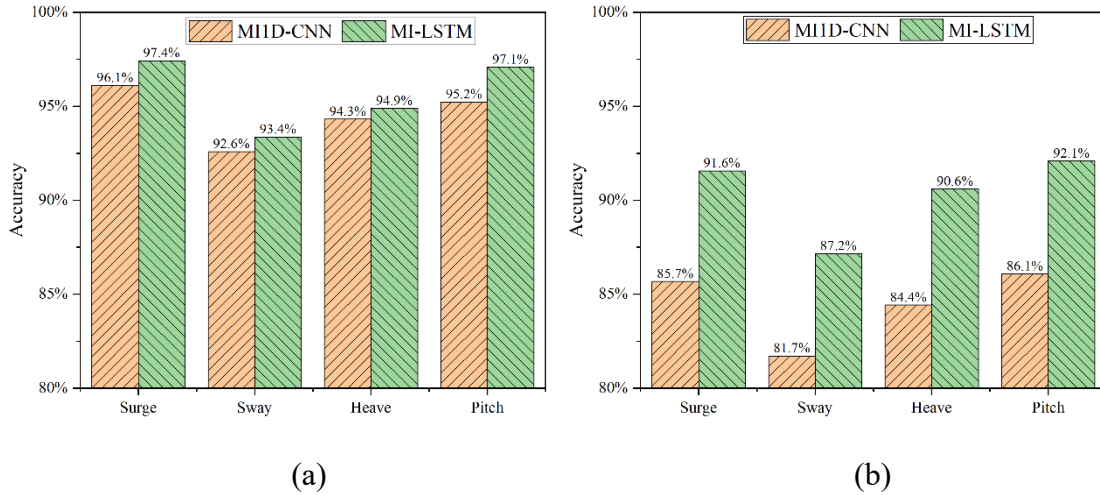


Figure 26. Comparison of the overall accuracy of different models in each direction:

(a) 2.5 s; (b) 5s

According to **Figure 26**, it can be found that there is no significant difference between the results of the two models when PAT is at 2.5 s, the overall effect of the MI-LSTM model is slightly better than the MI1D-CNN model, and the accuracy of the former is 1%-2% higher than the latter in all directions. But at PAT of 5 s, the situation is very different, the MI-LSTM model performs much better than the MI1D-CNN model, and the accuracy of the former is about 5% higher than the latter in all directions.

It can be seen that when the corresponding period of the prediction platform becomes longer, the traditional CNN model is not satisfactory, while the MI-LSTM model proposed in this paper performs well. Since 1D-CNN only performs convolution operations on time series information within the length of a convolution, heritability in time series information is only reflected in a single convolutional neuron. Therefore, when PAT is small, the effect on the MI1D-CNN model and the MI-LSTM model is insignificant. However, with the increase of

569 PAT, the disadvantage of the MI1D-CNN model in processing temporal genetic information
1
2 570 will become significant.
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4
5 571 In addition, the training time of the two models is also recorded, as shown in **Table 5**.
6
7 572 According to **Table 5**, the training time of the MI1D-CNN model is much shorter than that of
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9 573 the MI-LSTM model, which is related to the learning and calculation method of the model itself.
10
11 574 The training time of the MI1D-CNN model is short, but it sacrifices a part of the accuracy, and
12
13 575 the training time of the MI-LSTM model is relatively long, but the accuracy is greatly improved.
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17 576
18 577 **Table 5.** Statistics on the training duration of the two models
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Modes	PAT (s)	Epochs	Time (s)
MI-LSTM	2.5	50	912
	5	50	1053
MI1D-CNN	2.5	50	108
	5	50	157

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30 579 In summary, balancing training time and accuracy has always been an important issue in
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32 580 deep learning. If the goal is ultra-short-term forecasting of the FOWT motion response and the
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34 581 accuracy requirement is relatively low, the MI1D-CNN model can be chosen. However, to
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36 582 increase the time span of motion response forecasting and maintain the prediction accuracy,
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38 583 MI-LSTM model is a better choice.
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43 584 **7. Conclusion**

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45 585 Based on the motion response data of the Braceless platform, the MI-LSTM prediction
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47 586 model is established by the RNN deep learning method and is trained for different degrees of
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49 587 freedom under different environmental conditions. The accuracy of prediction results under
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51 588 different PAT and input methods are determined and compared using statistics. Based on the
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53 589 analysis and discussions, the conclusion can be made as follows:
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57 590 (1) Taking the previous data of platform motion response, mooring force, and wave
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59 591 elevation as input, after 50 rounds of training with two LSTM models, the Loss no longer
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592 decreases, resulting in accurate prediction results. The Loss of the MI-LSTM model is slightly
593 better than the SI-LSTM model. The MI-LSTM model more comprehensively learns the
594 relationship between multiple factors and the target output.

(2)Based on the established and trained LSTM neural network model, the prediction
596 results of the model fit well with the simulated value. The prediction accuracy with PAT at 2.5
597 s is slightly higher than the accuracy with PAT at 5 s and the overall performance of the MI-
598 LSTM model is better than the SI-LSTM model. The additional two factors can positively
599 improve the accuracy of the final prediction result.

(3) The established MI-LSTM model is applied to the situation where the platform is
601 affected by second-order hydrodynamics, and it is found that the model has a better predictive
602 effect on the response of the Braceless platform affected by second-order hydrodynamics. The
603 MI-LSTM model has a better performance for the case where the nonlinearity phenomenon is
604 more pronounced.

(4) The MI-LSTM model established in this paper is compared with the traditional MIID-
606 CNN model, and the advantages and disadvantages of the two models are clarified from the
607 aspects of training time and overall accuracy. When the PAT is small, the difference between
608 the results of the two models is not significant, while when the PAT increases, the results
609 obtained by the MI-LSTM model are better than those obtained by the MIID-CNN model.

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Short-term Motion Prediction of floating offshore wind turbine Based on Multi-input LSTM Neural Network

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Abstract: The motion response of an offshore floating wind turbine (FOWT) platform is closely related to the control operation regarding the safety of a wind turbine. It is affected by various factors such as sea state environments and mooring systems. In practice, how to predict the motion response of the wind turbine platform in the short term has always been a concern of engineering practice. At present, the development of deep learning technology has brought some potential solutions to this problem. In this paper, a Multi-Input Long-Short Term Memory (MI-LSTM) neural network method is proposed to predict the short-term motion response of a floating offshore wind turbine platform. Specifically, the numerical simulation of the 5MW Braceless platform is carried out under different environmental conditions, and the data of

24 platform motion response, wave elevation, and mooring force are selected as input variables.
25 Then the training and test groups are established after post-processing data. Subsequently, a
26 Single-Input LSTM (SI-LSTM) model and a Multi-Input LSTM (MI-LSTM) model are
27 established to learn the input data. After comparing the overall accuracy of the results, it is
28 found that the additional mooring force and wave elevation positively affects the platform
29 response prediction results. From the aspects of discreteness and overall accuracy, it is verified
30 that the established MI-LSTM model is also applicable, considering the influence of second-
31 order hydrodynamics. Lastly, compared with the prediction results obtained by the multi-input
32 one-dimensional convolutional neural network (MI1D-CNN), the advantages of the two
33 different models are expounded from the perspectives of training time and accuracy, which
34 provides ideas for the optimization of the FOWT motion response prediction model. This study
35 sheds insights on the short-term motion response forecast and platform positioning of a FOWT.
36 Short-term forecasts of a FOWT can be achieved under various sea conditions by combining
37 the global positioning system.

38 **Keywords:** Floating offshore wind turbine; deep learning; response prediction; multi-input
39 LSTM model; second-order hydrodynamic

40 1. Introduction

41 With the rapid development of the global economy, energy has become a critical factor in
42 determining social and economic development. To meet the Net Zero target by utilizing
43 sustainable energy, the vigorous growth of renewable energy has become an essential part of
44 the development strategy worldwide. Due to its high energy conversion ability, offshore wind
45 power has been gradually installed in various countries recently. Different foundations of
46 floating offshore wind turbines have been proposed, including spar, tension leg platform (TLP)
47 shape, semi-submersible, and barge [1]-[3]. Substantial research has been carried out in terms
48 of hydrodynamics, mooring systems, stability, performance, and survivability of a FOWT [4]-

49 [9].

50 Compared with the onshore wind turbine structure, a FOWT encounters a more complex
51 ocean environment. The motion response of a FOWT occurs in six degrees of freedom (6DOF)
52 and leads to significant challenges in design and assessment [10]. Therefore, it is of great
53 significance to propose an accurate prediction method for the motion response of the FOWT to
54 guide the design and assess structural safety. In the deep learning model, motion response
55 prediction is generally based on the historical data of motion response and many other results
56 from numerical and experimental measurements. In general, deep learning technology is
57 applied to predict the motion response of structures in the next few seconds [11]. According to
58 the length of the forecast time, motion response prediction can be categorized as short-term and
59 safe-period motion prediction. Short-term prediction plays a vital role in improving dynamic
60 positioning control performance, and it provides early warning in extreme sea conditions to
61 reduce platform damage to a certain extent. A short-term forecast's prediction advanced time
62 (PAT) is generally a few seconds, and it requires high forecast accuracy [12].

63 In recent years, the application of deep learning technology in offshore structures has
64 gradually expanded. The research is mainly carried out by the convolutional neural network
65 (CNN) and the recurrent neural network (RNN) methods [13]-[21]. Wang et al. [14] proposed
66 the Low-frequency adds wave-frequency responses (LAWR) method to predict the mooring
67 line tension of a semi-submersible platform. Combined with the LSTM method, accurate results
68 are obtained to predict mooring line tension under different cases. Pena et al. [18] proposed the
69 Wave-Generative Adversarial Network (Wave-GAN) technology, combined with CNN
70 convolutional neural network and CFD method, to predict the load of nonlinear waves on fixed
71 structural columns. Pena et al. [18] concluded the maximum error between the Wave-GAN
72 predicted value and CFD simulated value of 1.5%-2% by adjusting several parameters, and the
73 mean absolute error (MAE) of the test group is about 0.014. Lian et al. [19] constructed the

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74 digital twin of mesh clothing and established the deep neural network (DNN) to predict whether
75 the mesh clothing is damaged. The average accuracy of the final identification model is 94.3%.
76 Bjørni et al. [20] predicted the mooring line tension in the next 30 s by making use of the
77 platform motion response in the first 60 s as input and constructed a three-layer deep neural
78 network with bias term. It is concluded that the average error of anchor chain tension is 0.46%
79 through cross-sectional comparisons. According to the combined prediction method of the
80 Extreme Learning Machine (ELM), the Empirical Mode Decomposition (EMD), and LSTM
81 neural network, Zhang et al. [21] proved that the combined prediction method presented higher
82 prediction accuracy than the single LSTM model and ELM-LSTM model. However, when
83 considering the influence of environmental factors and mooring force, there is limited research
84 on predicting the motion response of a FOWT. At the same time, in practice, it needs to assess
85 the motion response of a FOWT under the influence of various complex factors and consider
86 the impact of second-order hydrodynamic force. Moreover, the amount of research on the
87 motion response prediction of a FOWT under the effect of the second-order hydrodynamic force
88 is also limited.

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89 To investigate the short-term motion prediction of a FOWT, the MI-LSTM Neural
90 Network model is used. This paper is organized as follows: Section 2 introduces the basic
91 principles of the RNN. The architecture and differences between the established SI-LSTM
92 model and the MI-LSTM model are explained in detail. The hyperparameters of the model and
93 the selection of the training and test groups are also given in this section. Then, in Section 3,
94 the structure size of the 5 MW Braceless platform model is shown. A detailed comparison is
95 made between the prediction results of the SI-LSTM and MI-LSTM models under different
96 environmental conditions in Section 4. This proves the positive excitation of the increased input
97 factor numbers on the prediction results and illustrates the advantages and benefits of the MI-
98 LSTM model. In Section 5, the applicability of the proposed model is demonstrated when the

99 second-order hydrodynamic force is considered. Given that there are few comparisons between
100 the RNN model and CNN model regarding time domain problems, in Section 6, by comparing
101 the prediction results of the proposed model with the multi-input one-dimensional
102 convolutional neural network (MIID-CNN) model, the advantages of the two models are
103 illustrated from the perspectives of overall accuracy and training time. Finally, the conclusions
104 and recommendations are made for the future optimization of the platform response prediction
105 model.

106 **2. Long-Short Term Memory (LSTM) Neural Network**

107 **2.1. Recurrent Neural Network (RNN)**

108 Recurrent neural network (RNN) is gradually emerging in the interdisciplinary field as a
109 typical representative of deep learning technology. RNN takes time series data as input and
110 performs recursion in the evolution direction of the sequence, where all nodes (cyclic units) are
111 linked in a chain [22]. RNN has memorization, parameter sharing, and turning completeness
112 [23]-[25], so it has clear advantages in learning the nonlinear features in sequences. RNNs are
113 widely used in natural language processing, such as speech recognition, language modeling,
114 and time series prediction. RNN performs outstandingly in solving scheduling problems, and
115 motion response prediction is the typical time domain problem. Therefore, in this paper, RNN
116 is selected for model architecture.

117 Since the motion of the platform at time t is affected by the motion at the previous time
118 $t - 1$, meanwhile, the motion at current time t will also have an impact at forward time $t + 1$,
119 platform motion response is a continuous process with time dependence. Considering this
120 characteristic, the traditional deep neural network (DNN) cannot convey information precisely
121 in the time sequence, but the RNN is developed to overcome this problem. Training input data
122 from a FOWT system to predict the motion response in the next few seconds can be viewed as
123 an adaptive function mapping. The input is the previous time series information of different

124 input factors, and the output is the motion response in the future. Hence, the trained deep
 125 learning model can achieve prediction in a short time.

126 The timeline expansion of the RNN is shown in **Figure 1**, where x is the network input
 127 layer, s is the network node hiding layer, and o is the network node output layer. After the
 128 network receives the input x_t at time t , the value of the hidden layer is s_t and the output
 129 value is o_t . The value of s_t depends not only on x_t , but also on s_{t-1} . In other words, s
 130 inherits the information from each node.

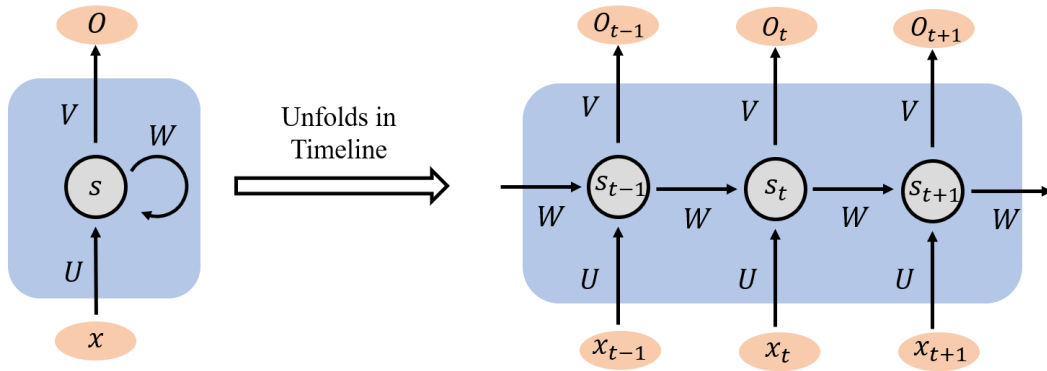


Figure 1. An unfolded RNN network

133 The calculation method of the RNN network is shown in Equations 1-2:

$$o_t = \mathbf{g}(\mathbf{V} \cdot s_t) \quad (1)$$

$$s_t = \mathbf{f}(\mathbf{U} \cdot x_t + \mathbf{W} \cdot s_{t-1}) \quad (2)$$

136 where \mathbf{V} is the weight matrix of the output layer, \mathbf{g} is the activation function for the output layer,
 137 \mathbf{U} is the weight matrix of the input layer x , and \mathbf{W} is the weight matrix of the last value, which
 138 is the input of the present time, and \mathbf{f} is the activation function for the hidden layer. Common
 139 activation functions, such as sigmoid, tanh, Rectified Linear Unit (ReLU), and linear activation
 140 function, can be selected according to data characteristics and experimental effects. The
 141 sigmoid activation function is generally selected for hidden layer activation function \mathbf{f} , while
 142 the linear activation function is generally chosen for output layer activation function \mathbf{g} . Equation
 143 1 is the calculation formula of the output layer. The output layer is fully connected, indicating

144 that every node in the output layer is connected to every node in the hidden layer. Equation 2 is
 145 the calculation formula of the hidden layer.

2.2. Long-Short Term Memory (LSTM) Network

147 LSTM is first proposed by Hochreiter and Schmidhuber [25]. Compared with traditional
 148 RNN, the LSTM network has improved the gradient explosion and gradient extinction. It has
 149 been one of the most popular RNN models and is widely applied in many fields, such as speech
 150 recognition, image description, and natural language processing. The internal structure of the
 151 LSTM node is shown in **Figure 2** [27].

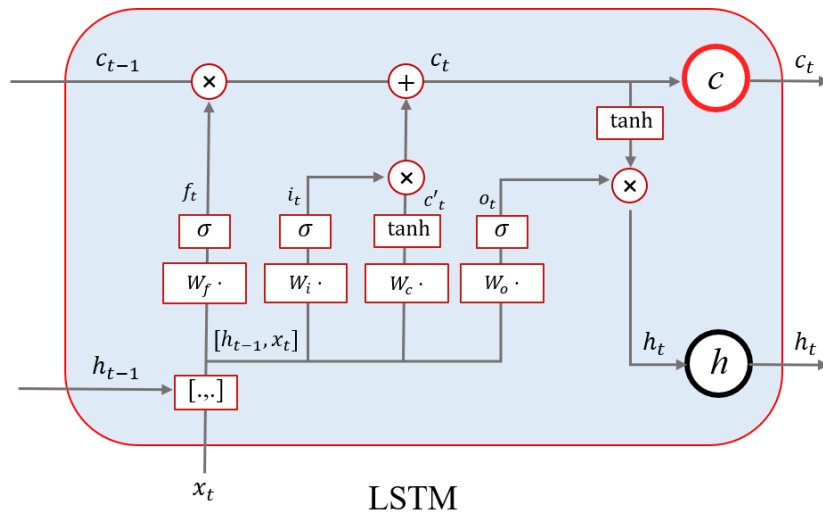


Figure 2. LSTM node unit internal structure

152
 153
 154 At time t , the LSTM network has three inputs: current time input value x_t , LSTM output
 155 value h_{t-1} at the last time, and the unit state c_{t-1} at the previous time. The output of LSTM
 156 has two parts: the output value of LSTM at the current time h_t , and the unit state at the current
 157 time c_t . x , h , and c are vectors. In addition, LSTM uses the concept of a Gate to control the
 158 state of the unit [27]. Gate is a full connection layer that controls information transmission
 159 between input and output. Its input is a vector of time series information, and its output is a
 160 vector of real numbers between 0 and 1. The gate can be expressed as:

$$G(x) = \sigma(W \cdot x + b) \quad (3)$$

162 where \mathbf{W} is the weight matrix of the gate, \mathbf{b} is the bias term, and σ is the generally sigmoid
 163 activation function.

164 The output vector of the gate is multiplied by the element and the vector is controlled to
 165 achieve the gate effect. The gated output is a vector of real numbers between 0 and 1. When the
 166 gated output is 0, any vectors multiplied by the output will get the 0 vectors, indicating that no
 167 information can pass through. When the gated output is 1, no changes are applied by multiplying,
 168 indicating that any information can pass through. Because σ has a range of (0,1), the gate is
 169 an intermediate state.

170 LSTM relies on two gates to control the content of the cell state: (1) one is the forget gate
 171 that determines the amount of the cell state c_{t-1} at the last moment. c_{t-1} is used to retain the
 172 current moment c_t ; (2) one is the input gate that determines the amount of the current network
 173 input x_t , which is saved to the unit state c_t . Meanwhile, LSTM uses an output gate to control
 174 the amount of unit state c_t that is generated from the current output value h_t . The governing
 175 equations of each gate are given as follows:

$$f_t = \sigma(\mathbf{W}_f \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_f) \quad (4)$$

$$i_t = \sigma(\mathbf{W}_i \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_i) \quad (5)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tanh(\mathbf{W}_c \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c) \quad (6)$$

$$o_t = \sigma(\mathbf{W}_o \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_o) \quad (7)$$

$$h_t = o_t \cdot \tanh(c_t) \quad (8)$$

181 where f_t is the forgetting gate equation, \mathbf{W}_f is the weight matrix of the forgetting gate,
 182 $[\mathbf{h}_{t-1}, \mathbf{x}_t]$ is joining two vectors into a longer vector, \mathbf{b}_f is the biased term of the forgetting gate,
 183 i_t is the input gate equation, \mathbf{W}_i is the weight matrix of the input gate, \mathbf{b}_i is the offset term
 184 of the input gate, c_t is the current moment element state equation, o_t is the output gate control
 185 equation, h_t is the final output equation determined by the output gate and unit state.

186 The unique Gate structure in the LSTM model effectively improves the phenomenon of

187 gradient explosion and gradient disappearance. the activation function of the gate structure in
 188 the LSTM model is the sigmoid function, and the Sigmoid function controls the value of the
 189 forgetting gate between 0 and 1. When the output of the gate is 1, the forgetting gate is saturated,
 190 at this time the long-range information gradient does not disappear, and the gradient can be well
 191 passed in the LSTM, largely mitigating the probability of gradient disappearance occurring;
 192 when the output of the gate is 0, at this time the model is blocking the gradient flow and
 193 forgetting the previous information, indicating that the information of the previous moment
 194 does not affect on the current moment. Through the gate structure and sigmoid activation
 195 function, the LSTM model can effectively solve the gradient disappearance and gradient
 196 explosion problems.

Existing LSTM network prediction modes mainly fall into the following four types [28]:
 point-to-point, point-to-sequence, sequence-to-point, and sequence-to-sequence, as shown in

Figure 3:

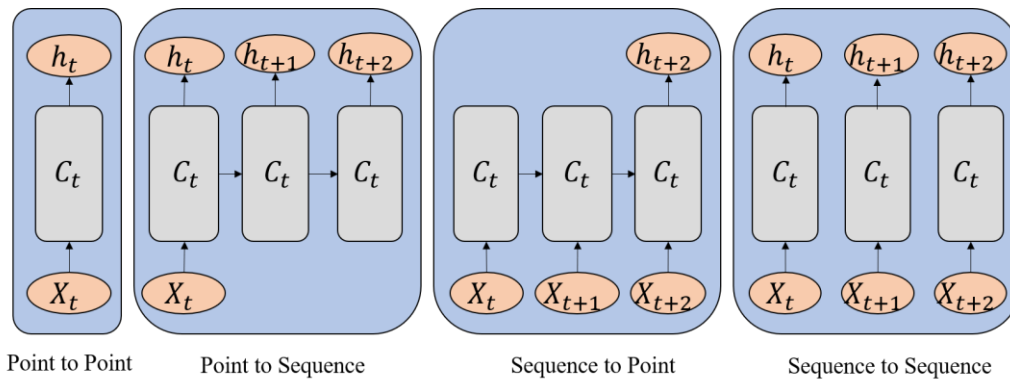


Figure 3. LSTM network prediction modes

The LSTM network in this paper is set up by using sequence-to-point mode for a prediction
 model, which uses forecasting point response from previous time series after the selected data
 input mode is adopted in the form of the sliding window. Each window length has 200 time
 points and the 10 s surge motion. The sliding window form is shown in **Figure 4**, where the
 mapping relationship between the data input and output is presented when the forecast time is
 5 s. Therefore, the response at $t + 5$ is predicted based on the response from $t-10$ to t .

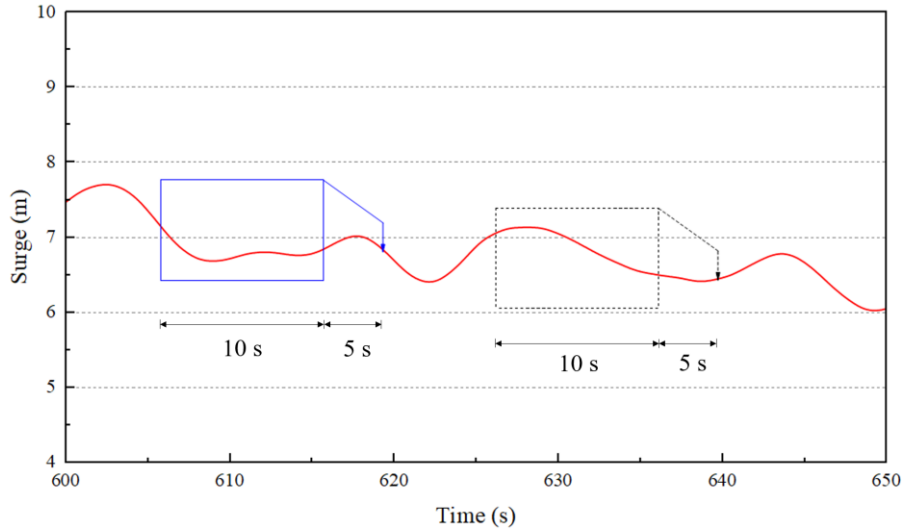


Figure 4. Sliding windows for data input and output

2.3. LSTM Model Structure

The LSTM network model established in this paper has three hidden layers and one fully connected output layer, shown in **Figure 5**. The data sampling frequency is 20 Hz. The input time step of the LSTM network contains 200 time series points with a motion response of 10s. The batch size is set to 256 sample sets, which are also the input for training and updating internal parameters. The number of neurons is set to 200. These two parameters are hyperparameters and can be adjusted according to the performance of the actual test.

Input layer: input time series with a window of 200 data points, representing the motion response of 10s. The input dimension of the single-input model is 1, and that of the multi-input model is 3.

Hidden layer: The hidden layer has 200 nodes.

Output layer: The output layer is dense, the activation function is linear, and the output result is the motion response at the target time.

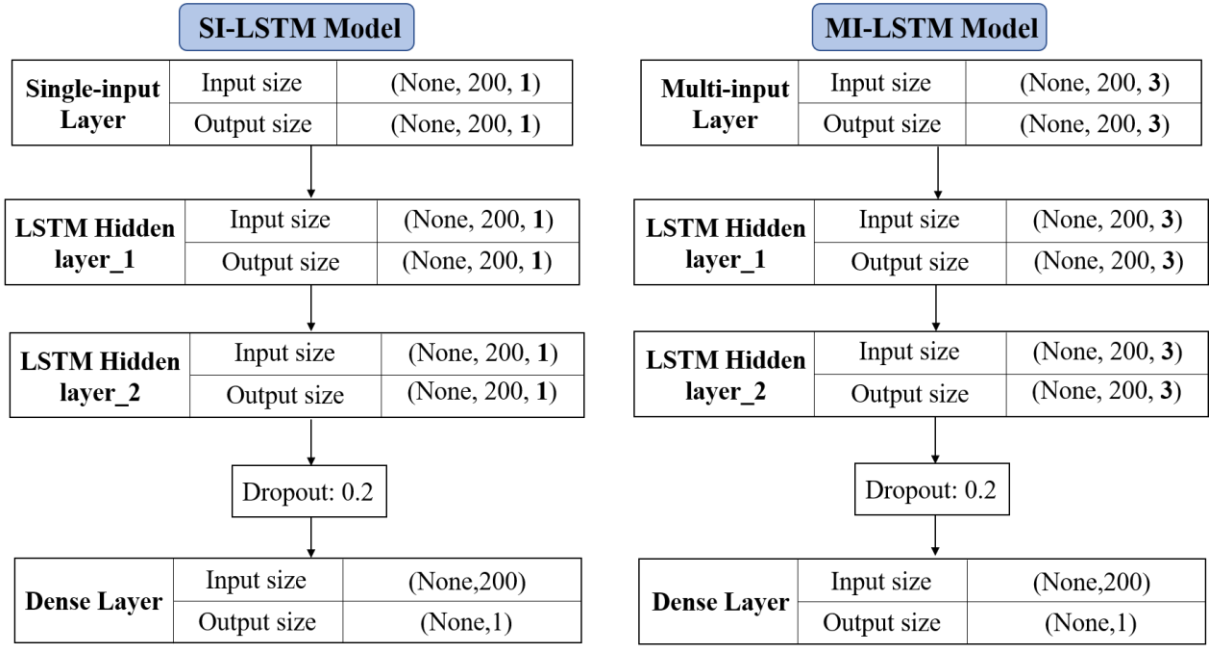


Figure 5. LSTM network model structure and data transfer format

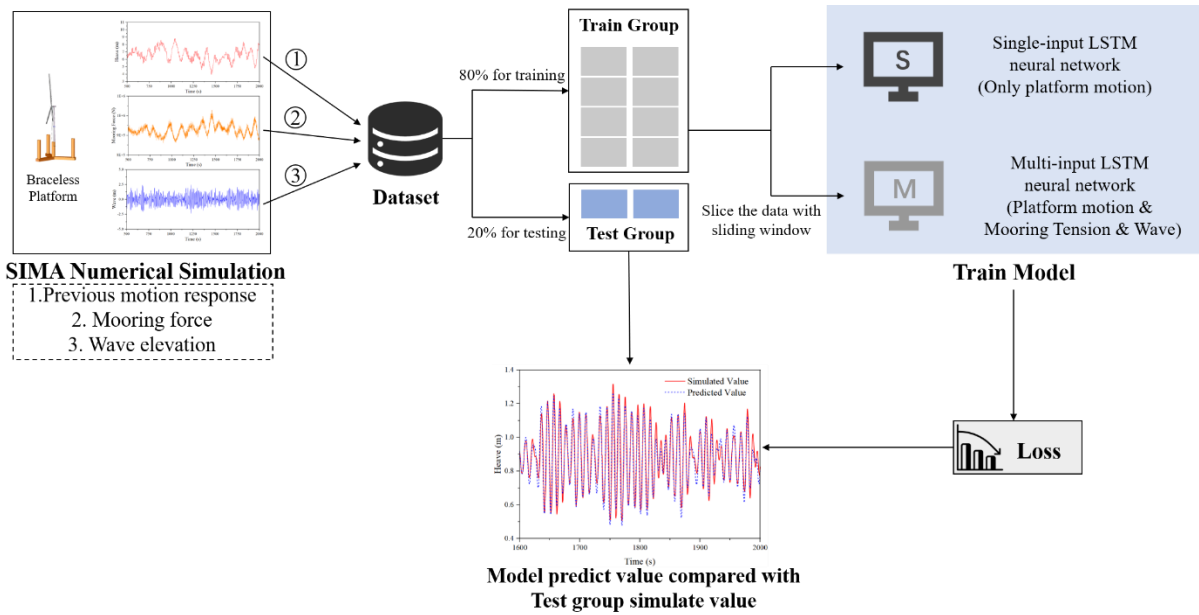
The Adam algorithm is configured for the LSTM network [30]. Adam algorithm is an advanced Stochastic Gradient Descent (SGD) algorithm, which introduces an adaptive learning rate for each parameter. The adaptive learning method and the Momentum method are combined. The learning rate is dynamically adjusted by the first and second moment estimation of the gradient. The gradient descent process is relatively stable and suitable for most non-convex optimization problems in large data sets and high-dimensional space.

Simultaneously, the Dropout layer is added after the input layer and the hidden layer to prevent overfitting [31-[32], and the Dropout_1 and Dropout_2 are set to 0.2. Overfitting may occur due to a large number of unknown network parameters or training times. The principle of dropout is that during the neural network training, some neurons are randomly discarded and not used for training at this round to avoid overfitting and accelerate loss convergence.

In this paper, the LSTM neural network is constructed, and the input data consists of three parts, including time series of previous motion response, mooring force, and wave elevation. And the current motion response is set as the output data. The process of using the LSTM neural network model to predict the motion response is shown in **Figure 6**. The process of predicting

240 motion response by LSTM neural network.

241



242

243 **Figure 6.** The process of predicting motion response by LSTM neural network

244 3. Braceless Platform model

245 The 5 MW Braceless model is established by SIMA, and the time domain response is
 246 obtained by numerical simulation. SIMA is developed for the analysis of flexible marine riser
 247 systems, but it is also suited for any slender structures, such as mooring lines, umbilicals, steel
 248 pipelines, and conventional risers. The data used in training in this paper came from the FOWT
 249 model of a 5 MW Braceless semi-submersible platform in the water depth of 100 m. The
 250 Braceless platform consists of one central column, three side columns, and three pontoons,
 251 shown in **Figure 7**.

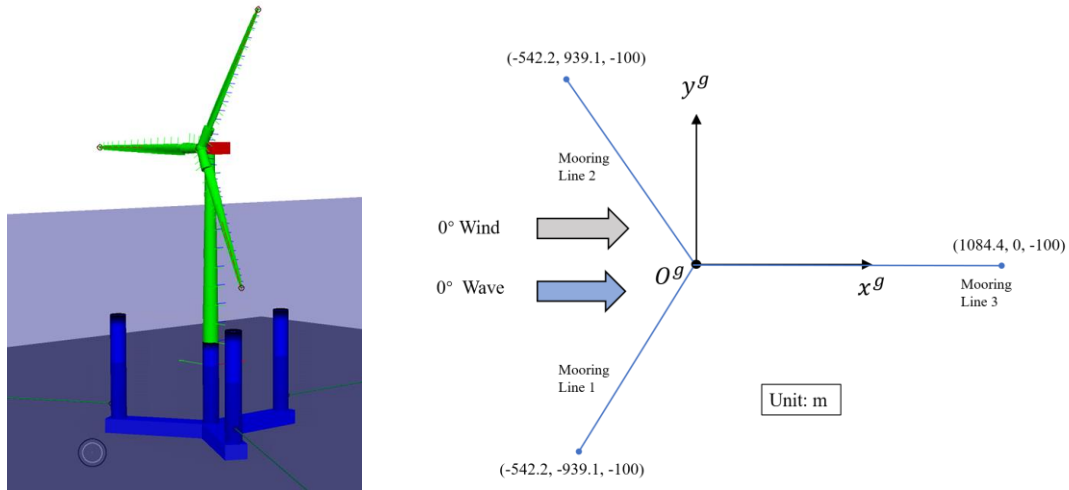


Figure 7. Schematic of 5-MW Braceless platform

Three side columns are evenly distributed around the central column at 120° . They are connected to the bottom of the central column by a floating buoy to form a Braceless semi-submersible platform. The three-point mooring system is adopted, and the anchor chain is set at the bottom of the side column. 0° wave-wind misalignment is considered in the simulation. The main parameters of the Braceless platform are shown in **Table 1**. Parameters of the 5 MW Braceless Platform:

Table 1. Parameters of the 5 MW Braceless Platform

Parameter	Value
Central column diameter (m)	6.5
Side column diameter (m)	6.5
Buoy height (m)	6
Buoy bottom width (m)	9
Buoy short radius (m)	41
Buoy long radius (m)	45.5
Depth of the draft (m)	30
Displacement (t)	10555
Steel weight (t)	1804

Based on the data given in Ref. [33], site 5 in Norway was selected as a representative site for the simulation. In the following cases, the water depth is 100 m. The average wind speed V_t , effective wave height H_s , and spectrum peak period T_p at the selected cabin height are listed. The JONSWAP spectrum is used to describe random ocean waves, and the JONSWAP spectrum is shown in Equations 9-1 to 9-3. The Kaimal wind speed spectrum is used to describe the offshore wind conditions.

$$S_{(f)} = \alpha \frac{H_s^2}{T_p^4 f^5} \exp\left[-\frac{5}{4}(T_p f)^{-4}\right] \gamma \exp\left[-\frac{(T_p f - 1)}{2\sigma^2}\right] \quad (9-1)$$

where f is the wave frequency, γ is the shape parameter, and σ and α are shown below,

$$\sigma = \begin{cases} 0.09 & f \geq f_p \\ 0.07 & f < f_p \end{cases} \quad (9-2)$$

$$\alpha = \frac{0.0624}{0.230 + 0.0336\gamma - 0.185/(1.9 + \gamma)} \quad (9-3)$$

Table 2. Environment matrix

Case	V_t (m/s)	γ	H_s (m)	T_p (s)
EC 1	9.8	3.3	2.9	9.98
EC 2	14.8	3.3	4.5	11.81
EC 3	16	3.3	5.3	12.81

4. Single-input and Multi-input

4.1. Data Partitioning and Error Measurement

The sampling frequency of the Braceless platform simulation test is 20 Hz. The total sampling length of motion response (surge, pitch, and sway) is 2000 s. The collected time series

279 contains 40000 data points. In the training model, the first 32000 points of response data are
1
2 280 the training groups and the last 8000 points of response data are the test groups. Three test cases
3
4 281 (EC1, EC2, and EC3) are selected, and each test case contained 2000 s surge, pitch, and sway
5
6
7 282 motion data.

8
9 283 The training group data is used to train and obtain the neural network model. The
10
11
12 284 relationship between training Epochs and Loss is observed through the Loss function. Then the
13
14 285 test group data is imported into the trained neural network model to verify the accuracy and
15
16
17 286 performance of the trained model.

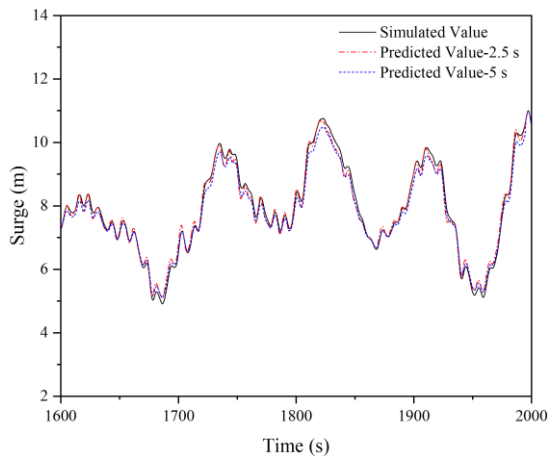
18
19 287 The Loss function adopted in this paper is the Mean Squared Error (MSE), which is the
20
21
22 288 averaged squared difference between the predicted value and the measured value as shown in
23
24 289 Equation 10:

$$27 \text{ 290} \quad MSE = \frac{\sum (y'_t - y_t)^2}{n} \quad (10)$$

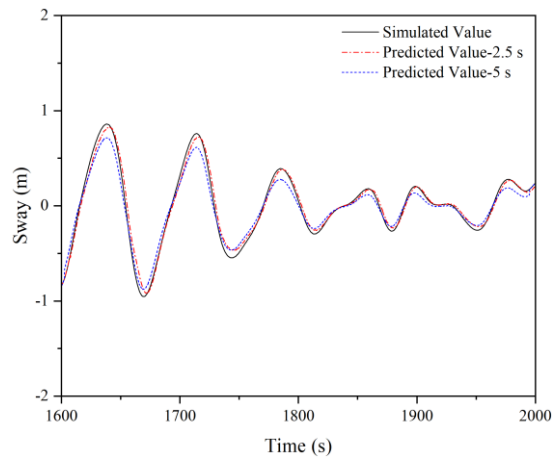
28
29 291 where y'_t is the predicted value of the motion response at time t , y_t is the measured value
30
31
32 292 of the motion response at time t , and n is the total number of predicted values 8000 in this
33
34 293 study.

35 36 37 38 294 4.2. Single-input Predicted Results

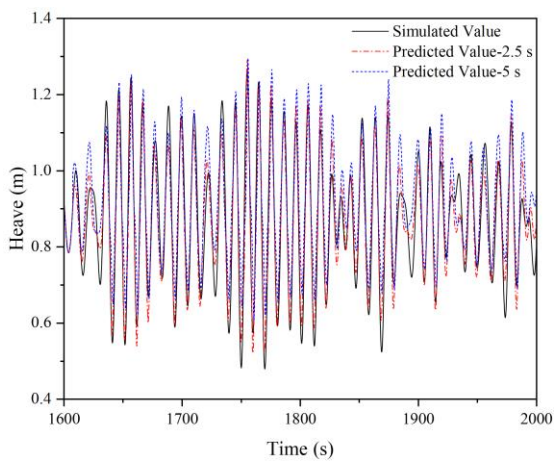
39
40
41 295 Single-input LSTM (SI-LSTM) model is used to train the motion response data in the
42
43
44 296 training group in terms of the heave, surge, sway, and pitch. The training input of the model is
45
46 297 only based on the previous motions. The output of the model is compared and analyzed with
47
48
49 298 the data of the test group. The predicted advance time is set as 2.5 s and 5 s respectively. The
50
51 299 actual and predicted values are shown in **Figures 8-10**.



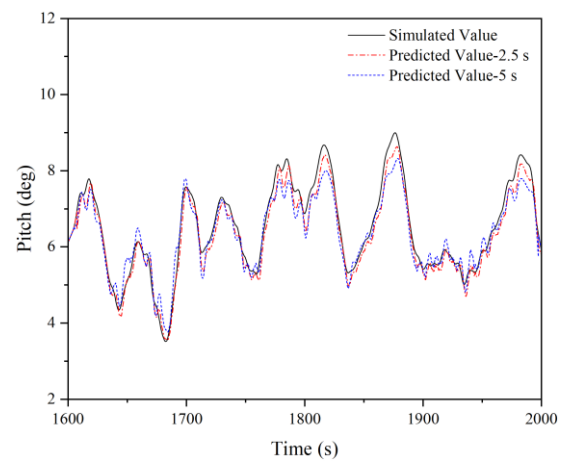
(a)



(b)



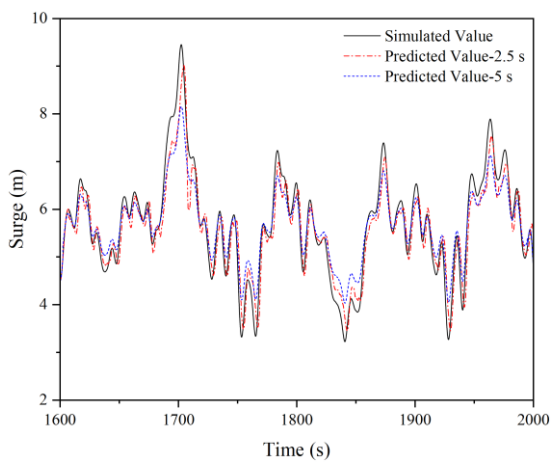
(c)



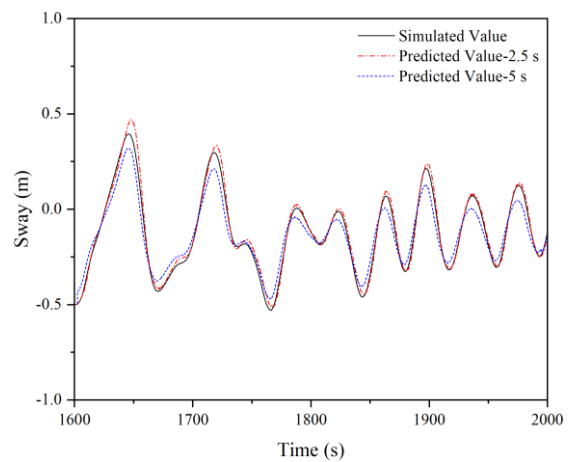
(d)

Figure 8. Simulated and predicted values of EC 1 at 2.5 s and 5 s :

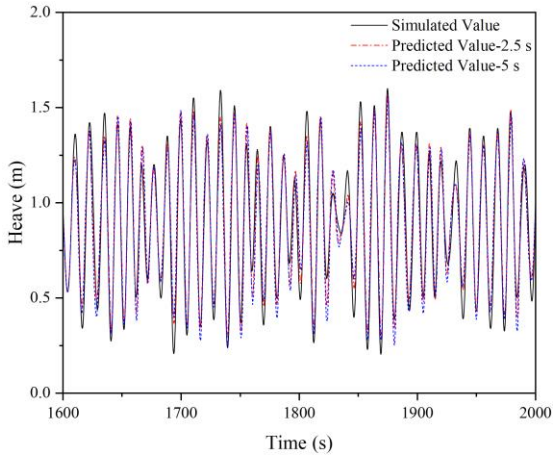
(a) Surge; (b) Sway; (c) Heave; (d) Pitch



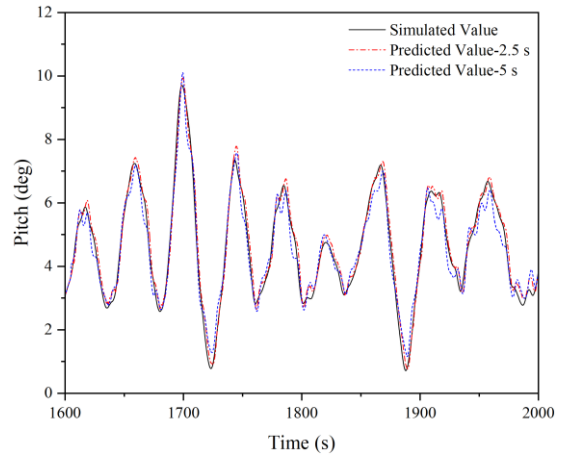
(a)



(b)



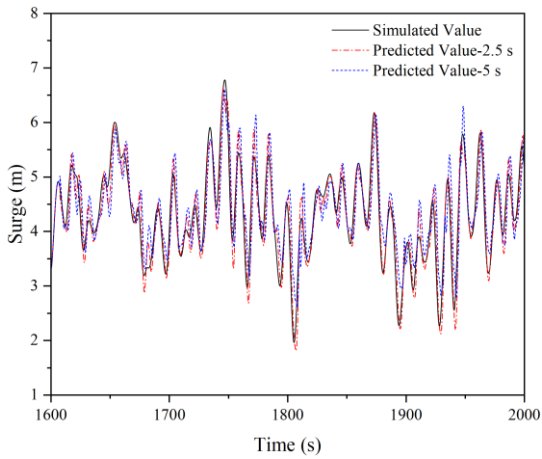
(c)



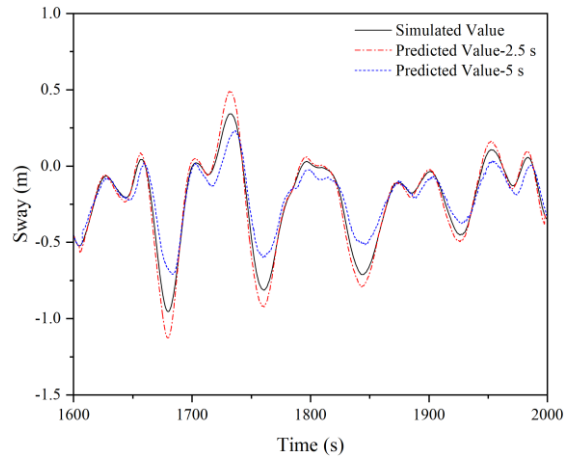
(d)

Figure 9. Simulated and predicted values of EC 2 at 2.5 s and 5 s:

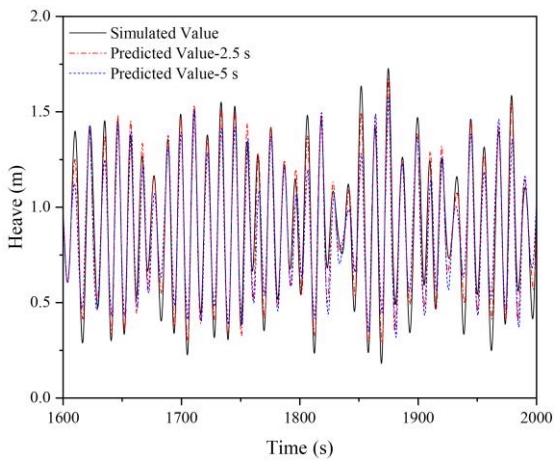
(a) Surge; (b) Sway; (c) Heave; (d) Pitch



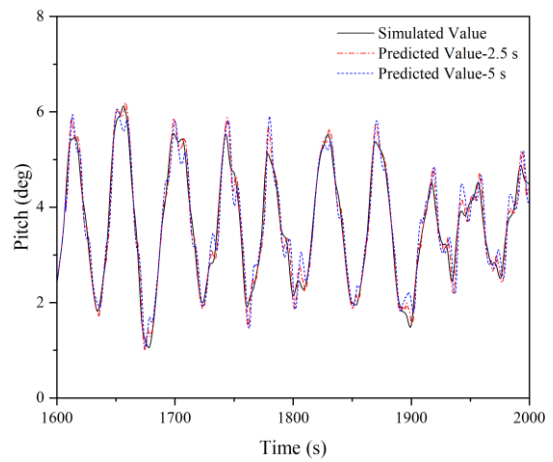
(a)



(b)



(c)



(d)

316 **Figure 10.** Simulated and predicted values of EC 3 at 2.5 s and 5 s:

317 (a) Surge; (b) Sway; (c) Heave; (d) Pitch

318 It can be seen from **Figures 8-10** that when the previous motion response is used as the
319 single input, the predicted value at PAT of 2.5 s is closer to the simulated value. Due to the large
320 amplitude of motion in the surge, the predicted results in **Figure 8(a)** agree well with the
321 simulation results, apart from the minor discrepancy at the peak of the surge in **Figures 9-10(a)**.
322 Due to the small amplitude in sway, the predicted results under the two PATs generally agree
323 with simulated results compared to the agreement between predicted and simulated surge.
324 Similarly, there is also a minor discrepancy at the peak. The amplitude of heave motion is the
325 smallest among the three motions, but it contains higher frequency components. The predicted
326 heave motion in three test cases in **Figures 8-10** presents better agreement with simulated
327 results at PAT of 2.5 s, but a minor discrepancy can be noted at the peak and trough at PAT of 5
328 s. The peak value of pitch in **Figures 8-10(d)** is also large, but there is higher-order fluctuation
329 at the peak and trough due to the nonlinear motion induced by wind and waves. Single-input
330 LSTM model learned the nonlinear features from the training data group, so the predicted value
331 agrees well with the simulated results.

332 In summary, compared with the simulated values, the predicted values in all motions have
333 very minor discrepancies at peak and trough, but a fairly good agreement has been presented.
334 The discrepancy at peak and trough can be attributed to the limited input factors to train the
335 neural network. To unravel this, the multi-input network structure is investigated in detail in
336 Section 4.3.

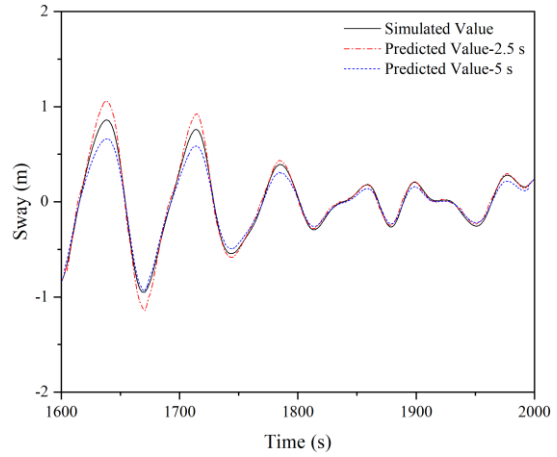
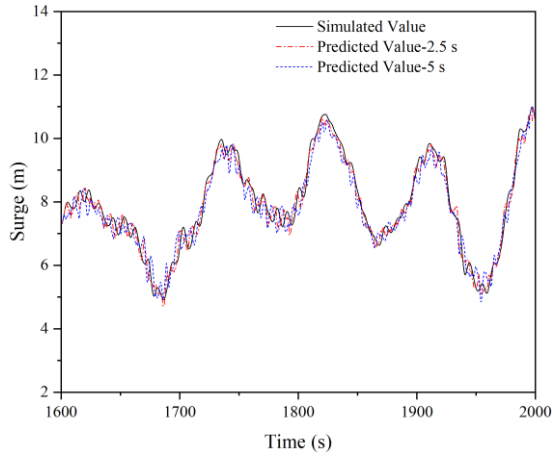
337 4.3. Muti-input Predicted Results

338 A multi-input model is trained to explore the effects of multiple factors as input conditions
339 on the predicted results. Unlike the single-input model, the training input of the multi-input
340 LSTM (MI-LSTM) model is based on the previous motions, mooring forces, and wave

341 elevation. The output of the model is compared and analyzed with the data of the test group.

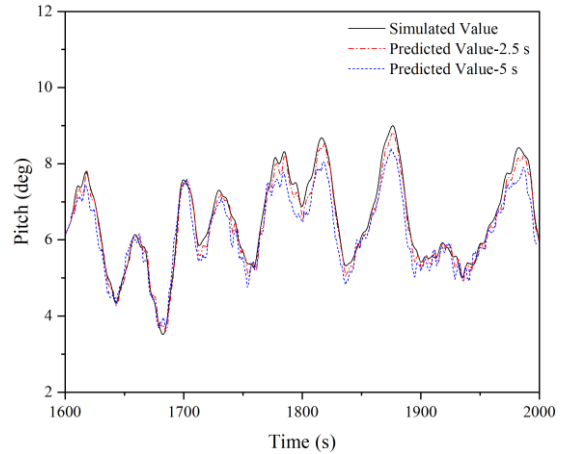
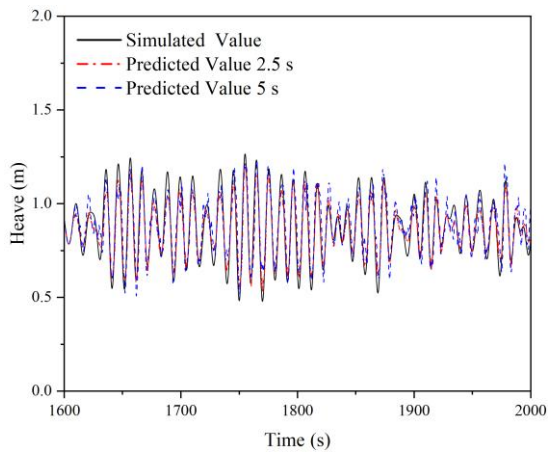
342 The predicted advance time is set as 2.5 s and 5 s respectively. The test and predicted results

343 are shown in **Figures 11-13**:



344 (a)

345 (b)

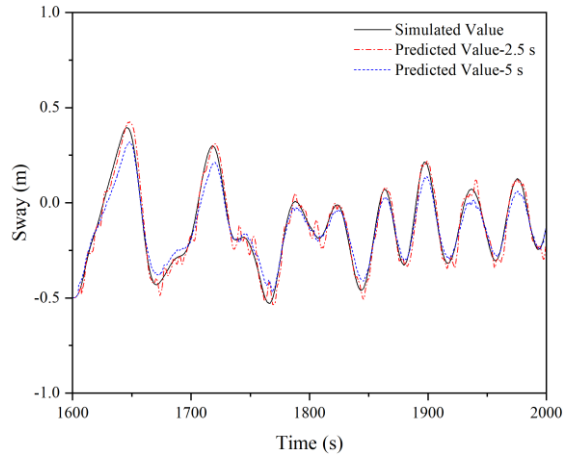
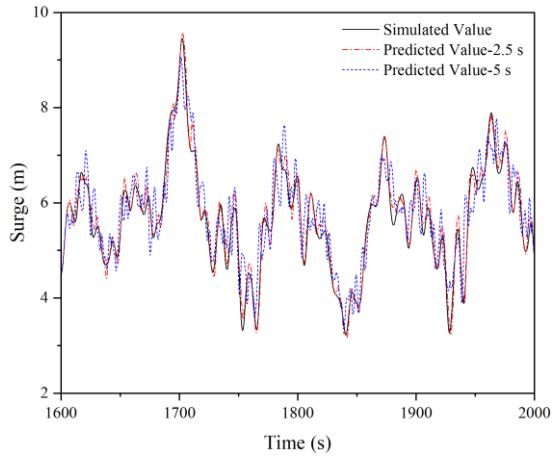


346 (c)

347 (d)

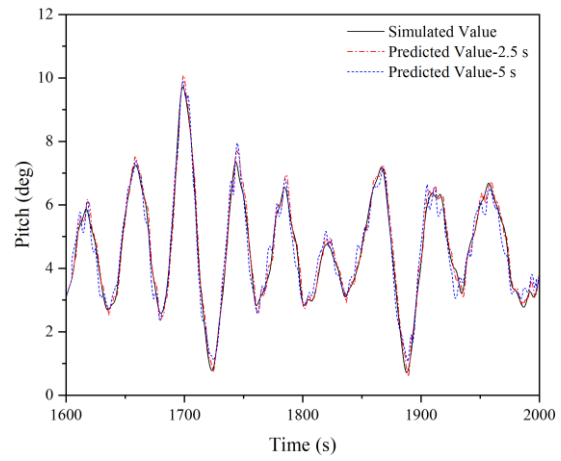
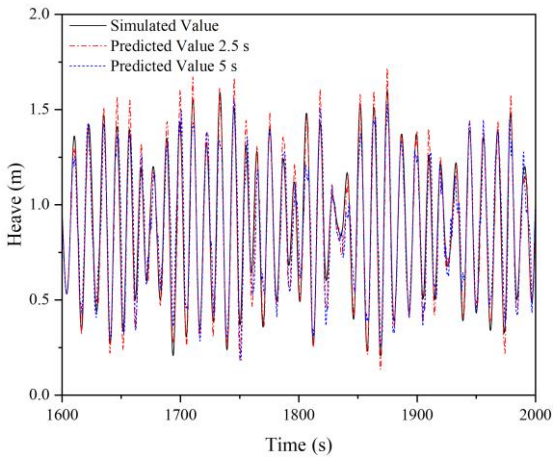
348 **Figure 11.** Simulated and predicted values of EC 1 at 2.5 s and 5 s:

349 (a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)

(b)

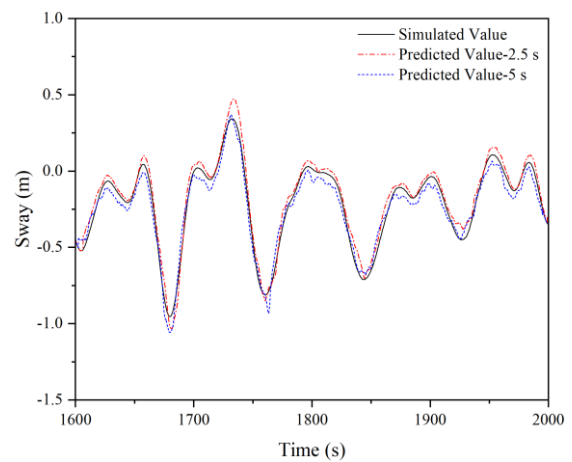
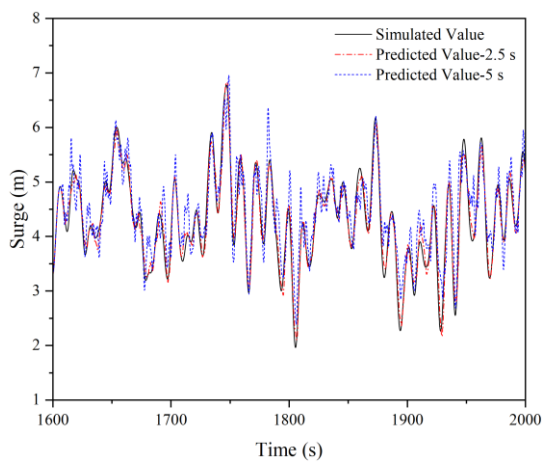


(c)

(d)

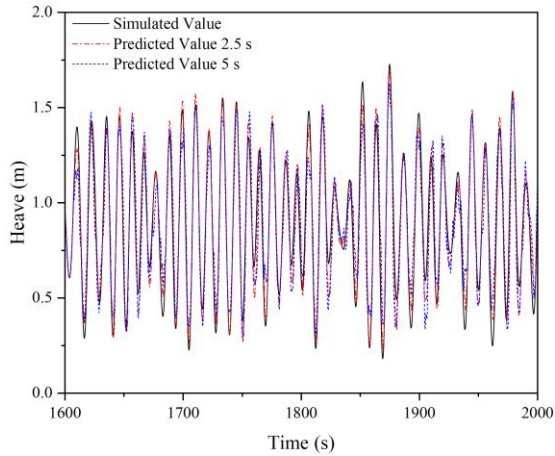
Figure 12. Simulated and predicted values of EC 2 at 2.5 s and 5 s:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

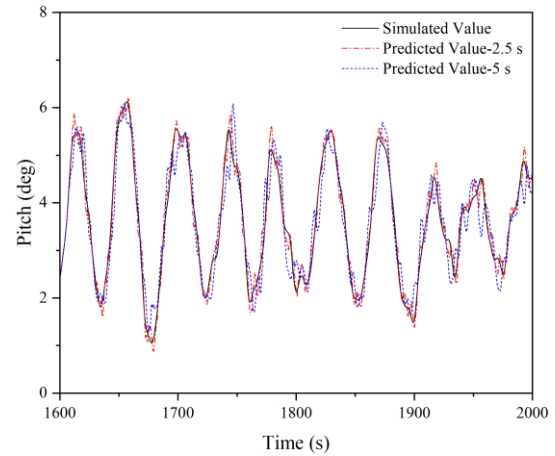


(a)

(b)



(c)



(d)

Figure 13. Simulated and predicted values of EC 3 at 2.5 s and 5 s:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

When the model input factors become multiple, i.e., adding mooring force and wave elevation, a better agreement between the predicted value and the simulated value is obtained compared with the single input case. Improved agreement of surge prediction at peak in **Figure 12(a)** is presented compared to **Figure 9(a)**. But in the case of multiple inputs, the fluctuations can also be noticed from the predicted surge. Sway and heave are not significantly improved due to their less sensitivity to mooring force. With the additional input factors, the accuracy of the predicted pitch has been improved significantly as pitch motion is sensitive to mooring forces, comparing **Figure 9(d)** and **12(d)**. It can be found that in the period 1900s-2000s, the discrepancy of the single-input model can be found, while the multi-input model presented better performance with additional input data sets. Similar to the pitch, better agreements have been achieved for the predicted surge.

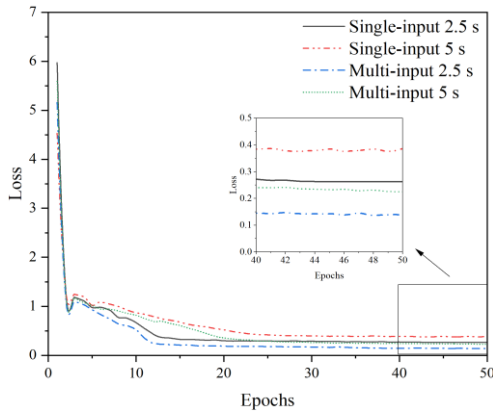
In a word, after adding the additional input factors to train the multi-input model, better performance in predicting the FOWT motion response has been demonstrated. However, the saw-tooth effect of the MI-LSTM model is more obvious, caused by the deep learning of the additional input information. The saw tooth effect is further analyzed after analyzing the scatterplot of discrete situations in Section 4.4.

378 4.4 Error Analysis

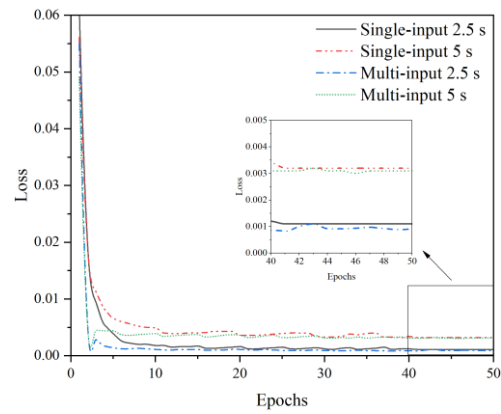
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In this study, the number of Epochs is set to 50 rounds. It is shown in **Figure 14** the trend of the Loss function changing with the Epochs is generated and recorded during the training. It can be noted that with the increment of Epochs, Loss decreases rapidly in the beginning. Then after the rapid decrease stage, Loss finally tended to be stable. After the Epochs reaches 50, Loss remains unchanged. It can be concluded that the network training effect will not be further improved after 50 rounds and a neural network model with good accuracy is generated. The model has completed learning about the relationship between the input and output data.

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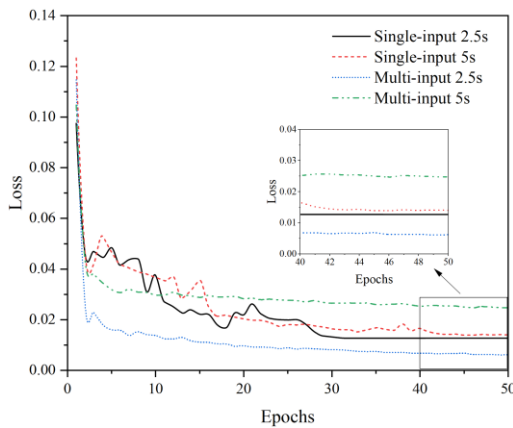


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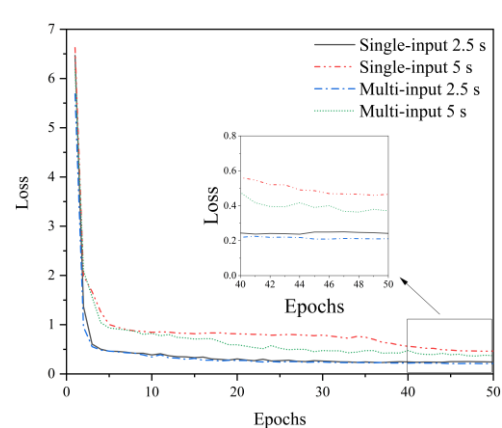


35 (b)

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53 (c)



54 (d)

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Figure 14. The curve of Loss affected by Epochs for different directions:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

At the same time, the Loss of the MI-LSTM model is found to be lower than that of the

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393 SI-LSTM model both in 2.5 s and 5 s. It can be considered that the learning ability of the model
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2 394 is improved after additional factors are added to the training. The predicted results are shown
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4 395 in sections 4.2 and 4.3 and compared with simulation data. It is difficult to observe their overall
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7 396 discretization, so a scatter plot of the prediction results in different input modes is plotted in
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10 397 this section, as shown in **Figure 15**.

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12 398 According to **Figure 15**, comparing the SI-LSTM model with the MI-LSTM model under
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14 399 the different cases, it can be found that after adding two additional input factors, the discrete
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16 400 situation of the MI-LSTM model prediction results is significantly smaller than that of the SI-
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19 401 LSTM model prediction results. This phenomenon is more evident in the sway and heave of
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22 402 EC1, surge and sway of EC2, and sway and heave of EC3. The use of the MI-LSTM model is
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24 403 beneficial in reducing the discrete nature of predicted results.
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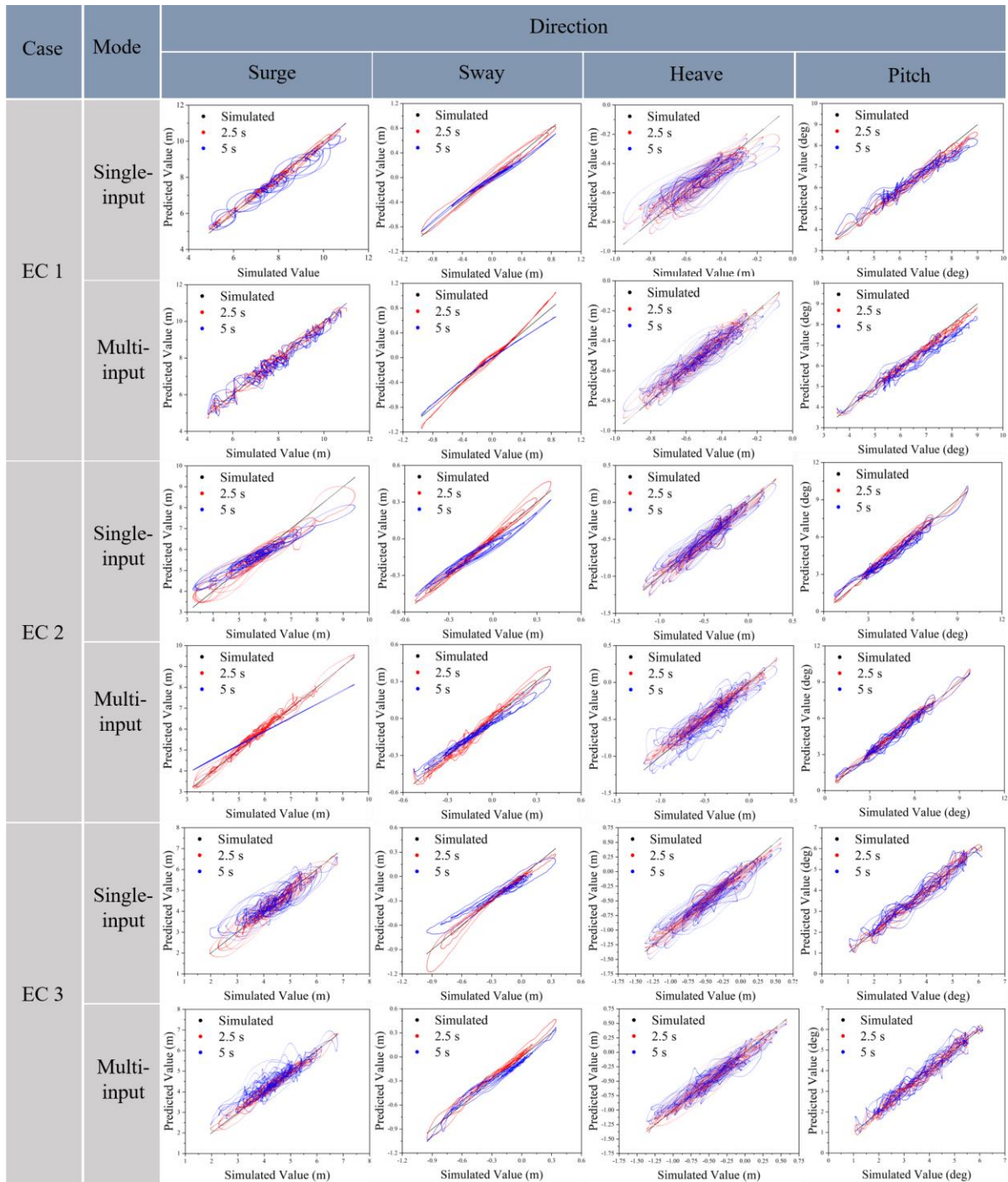
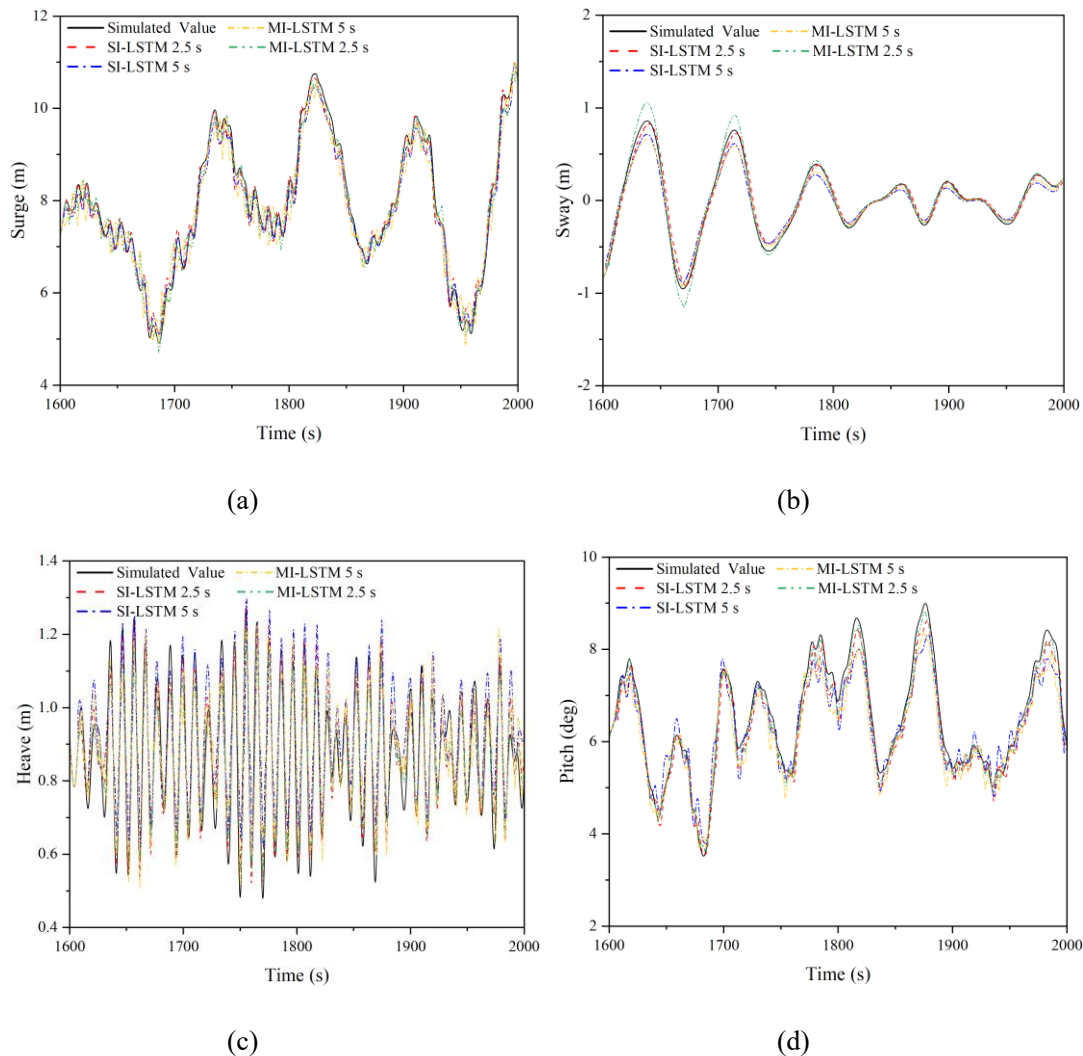


Figure 15. The discrete scatter plot of prediction results with two models

Comparing the prediction results of the SI-LSTM model with the MI-LSTM model on the same image, the comparison results for EC 1 are shown in Figure 16. From the figure, one can find that the prediction results of both SI-LSTM model and MI-LSTM model have high accuracy. For the surge motion, both models have the best results and have a good fit in both

411 peak and trough positions as well. For the sway motion, the MI-LSTM model predicts a certain
 412 absolute value bias at the response extremes, while the SI-LSTM model predicts a certain
 413 absolute value bias at the response extremes. For the heave motion, since the SI-LSTM model
 414 does not take into account the effect of wave elevation, and the response in the heave direction
 415 happens to be most affected by the wave, the accuracy of the SI-LSTM model in this direction
 416 is not as good as that of the MI-LSTM model. For the pitch motion, the results of both models
 417 are similar to those of the surge direction, but the predicted values are smaller at the peak, which
 418 is more obvious in the SI-LSTM model.



423 **Figure 16.** Comparison of 1st-order and 2nd-order hydrodynamic prediction results:

424 (a) Surge; (b) Sway; (c) Heave; (d) Pitch

426 In addition to the impact of discrete situations, the overall accuracy of the MI-LSTM
 427 model and the single-input model is also important. The individual statistics for predicting the
 428 final result of the FOWT motion response using both models are listed in Table 3. The overall
 429 accuracy of both models is presented in **Figure 17**.

430 Based on Table 3 and Figure 16, the results at PAT of 2.5 s present better agreements than
 431 at PAT of 5 s. After adopting the MI-LSTM model, the accuracy of the prediction results in
 432 pitch and heave has been significantly improved. With the increment of PAT, the period between
 433 input and output becomes larger, so the time correlation between the two decreases and the
 434 uncertainty increases. The upper limit of learning ability decreases as the correlation between
 435 input and output information decreases. Therefore, the accuracy at PAT of 5 s is lower than that
 436 of 2.5 s.

Mode	Statistics	EC 1				EC 2				EC 3			
		Heave	Pitch	Surge	Sway	Heave	Pitch	Surge	Sway	Heave	Pitch	Surge	Sway
Single- input 2.5 s	Max	73.2%	95.9%	99.9%	96.7%	96.2%	92.6%	95.3%	81.2%	84.3%	98.8%	97.8%	81.0%
	Min	92.3%	99.0%	96.2%	96.2%	93.4%	92.4%	93.0%	97.1%	96.8%	96.2%	92.4%	76.9%
	Average	99.7%	97.2%	99.8%	88.6%	95.6%	92.4%	98.5%	90.6%	96.9%	93.3%	96.5%	94.9%
	STD	87.5%	93.7%	94.3%	94.0%	97.7%	98.9%	83.7%	90.6%	96.0%	92.1%	93.5%	97.7%
	Overall	88.2%	96.4%	97.6%	93.9%	95.7%	94.1%	92.6%	89.9%	93.5%	95.1%	95.0%	87.6%
Multi- input 2.5 s	Max	73.2%	98.0%	97.6%	97.1%	97.4%	96.1%	96.8%	92.5%	95.8%	98.5%	99.4%	82.9%
	Min	96.0%	97.8%	95.8%	89.6%	93.3%	93.9%	98.2%	98.7%	98.3%	93.5%	96.6%	91.9%
	Average	97.5%	98.2%	99.4%	88.6%	96.0%	98.5%	98.9%	96.6%	99.2%	98.2%	99.0%	92.4%
	STD	97.3%	95.3%	96.8%	97.9%	97.8%	98.8%	95.6%	95.5%	96.6%	98.1%	94.9%	96.6%
	Overall	91.0%	97.3%	97.4%	93.3%	96.1%	96.8%	97.4%	95.8%	97.5%	97.1%	97.5%	91.0%
Single- input 5 s	Max	73.2%	92.5%	98.7%	83.2%	82.9%	95.9%	86.1%	81.1%	69.7%	88.9%	97.4%	67.9%
	Min	89.3%	93.0%	96.7%	92.2%	91.4%	80.1%	74.9%	94.4%	90.8%	89.5%	67.2%	74.3%
	Average	98.9%	97.7%	97.8%	75.0%	93.0%	89.0%	89.8%	91.7%	92.3%	93.5%	98.3%	92.9%
	STD	75.6%	81.5%	88.3%	82.6%	93.3%	89.8%	76.2%	78.7%	90.4%	87.3%	85.3%	70.2%
	Overall	84.3%	91.2%	95.4%	83.3%	90.1%	88.7%	81.8%	86.5%	85.8%	89.8%	87.1%	76.3%
Multi- input 5 s	Max	73.2%	93.3%	98.1%	76.8%	82.5%	98.2%	87.8%	80.8%	85.3%	89.1%	97.4%	82.1%
	Min	91.3%	95.1%	98.5%	98.4%	96.0%	76.5%	85.7%	94.4%	91.0%	94.3%	78.4%	89.0%
	Average	97.7%	95.5%	98.6%	83.7%	96.9%	89.8%	88.4%	91.9%	98.0%	97.5%	96.4%	89.3%
	STD	89.7%	86.2%	91.3%	85.3%	97.0%	98.0%	90.8%	81.0%	88.8%	91.6%	87.2%	93.2%
	Overall	88.0%	92.5%	96.7%	86.1%	93.1%	90.6%	88.2%	87.0%	90.8%	93.1%	89.8%	88.4%

437 **Table 3.** The accuracy of each statistic under the different input model

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At the same time, the overall prediction result of the MI-LSTM model is better than the SI-LSTM model. The additional input factors increase the dimension of information, which enables the MI-LSTM model to explore more relationships between different input factors and the motion response of the target output. MI-LSTM model also adds more details to the final prediction results, improving the overall accuracy of the prediction results. In other words, there is a positive correlation between mooring force, wave elevation, and the motion response of the platform.

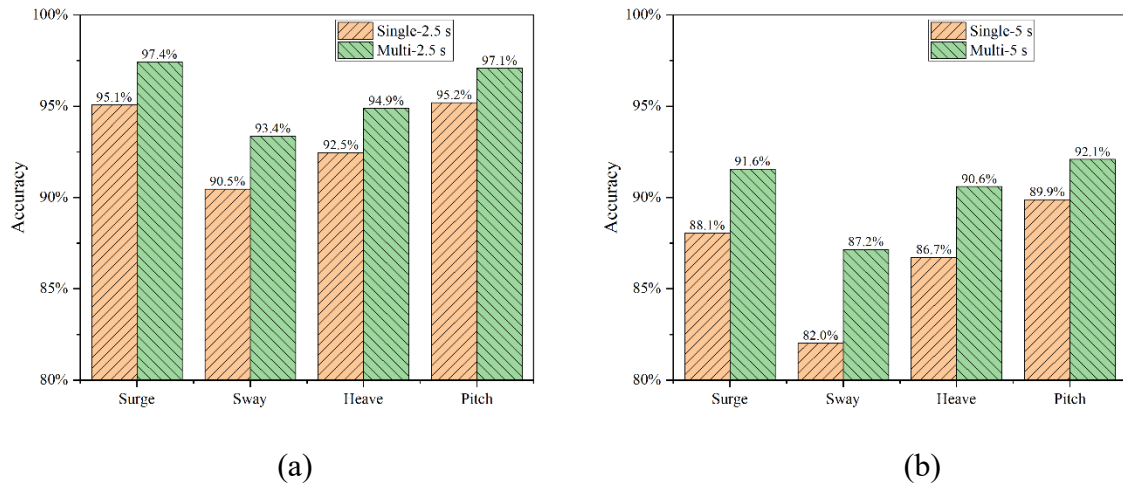
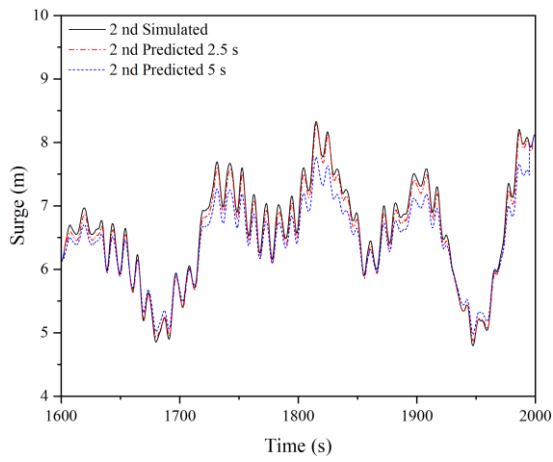


Figure 17. Overall accuracy under different PATs: (a) 2.5 s; (b) 5 s

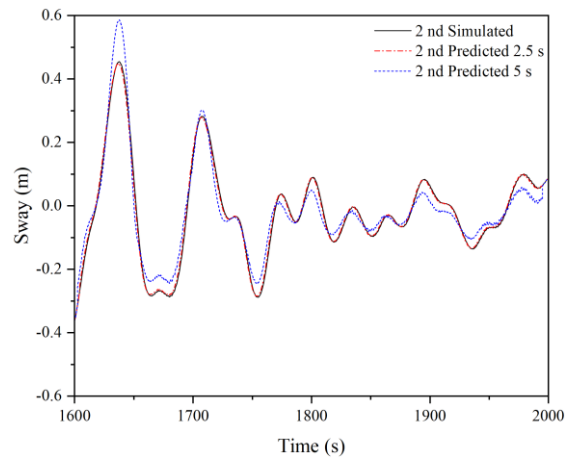
5. Second-order Hydrodynamic Effects

5.1 Prediction results under the influence of second-order hydrodynamic effects

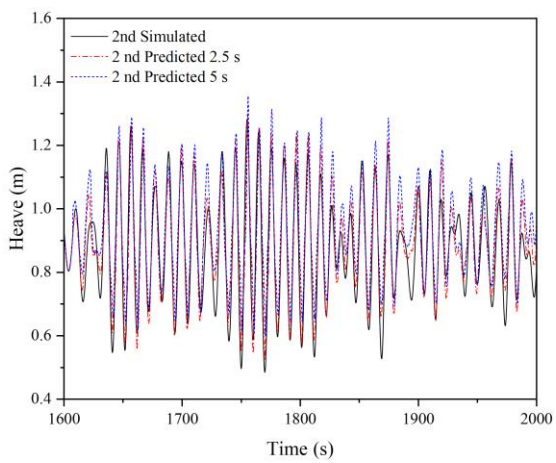
The influence of second-order hydrodynamics is significant for the load prediction of a FOWT [34]. EC1-EC3 are again simulated considering second-order hydrodynamic effects, the simulation data is imported into the MI-LSTM model for training. The prediction results under the second-order hydrodynamic force are obtained after the training, shown in Figures 18-20.



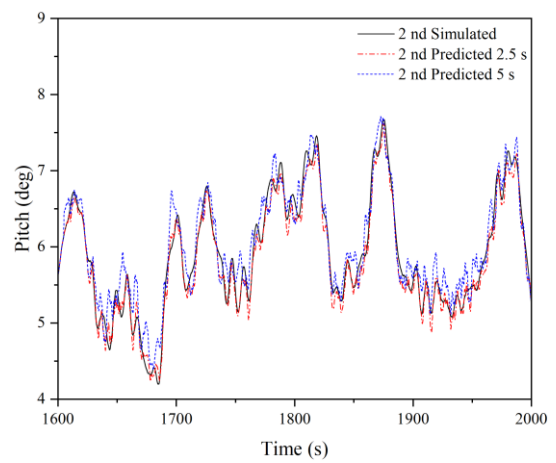
(a)



(b)



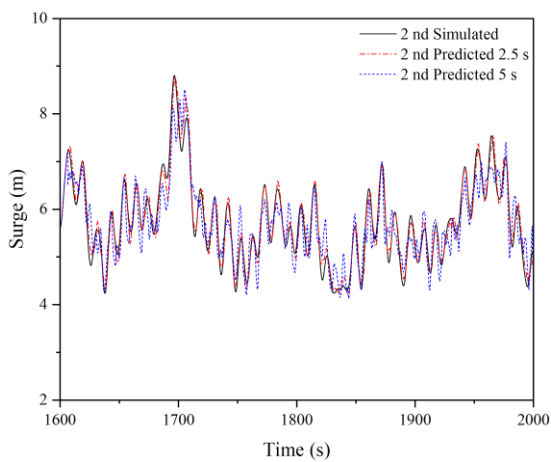
(c)



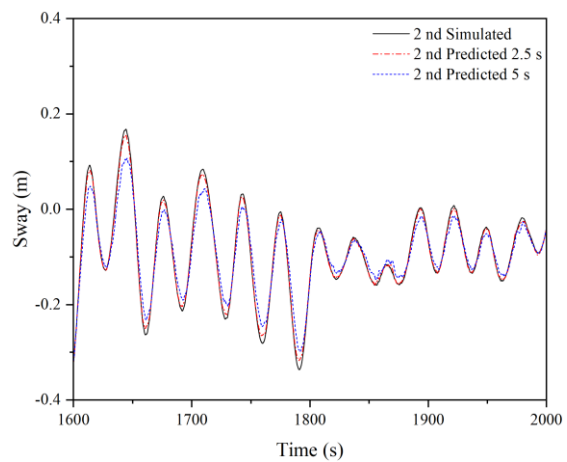
(d)

Figure 18. Simulated and predicted values of EC 1 at 2.5 s and 5 s:

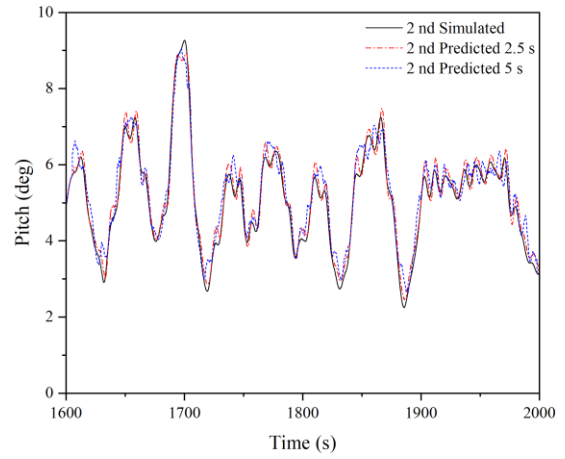
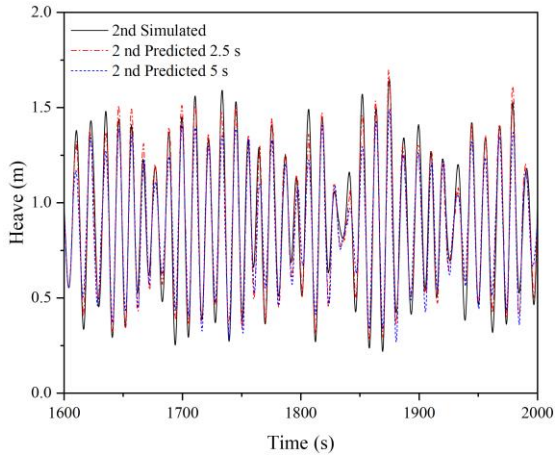
(a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)



(b)

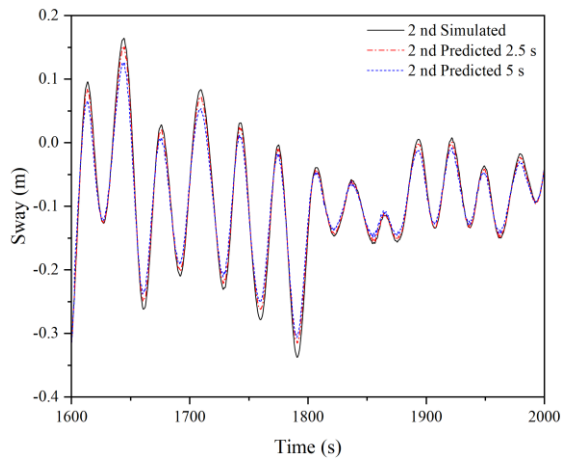
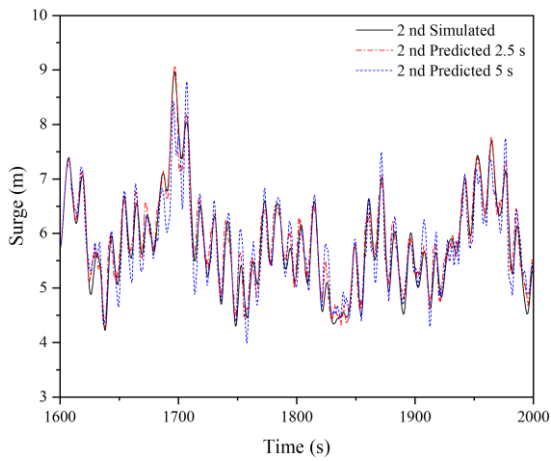


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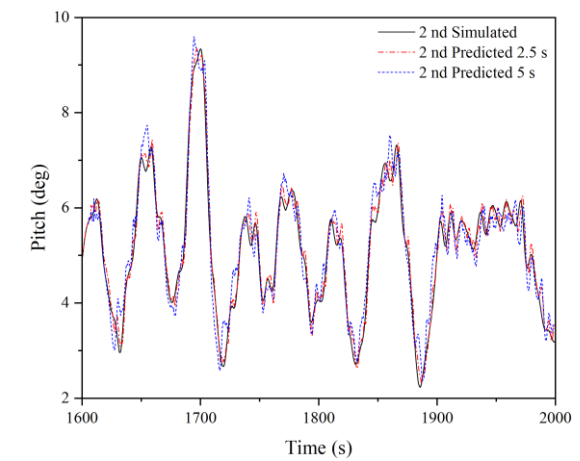
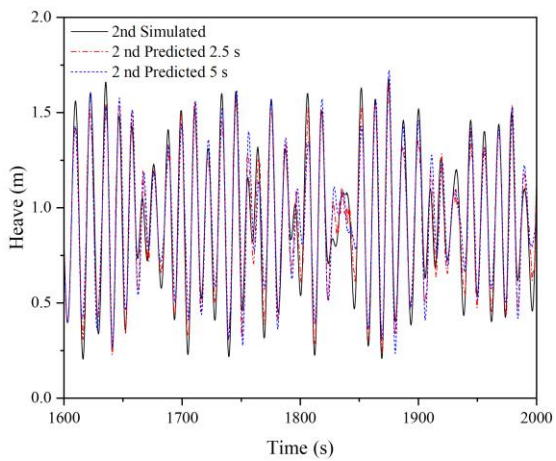
Figure 19. Simulated and predicted values of EC 2 at 2.5 s and 5 s:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch



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(c)

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Figure 20. Simulated and predicted values of EC 3 at 2.5 s and 5 s:

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(a) Surge; (b) Sway; (c) Heave; (d) Pitch

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Figures 18-20 show that the peak fitting in all directions at 5 s is weaker than that of 2.5

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s, similar to the case when the platform model is affected by first-order hydrodynamic forces.

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Compared with the first-order hydrodynamic influence, the prediction results under the second-

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order hydrodynamics show smaller fluctuations in both surge and pitch. On the other hand, the

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predicted value of sway is smooth, and there is no slight fluctuation. The error of prediction

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results in heave mainly occurs in peaks and troughs, but it is not obvious. The statistical

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accuracy in each direction, as well as the overall accuracy, is further analyzed in section 5.2.

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5.2. Error Analysis

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To compare the short-term prediction effect of the MI-LSTM model in both first-order

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hydrodynamics and second-order hydrodynamics cases, the results of the PAT of 2.5 s under

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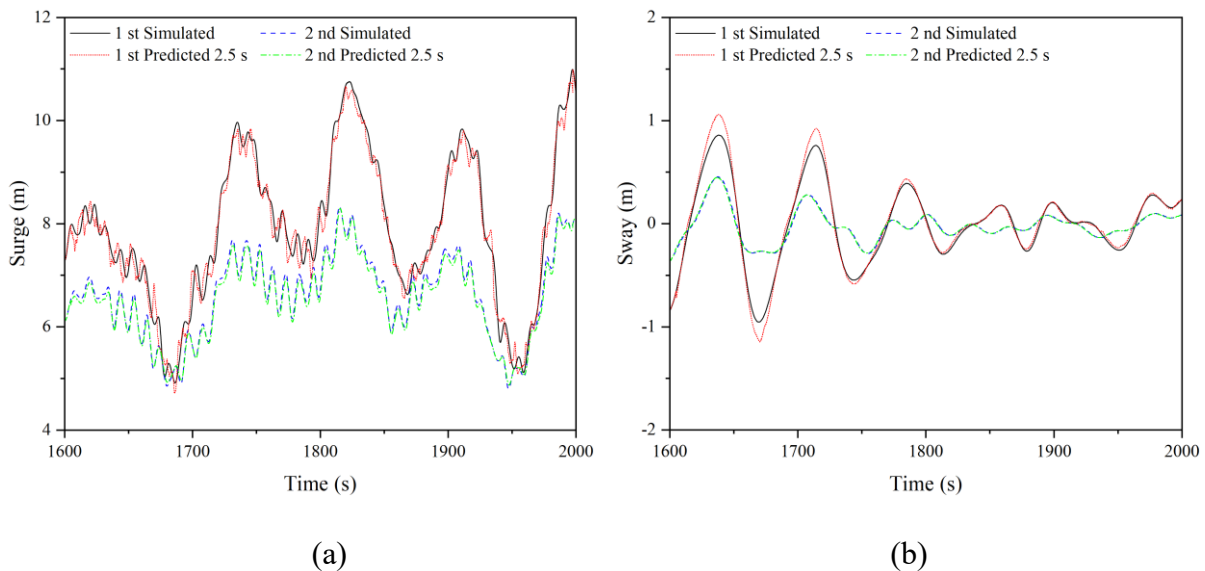
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EC 1 are selected for comparison, shown in **Figure 21**.

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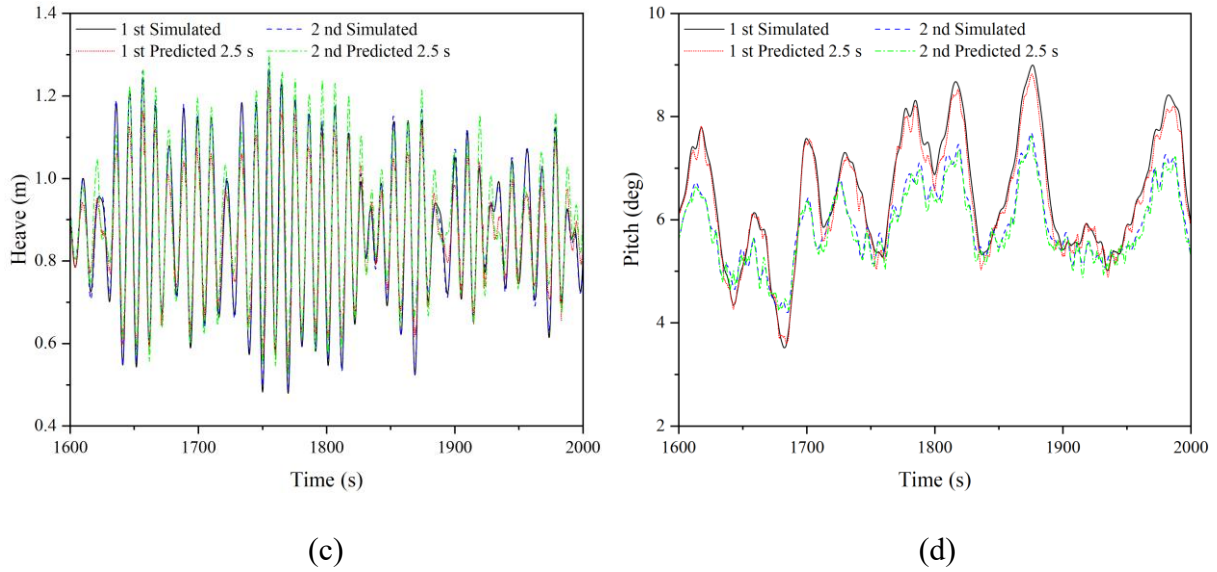


Figure 21. Comparison of 1st-order and 2nd-order hydrodynamic prediction results:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

According to **Figure 21**, it is observed that the motion response exhibits a stronger nonlinear characteristic under the influence of second-order hydrodynamic forces. This phenomenon is particularly evident in the surge, pitch, and sway directions, where more nonlinear fluctuations appear at the extremes of the kinematic response in all three directions. The effect of second-order hydrodynamic forces did not have much influence in the heave direction.

At the same time, in the surge, sway and pitch directions, there are significant deviations in the predicted values at the extremes of the motion response for the first-order hydrodynamics case. While in the second-order hydrodynamics case, the MI-LSTM model has better prediction at both peak and trough values. In the heave direction, the motion response of the platform in the two cases does not differ much and does not have the nonlinear characteristics in the other three directions. Therefore, the prediction effect of the MI-LSTM model in the heave direction under the influence of second-order hydrodynamics is not significantly improved.

The response spectrum analysis of the platform under the influence of second-order hydrodynamics are supplemented and chose EC 1 to plot the power spectrum density (PSD), as

508 shown in **Figure 22**. There is a common phenomenon in all four directions, the predicted value
 509 of 2.5s is better than 5s in the performance of PSD, and both of them fit better with the PSD
 510 results of simulation values. The difference between the predicted and simulated values is
 511 mainly in the low-frequency peak of the response spectrum, while the PSD performance of the
 512 model predictions is better at the off-peak.

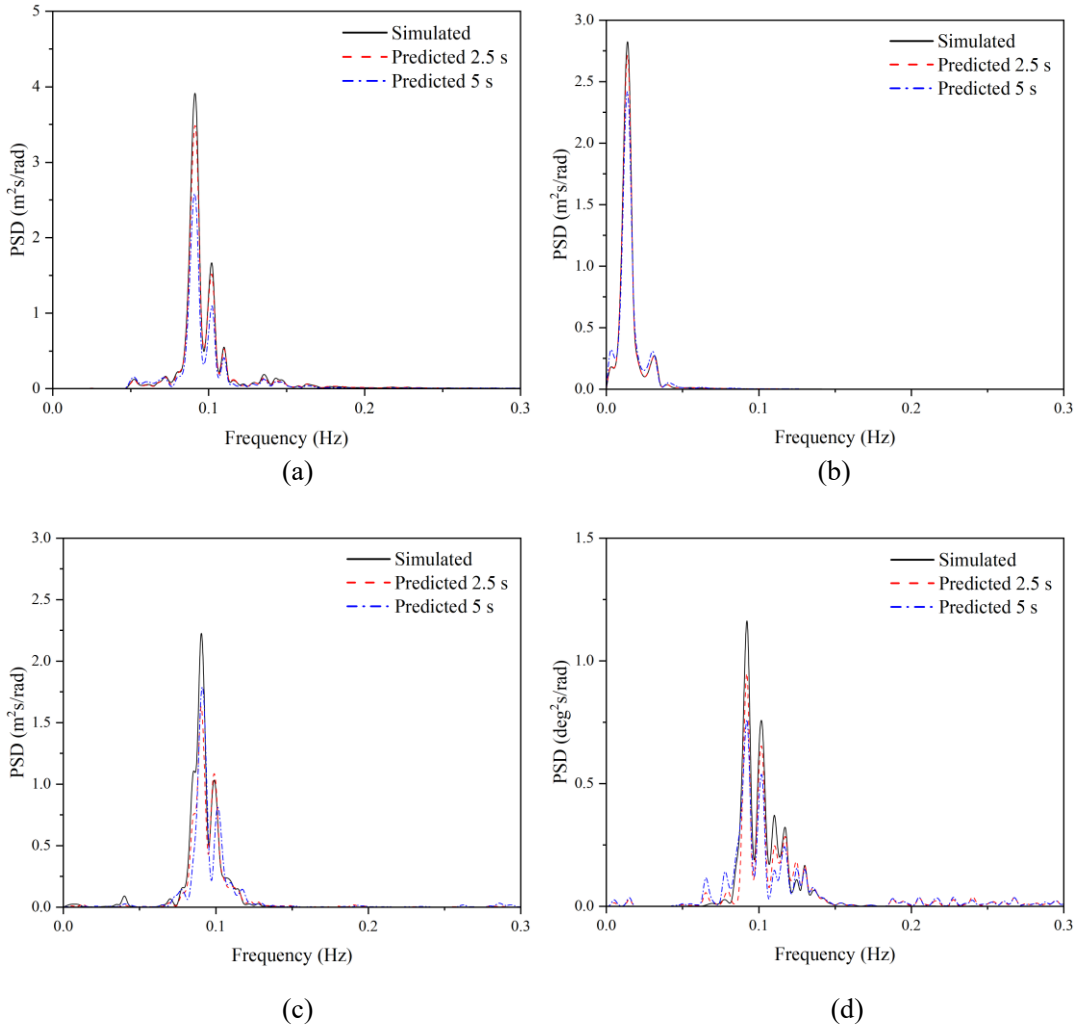


Figure 22. Power spectral density of motion response in different directions

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

520 Under the influence of second-order hydrodynamics, this section also analyzes the
 521 individual statistics of the prediction results and calculates the overall accuracy of each
 522 direction of motion response, shown in **Table 4**.

Table 4. The accuracy of each statistic under the influence of second-order hydrodynamics

Mode	Statistics	EC 1				EC 2				EC 3			
		Heave	Pitch	Surge	Sway	Heave	Pitch	Surge	Sway	Heave	Pitch	Surge	Sway
Multi- input 2.5 s	Max	96.5%	99.4%	99.6%	98.7%	92.6%	96.3%	99.5%	92.2%	98.0%	98.9%	98.8%	91.8%
	Min	88.5%	99.2%	98.5%	99.1%	90.9%	90.7%	99.2%	97.0%	90.2%	96.2%	99.1%	94.9%
	Average	98.8%	98.8%	98.9%	96.5%	98.0%	97.6%	99.7%	99.0%	99.9%	99.0%	98.9%	99.2%
	STD	89.9%	96.2%	96.1%	98.6%	95.8%	96.5%	99.6%	94.6%	98.6%	99.2%	96.7%	92.8%
	Overall	93.4%	98.4%	98.3%	98.2%	94.3%	95.3%	99.5%	95.7%	96.7%	98.3%	98.4%	94.7%
Multi- input 5 s	Max	87.0%	99.5%	97.6%	71.0%	97.1%	97.5%	96.6%	63.4%	94.2%	97.2%	97.8%	77.1%
	Min	94.3%	95.5%	96.5%	97.5%	89.5%	82.5%	97.4%	97.0%	94.3%	93.4%	94.4%	94.9%
	Average	98.6%	98.1%	97.3%	80.7%	94.6%	96.5%	99.3%	98.2%	94.5%	98.8%	99.6%	99.0%
	STD	87.9%	92.3%	91.4%	98.1%	93.1%	92.5%	90.9%	80.4%	92.6%	98.0%	91.3%	84.1%
	Overall	92.0%	96.3%	95.7%	86.8%	93.6%	92.3%	96.0%	84.8%	93.9%	96.9%	95.8%	88.8%

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525 According to the results given in **Table 4**, it can be seen that the accuracy of the predicted
526 results in all directions under the influence of second-order hydrodynamics is still at a high
527 level, overall accuracy exceeds 90% at PAT of 2.5 s and 85% at PAT of 5 s. This phenomenon
528 verifies the conclusions of Section 4 and confirms that an increase in PAT leads to a decrease
529 in prediction accuracy.

530 The overall accuracy of the 4 degrees of freedom directions calculated from **Table 4** is
531 shown in **Figure 23**. At PAT of 2.5 s, the difference in prediction accuracy between the second-
532 order hydrodynamics and the first-order hydrodynamics is more obvious in surge and sway. At
533 PAT of 5 s, in the direction of surge, heave, and pitch, the prediction accuracy in the second-
534 order hydrodynamics case is about 3% higher than that in the first-order hydrodynamics.

535 By comparing with the results in the first-order hydrodynamics in Section 4, it can be
536 found that the MI-LSTM model in the second-order hydrodynamics case not only has a good
537 ability to learn multi-factor relationships and platform response prediction but also has a higher
538 prediction accuracy than the first-order hydrodynamics case.

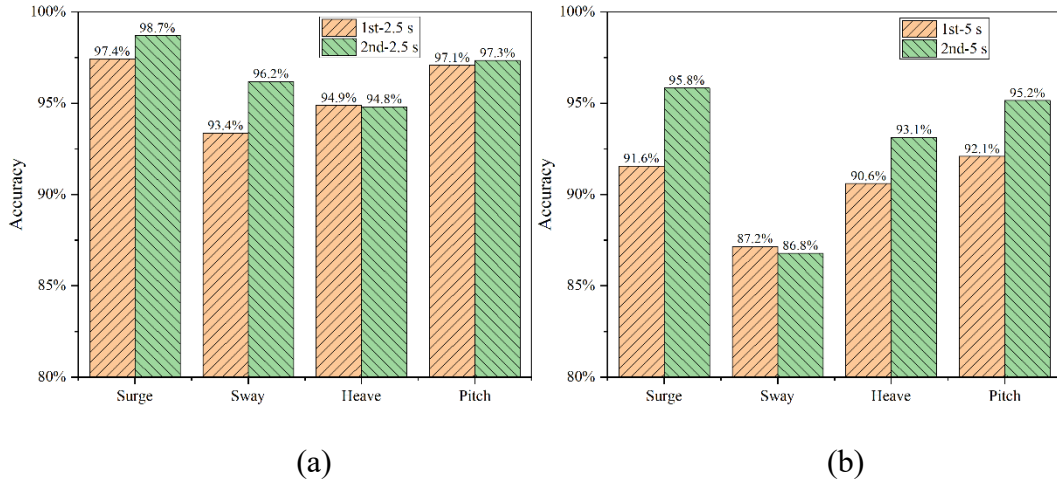


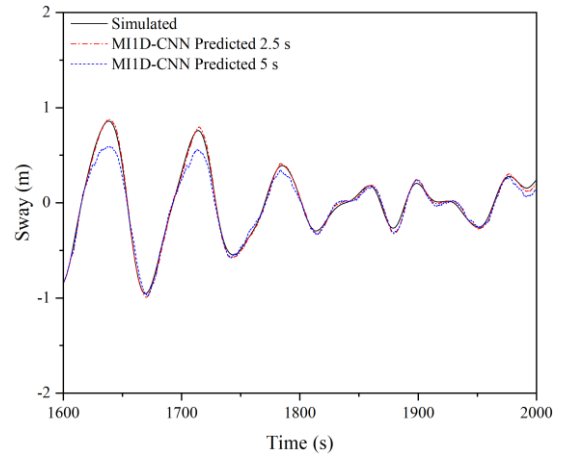
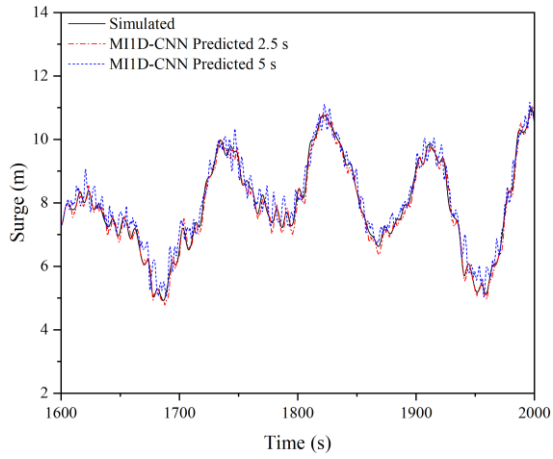
Figure 23. Overall accuracy under different PATs: (a) 2.5 s; (b) 5 s

6. Comparison with the MI1D-CNN model

6.1 Predicted results with MI1D-CNN model

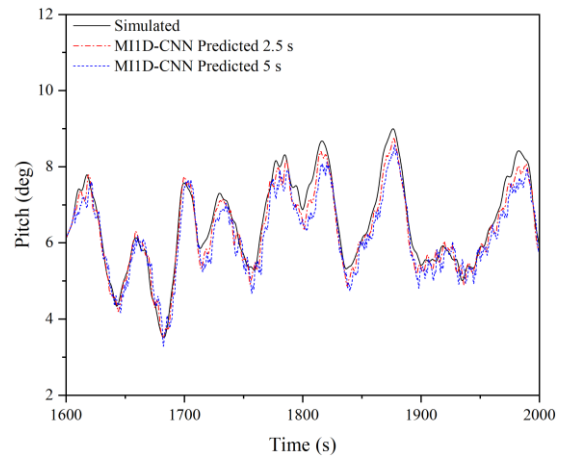
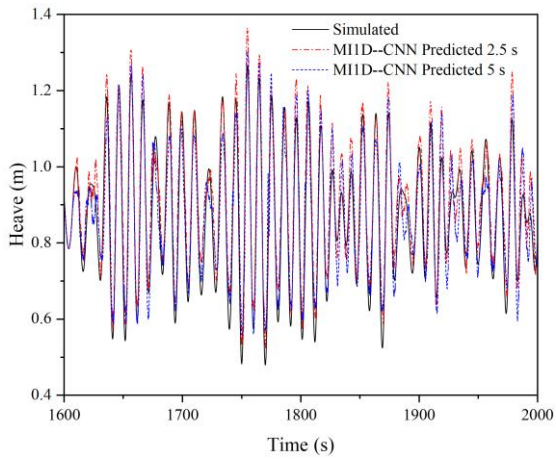
Currently, the mainstream deep learning methods mainly include the CNN method and the RNN method, and the MI-LSTM model established in Section 4 belongs to the RNN method. CNN methods are mostly used in image recognition and text recognition. As a representative method to deal with time series problems in CNN, a one-dimensional convolutional neural network (1D-CNN) has a certain effect on short-term prediction by adding a pooling layer.

In this section, a multi-input one-dimensional convolutional neural network (MI1D-CNN) is built to compare the CNN method with the LSTM method for the motion response prediction problem, using the same training data as in Section 4. The training of the MI1D-CNN model is completed, and the results obtained from the multi-input LSTM model are compared in Section 6.2 in terms of training time and overall accuracy. The prediction results obtained by the MI1D-CNN model are shown in **Figures 24-26**.



(a)

(b)

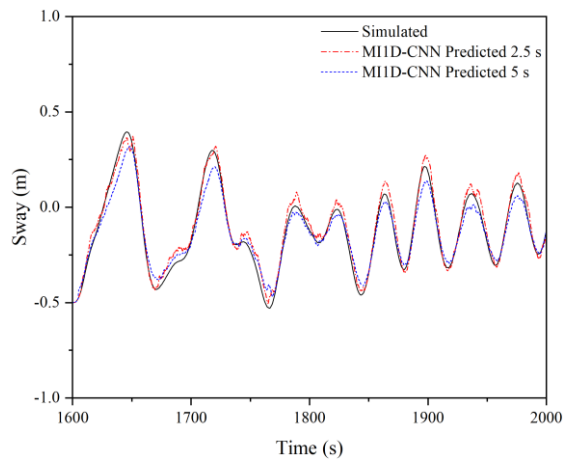
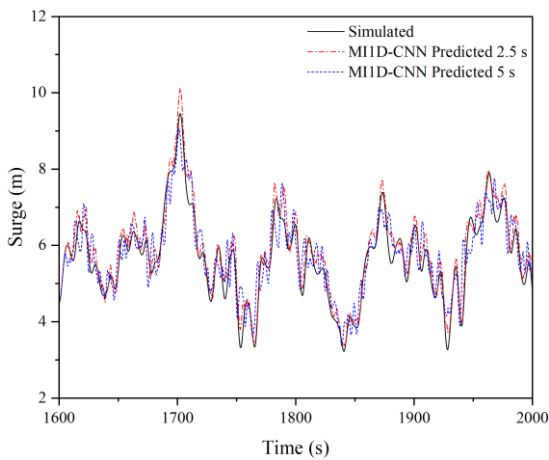


(c)

(d)

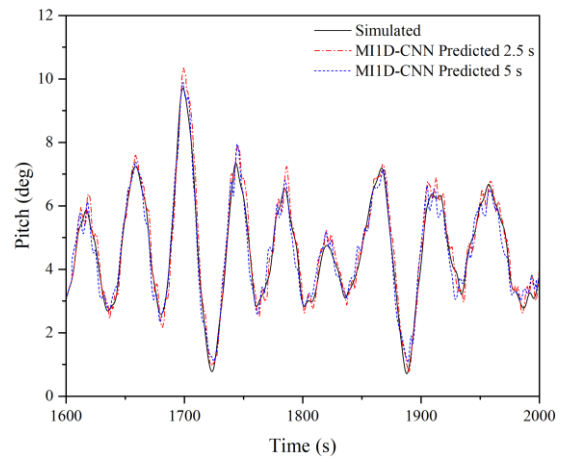
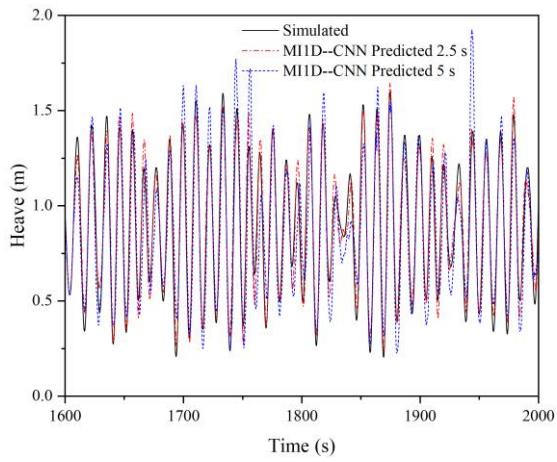
Figure 24. Simulated and predicted values of EC 1 at 2.5 s and 5 s:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)

(b)

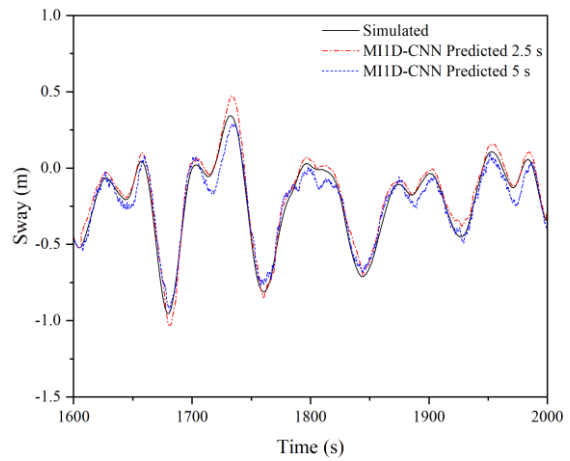
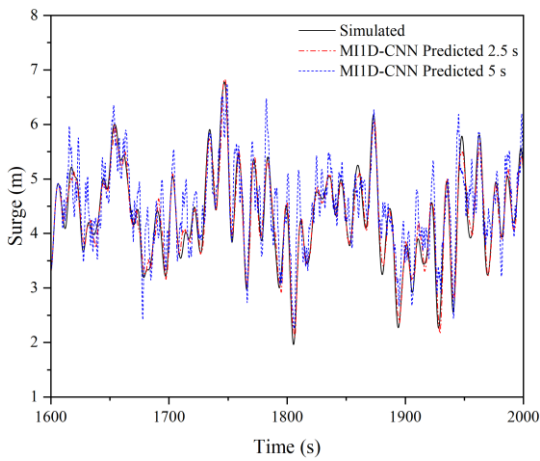


(c)

(d)

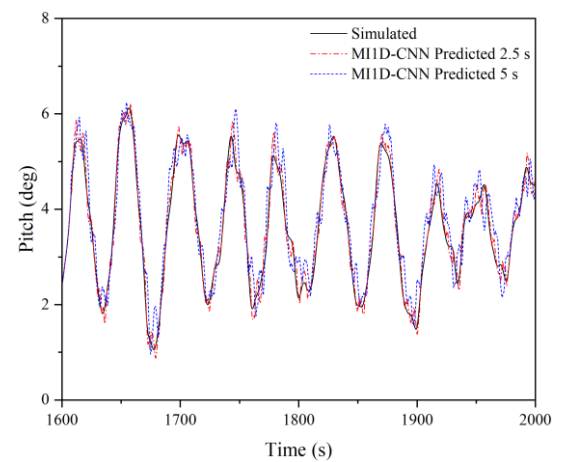
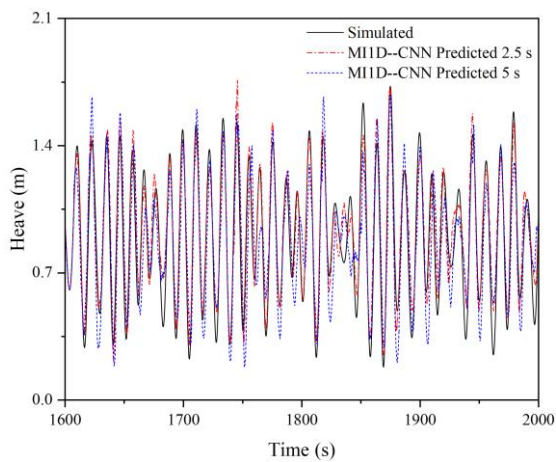
Figure 25. Simulated and predicted values of EC 2 at 2.5 s and 5 s :

(a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)

(b)



(c)

(d)

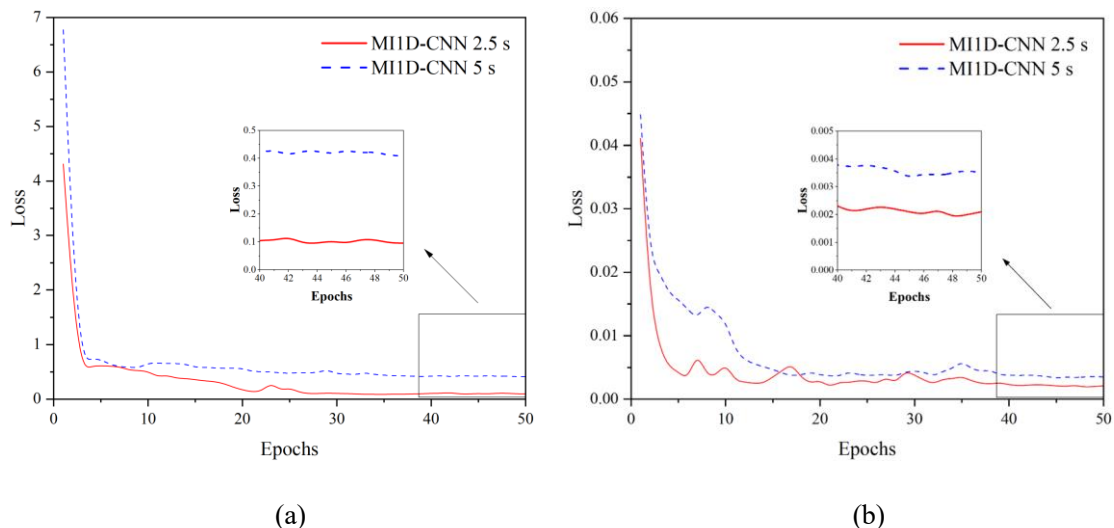
572 **Figure 26.** Simulated and predicted values of EC 3 at 2.5 s and 5 s:

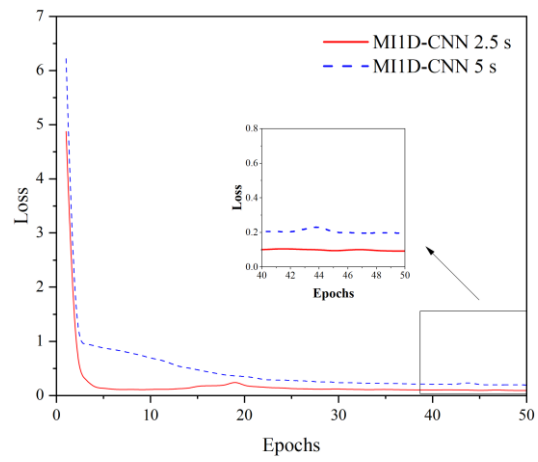
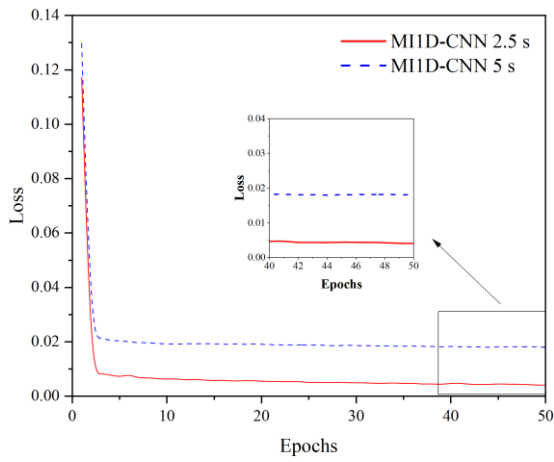
573 (a) Surge; (b) Sway; (c) Heave; (d) Pitch

574 According to **Figures 24-26**, and compared with **Figures 11-13** in Section 4.3, it can be
575 found that the motion response predicted by the MI1D-CNN model produces a large number of
576 serrations in surge and pitch of each environmental condition, especially at PAT of 2.5 s. At the
577 same time, the prediction result at PAT of 5 s in sway does not fit well with the simulation
578 results. To further compare the results of the MI-LSTM model with the MI1D-CNN model, it
579 is further explained from the aspects of training time and overall accuracy in Section 6.2.

580 6.2 Comparison with Multi-input LSTM Model

581 By counting the Loss values during the training of the MI1D-CNN model, we show the
582 decrease of the model training Loss for EC 1, shown in **Figure 27**. One can observe that, unlike
583 the change process of the MI-LSTM model's Loss value, the oscillation phase of the MI1D-
584 CNN model's Loss value is not obvious in the decreasing process. the MI1D-CNN model's Loss
585 value stops changing when the number of training rounds reaches 50 rounds, which indicates
586 that the model training has been completed and the performance is satisfactory. To further
587 observe the imitative effect between the predicted values obtained by the two models and the
588 simulated values, EC1 is selected and the results are summarized as shown in **Figure 28**.



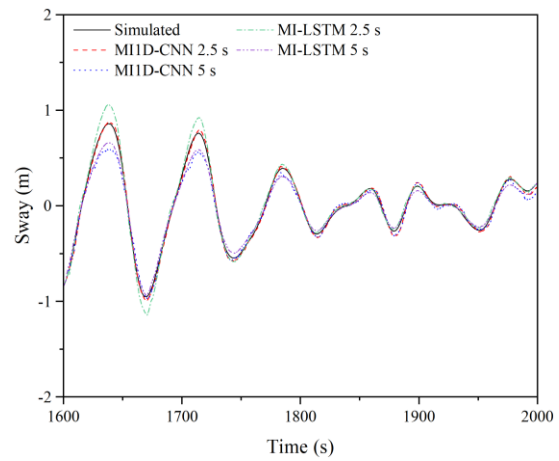
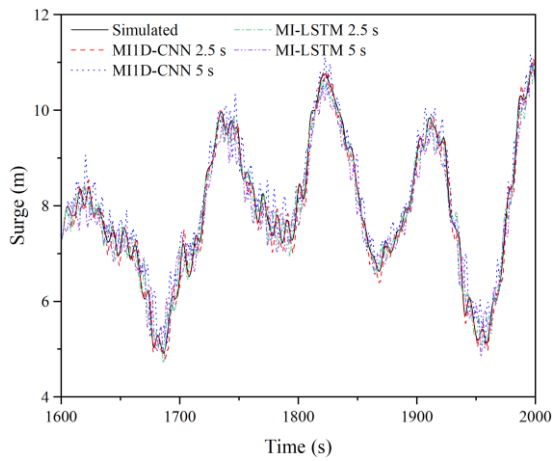


(c)

(d)

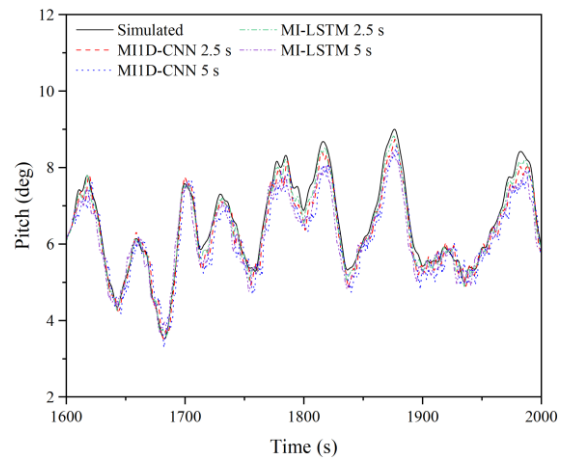
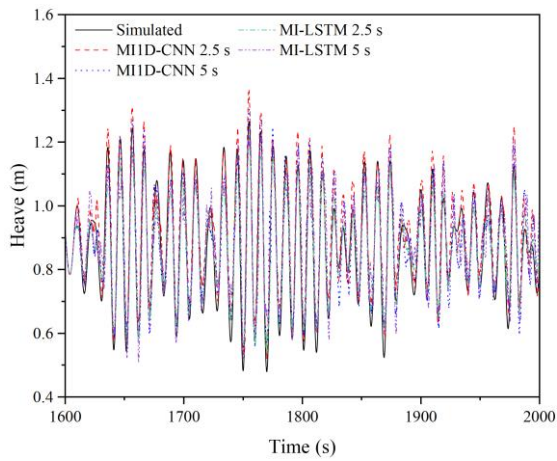
Figure 27. The curve of Loss affected by Epochs for different directions:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)

(b)



(c)

(d)

Figure 28. The results of the MI1D-CNN model and the MI-LSTM model are compared:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

According to **Figure 28**, from the overall imitative effect of the time series curve, the prediction results of both models fit well with the simulation results at PAT of 2.5 s. However, at PAT of 5 s, the result of the MI1D-CNN model is slightly inferior to the MI-LSTM model result, and when the PAT is at 5 s, the predicted value of the former has a large fluctuation. This volatility does not exist in the simulation value, particularly in **Figures 28(a)** and **(d)**. The time series of the platform response has a certain smoothness in sway, so both models' imitative effects are good. While the time series of the platform response itself is more volatile in heave, the imitative effects of the peak are not as good as in other directions.

To find out the difference between the MI1D-CNN model and the MI-LSTM model, the overall accuracy of the MI1D-CNN model is calculated by combining each operating condition. Then compare the overall accuracy of the MI1D-CNN model with the MI-LSTM model proposed in Section 4 and the result is shown in **Figure 29**.

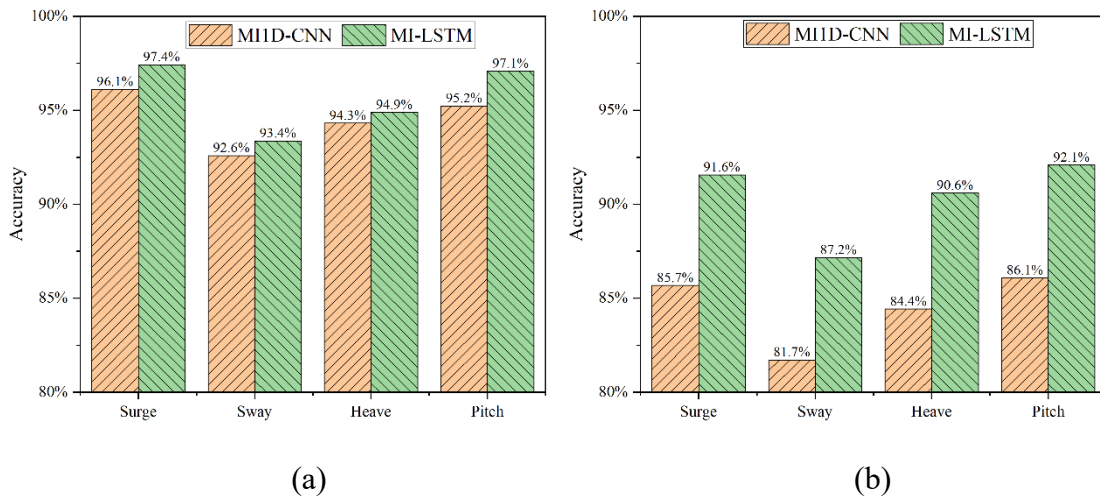


Figure 29. Comparison of the overall accuracy of different models in each direction:

(a) 2.5 s; (b) 5s

According to **Figure 29**, it can be found that there is no significant difference between the results of the two models when PAT is at 2.5 s, the overall effect of the MI-LSTM model is

620 slightly better than the MI1D-CNN model, and the accuracy of the former is 1%-2% higher
 621 than the latter in all directions. But at PAT of 5 s, the situation is very different, the MI-LSTM
 622 model performs much better than the MI1D-CNN model, and the accuracy of the former is
 623 about 5% higher than the latter in all directions.

624 It can be seen that when the corresponding period of the prediction platform becomes
 625 longer, the traditional CNN model is not satisfactory, while the MI-LSTM model proposed in
 626 this paper performs well. Since 1D-CNN only performs convolution operations on time series
 627 information within the length of a convolution, heritability in time series information is only
 628 reflected in a single convolutional neuron. Therefore, when PAT is small, the effect on the
 629 MI1D-CNN model and the MI-LSTM model is insignificant. However, with the increase of
 630 PAT, the disadvantage of the MI1D-CNN model in processing temporal genetic information
 631 will become significant.

632 In addition, the training time of the two models is also recorded, as shown in **Table 5**.
 633 According to **Table 5**, the training time of the MI1D-CNN model is much shorter than that of
 634 the MI-LSTM model, which is related to the learning and calculation method of the model itself.
 635 The training time of the MI1D-CNN model is short, but it sacrifices a part of the accuracy, and
 636 the training time of the MI-LSTM model is relatively long, but the accuracy is greatly improved.

Table 5. Statistics on the training duration of the two models

Modes	PAT (s)	Epochs	Time (s)
MI-LSTM	2.5	50	912
	5	50	1053
MI1D-CNN	2.5	50	108
	5	50	157

639
 640 In summary, balancing training time and accuracy has always been an important issue in
 641 deep learning. If the goal is ultra-short-term forecasting of the FOWT motion response and the

642 accuracy requirement is relatively low, the MI1D-CNN model can be chosen. However, to
1
2 643 increase the time span of motion response forecasting and maintain prediction accuracy, the
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4
5 644 MI-LSTM model is a better choice.
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7

8 645 7. Conclusion

9
10 646 Based on the motion response data of the Braceless platform, the MI-LSTM prediction
11
12 647 model is established by the RNN deep learning method and is trained for different degrees of
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14
15 648 freedom under different environmental conditions. The accuracy of prediction results under
16
17 649 different PAT and input methods are determined and compared using statistics. Based on the
18
19
20 650 analysis and discussions, the conclusion can be made as follows:
21

22 651 (1) Taking the previous data of platform motion response, mooring force, and wave
23
24 652 elevation as input, after 50 rounds of training with two LSTM models, the Loss no longer
25
26
27 653 decreases, resulting in accurate prediction results. The Loss of the MI-LSTM model is slightly
28
29 654 better than the SI-LSTM model. The MI-LSTM model more comprehensively learns the
30
31
32 655 relationship between multiple factors and the target output.
33

34 656 (2) Based on the established and trained LSTM neural network model, the prediction
35
36
37 657 results of the model fit well with the simulated value. The prediction accuracy with PAT at 2.5
38
39 658 s is slightly higher than the accuracy with PAT at 5 s and the overall performance of the MI-
40
41
42 659 LSTM model is better than the SI-LSTM model. The additional two factors can positively
43
44 660 improve the accuracy of the final prediction result.
45

46 661 (3) The established MI-LSTM model is applied to the situation where the platform is
47
48
49 662 affected by second-order hydrodynamics, and it is found that the model has a better predictive
50
51
52 663 effect on the response of the Braceless platform affected by second-order hydrodynamics. The
53
54 664 MI-LSTM model has a better performance for the case where the nonlinearity phenomenon is
55
56 665 more pronounced.
57

58
59 666 (4) The MI-LSTM model established in this paper is compared with the traditional MI1D-
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667 CNN model, and the advantages and disadvantages of the two models are clarified from the
668 aspects of training time and overall accuracy. When the PAT is small, the difference between
669 the results of the two models is not significant, while when the PAT increases, the results
670 obtained by the MI-LSTM model are better than those obtained by the MIID-CNN model.

671

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679

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Short-term Motion Prediction of floating offshore wind turbine Based on Multi-input LSTM Neural Network

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Abstract: The motion response of an offshore floating wind turbine (FOWT) platform is closely related to the control operation regarding the safety of a wind turbine. It is affected by various factors such as sea state environments and mooring systems. In practice, how to predict the motion response of the wind turbine platform in the short term has always been a concern of engineering practice. At present, the development of deep learning technology has brought some potential solutions to this problem. In this paper, a Multi-Input Long-Short Term Memory (MI-LSTM) neural network method is proposed to predict the short-term motion response of a floating offshore wind turbine platform. Specifically, the numerical simulation of the 5MW Braceless platform is carried out under different environmental conditions, and the data of

24 platform motion response, wave elevation, and mooring force are selected as input variables.
25 Then the training and test groups are established after post-processing data. Subsequently, a
26 Single-Input LSTM (SI-LSTM) model and a Multi-Input LSTM (MI-LSTM) model are
27 established to learn the input data. After comparing the overall accuracy of the results, it is
28 found that the additional mooring force and wave elevation positively affects the platform
29 response prediction results. From the aspects of discreteness and overall accuracy, it is verified
30 that the established MI-LSTM model is also applicable, considering the influence of second-
31 order hydrodynamics. Lastly, compared with the prediction results obtained by the multi-input
32 one-dimensional convolutional neural network (MI1D-CNN), the advantages of the two
33 different models are expounded from the perspectives of training time and accuracy, which
34 provides ideas for the optimization of the FOWT motion response prediction model. This study
35 sheds insights on the short-term motion response forecast and platform positioning of a FOWT.
36 Short-term forecasts of a FOWT can be achieved under various sea conditions by combining
37 the global positioning system.

38 **Keywords:** Floating offshore wind turbine; deep learning; response prediction; multi-input
39 LSTM model; second-order hydrodynamic

40 1. Introduction

41 With the rapid development of the global economy, energy has become a critical factor in
42 determining social and economic development. To meet the Net Zero target by utilizing
43 sustainable energy, the vigorous growth of renewable energy has become an essential part of
44 the development strategy worldwide. Due to its high energy conversion ability, offshore wind
45 power has been gradually installed in various countries recently. Different foundations of
46 floating offshore wind turbines have been proposed, including spar, tension leg platform (TLP)
47 shape, semi-submersible, and barge [1]-[3]. Substantial research has been carried out in terms
48 of hydrodynamics, mooring systems, stability, performance, and survivability of a FOWT [4]-

49 [9].

50 Compared with the onshore wind turbine structure, a FOWT encounters a more complex
51 ocean environment. The motion response of a FOWT occurs in six degrees of freedom (6DOF)
52 and leads to significant challenges in design and assessment [10]. Therefore, it is of great
53 significance to propose an accurate prediction method for the motion response of the FOWT to
54 guide the design and assess structural safety. In the deep learning model, motion response
55 prediction is generally based on the historical data of motion response and many other results
56 from numerical and experimental measurements. In general, deep learning technology is
57 applied to predict the motion response of structures in the next few seconds [11]. According to
58 the length of the forecast time, motion response prediction can be categorized as short-term and
59 safe-period motion prediction. Short-term prediction plays a vital role in improving dynamic
60 positioning control performance, and it provides early warning in extreme sea conditions to
61 reduce platform damage to a certain extent. A short-term forecast's prediction advanced time
62 (PAT) is generally a few seconds, and it requires high forecast accuracy [12].

63 In recent years, the application of deep learning technology in offshore structures has
64 gradually expanded. The research is mainly carried out by the convolutional neural network
65 (CNN) and the recurrent neural network (RNN) methods [13]-[21]. Wang et al. [14] proposed
66 the Low-frequency adds wave-frequency responses (LAWR) method to predict the mooring
67 line tension of a semi-submersible platform. Combined with the LSTM method, accurate results
68 are obtained to predict mooring line tension under different cases. Pena et al. [18] proposed the
69 Wave-Generative Adversarial Network (Wave-GAN) technology, combined with CNN
70 convolutional neural network and CFD method, to predict the load of nonlinear waves on fixed
71 structural columns. Pena et al. [18] concluded the maximum error between the Wave-GAN
72 predicted value and CFD simulated value of 1.5%-2% by adjusting several parameters, and the
73 mean absolute error (MAE) of the test group is about 0.014. Lian et al. [19] constructed the

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74 digital twin of mesh clothing and established the deep neural network (DNN) to predict whether
75 the mesh clothing is damaged. The average accuracy of the final identification model is 94.3%.
76 Bjørni et al. [20] predicted the mooring line tension in the next 30 s by making use of the
77 platform motion response in the first 60 s as input and constructed a three-layer deep neural
78 network with bias term. It is concluded that the average error of anchor chain tension is 0.46%
79 through cross-sectional comparisons. According to the combined prediction method of the
80 Extreme Learning Machine (ELM), the Empirical Mode Decomposition (EMD), and LSTM
81 neural network, Zhang et al. [21] proved that the combined prediction method presented higher
82 prediction accuracy than the single LSTM model and ELM-LSTM model. However, when
83 considering the influence of environmental factors and mooring force, there is limited research
84 on predicting the motion response of a FOWT. At the same time, in practice, it needs to assess
85 the motion response of a FOWT under the influence of various complex factors and consider
86 the impact of second-order hydrodynamic force. Moreover, the amount of research on the
87 motion response prediction of a FOWT under the effect of the second-order hydrodynamic force
88 is also limited.

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89 To investigate the short-term motion prediction of a FOWT, the MI-LSTM Neural
90 Network model is used. This paper is organized as follows: Section 2 introduces the basic
91 principles of the RNN. The architecture and differences between the established SI-LSTM
92 model and the MI-LSTM model are explained in detail. The hyperparameters of the model and
93 the selection of the training and test groups are also given in this section. Then, in Section 3,
94 the structure size of the 5 MW Braceless platform model is shown. A detailed comparison is
95 made between the prediction results of the SI-LSTM and MI-LSTM models under different
96 environmental conditions in Section 4. This proves the positive excitation of the increased input
97 factor numbers on the prediction results and illustrates the advantages and benefits of the MI-
98 LSTM model. In Section 5, the applicability of the proposed model is demonstrated when the

99 second-order hydrodynamic force is considered. Given that there are few comparisons between
100 the RNN model and CNN model regarding time domain problems, in Section 6, by comparing
101 the prediction results of the proposed model with the multi-input one-dimensional
102 convolutional neural network (MIID-CNN) model, the advantages of the two models are
103 illustrated from the perspectives of overall accuracy and training time. Finally, the conclusions
104 and recommendations are made for the future optimization of the platform response prediction
105 model.

106 **2. Long-Short Term Memory (LSTM) Neural Network**

107 **2.1. Recurrent Neural Network (RNN)**

108 Recurrent neural network (RNN) is gradually emerging in the interdisciplinary field as a
109 typical representative of deep learning technology. RNN takes time series data as input and
110 performs recursion in the evolution direction of the sequence, where all nodes (cyclic units) are
111 linked in a chain [22]. RNN has memorization, parameter sharing, and turning completeness
112 [23]-[25], so it has clear advantages in learning the nonlinear features in sequences. RNNs are
113 widely used in natural language processing, such as speech recognition, language modeling,
114 and time series prediction. RNN performs outstandingly in solving scheduling problems, and
115 motion response prediction is the typical time domain problem. Therefore, in this paper, RNN
116 is selected for model architecture.

117 Since the motion of the platform at time t is affected by the motion at the previous time
118 $t - 1$, meanwhile, the motion at current time t will also have an impact at forward time $t + 1$,
119 platform motion response is a continuous process with time dependence. Considering this
120 characteristic, the traditional deep neural network (DNN) cannot convey information precisely
121 in the time sequence, but the RNN is developed to overcome this problem. Training input data
122 from a FOWT system to predict the motion response in the next few seconds can be viewed as
123 an adaptive function mapping. The input is the previous time series information of different

124 input factors, and the output is the motion response in the future. Hence, the trained deep
 125 learning model can achieve prediction in a short time.

126 The timeline expansion of the RNN is shown in **Figure 1**, where x is the network input
 127 layer, s is the network node hiding layer, and o is the network node output layer. After the
 128 network receives the input x_t at time t , the value of the hidden layer is s_t and the output
 129 value is o_t . The value of s_t depends not only on x_t , but also on s_{t-1} . In other words, s
 130 inherits the information from each node.

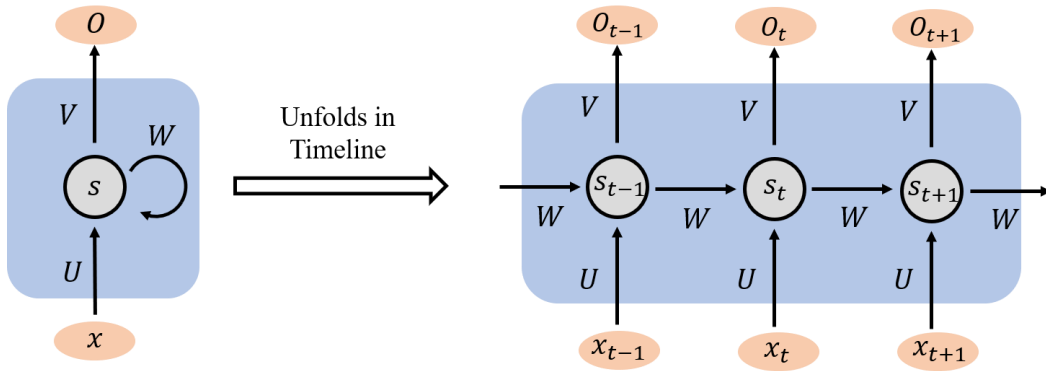


Figure 1. An unfolded RNN network

133 The calculation method of the RNN network is shown in Equations 1-2:

$$o_t = \mathbf{g}(\mathbf{V} \cdot s_t) \quad (1)$$

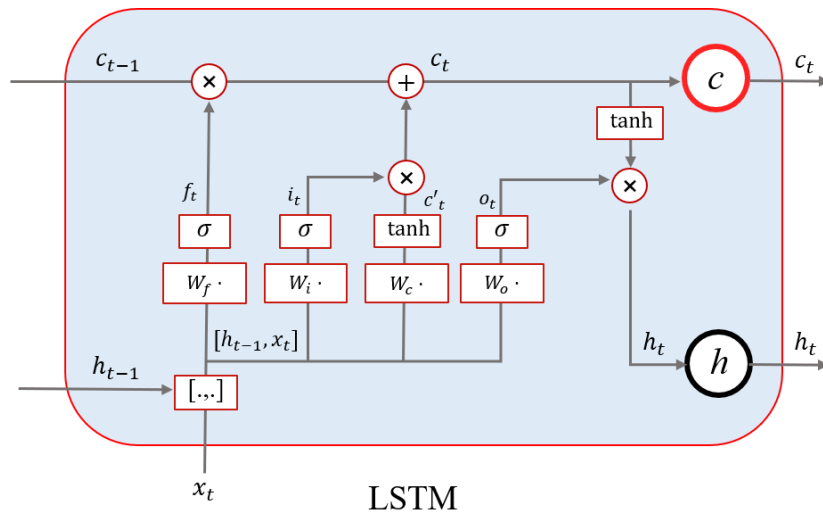
$$s_t = \mathbf{f}(\mathbf{U} \cdot x_t + \mathbf{W} \cdot s_{t-1}) \quad (2)$$

136 where \mathbf{V} is the weight matrix of the output layer, \mathbf{g} is the activation function for the output layer,
 137 \mathbf{U} is the weight matrix of the input layer x , and \mathbf{W} is the weight matrix of the last value, which
 138 is the input of the present time, and \mathbf{f} is the activation function for the hidden layer. Common
 139 activation functions, such as sigmoid, tanh, Rectified Linear Unit (ReLU), and linear activation
 140 function, can be selected according to data characteristics and experimental effects. The
 141 sigmoid activation function is generally selected for hidden layer activation function \mathbf{f} , while
 142 the linear activation function is generally chosen for output layer activation function \mathbf{g} . Equation
 143 1 is the calculation formula of the output layer. The output layer is fully connected, indicating

144 that every node in the output layer is connected to every node in the hidden layer. Equation 2 is
 145 the calculation formula of the hidden layer.

146 2.2. Long-Short Term Memory (LSTM) Network

147 LSTM is first proposed by Hochreiter and Schmidhuber [25]. Compared with traditional
 148 RNN, the LSTM network has improved the gradient explosion and gradient extinction. It has
 149 been one of the most popular RNN models and is widely applied in many fields, such as speech
 150 recognition, image description, and natural language processing. The internal structure of the
 151 LSTM node is shown in **Figure 2** [27].



152
 153 **Figure 2.** LSTM node unit internal structure

154 At time t , the LSTM network has three inputs: current time input value x_t , LSTM output
 155 value h_{t-1} at the last time, and the unit state c_{t-1} at the previous time. The output of LSTM
 156 has two parts: the output value of LSTM at the current time h_t , and the unit state at the current
 157 time c_t . x , h , and c are vectors. In addition, LSTM uses the concept of a Gate to control the
 158 state of the unit [27]. Gate is a full connection layer that controls information transmission
 159 between input and output. Its input is a vector of time series information, and its output is a
 160 vector of real numbers between 0 and 1. The gate can be expressed as:

$$161 \quad G(x) = \sigma(W \cdot x + b) \quad (3)$$

162 where \mathbf{W} is the weight matrix of the gate, \mathbf{b} is the bias term, and σ is the generally sigmoid
163 activation function.

164 The output vector of the gate is multiplied by the element and the vector is controlled to
165 achieve the gate effect. The gated output is a vector of real numbers between 0 and 1. When the
166 gated output is 0, any vectors multiplied by the output will get the 0 vectors, indicating that no
167 information can pass through. When the gated output is 1, no changes are applied by multiplying,
168 indicating that any information can pass through. Because σ has a range of (0,1), the gate is
169 an intermediate state.

170 LSTM relies on two gates to control the content of the cell state: (1) one is the forget gate
171 that determines the amount of the cell state c_{t-1} at the last moment. c_{t-1} is used to retain the
172 current moment c_t ; (2) one is the input gate that determines the amount of the current network
173 input x_t , which is saved to the unit state c_t . Meanwhile, LSTM uses an output gate to control
174 the amount of unit state c_t that is generated from the current output value h_t . The governing
175 equations of each gate are given as follows:

$$176 \quad f_t = \sigma(\mathbf{W}_f \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_f) \quad (4)$$

$$177 \quad i_t = \sigma(\mathbf{W}_i \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_i) \quad (5)$$

$$178 \quad c_t = f_t \cdot c_{t-1} + i_t \cdot \tanh(\mathbf{W}_c \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c) \quad (6)$$

$$179 \quad o_t = \sigma(\mathbf{W}_o \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_o) \quad (7)$$

$$180 \quad h_t = o_t \cdot \tanh(c_t) \quad (8)$$

181 where f_t is the forgetting gate equation, \mathbf{W}_f is the weight matrix of the forgetting gate,
182 $[\mathbf{h}_{t-1}, \mathbf{x}_t]$ is joining two vectors into a longer vector, \mathbf{b}_f is the biased term of the forgetting gate,
183 i_t is the input gate equation, \mathbf{W}_i is the weight matrix of the input gate, \mathbf{b}_i is the offset term
184 of the input gate, c_t is the current moment element state equation, o_t is the output gate control
185 equation, h_t is the final output equation determined by the output gate and unit state.

186 The unique Gate structure in the LSTM model effectively improves the phenomenon of

187 gradient explosion and gradient disappearance. the activation function of the gate structure in
 188 the LSTM model is the sigmoid function, and the Sigmoid function controls the value of the
 189 forgetting gate between 0 and 1. When the output of the gate is 1, the forgetting gate is saturated,
 190 at this time the long-range information gradient does not disappear, and the gradient can be well
 191 passed in the LSTM, largely mitigating the probability of gradient disappearance occurring;
 192 when the output of the gate is 0, at this time the model is blocking the gradient flow and
 193 forgetting the previous information, indicating that the information of the previous moment
 194 does not affect on the current moment. Through the gate structure and sigmoid activation
 195 function, the LSTM model can effectively solve the gradient disappearance and gradient
 196 explosion problems.

Existing LSTM network prediction modes mainly fall into the following four types [28]:
 point-to-point, point-to-sequence, sequence-to-point, and sequence-to-sequence, as shown in

Figure 3:

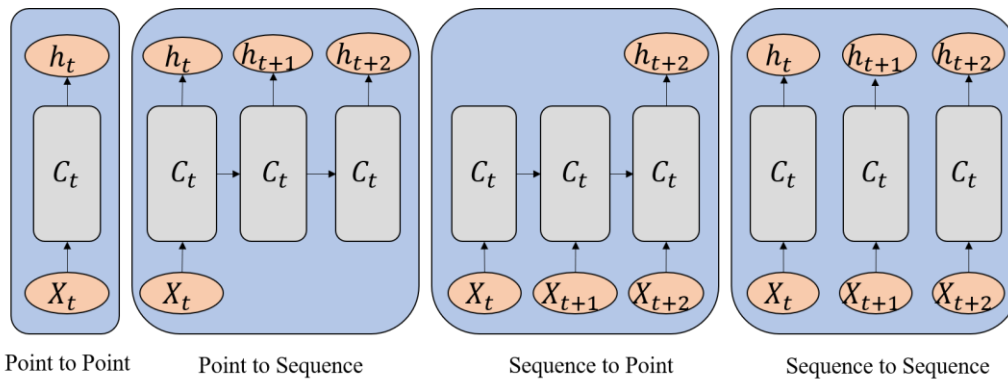


Figure 3. LSTM network prediction modes

The LSTM network in this paper is set up by using sequence-to-point mode for a prediction
 model, which uses forecasting point response from previous time series after the selected data
 input mode is adopted in the form of the sliding window. Each window length has 200 time
 points and the 10 s surge motion. The sliding window form is shown in **Figure 4**, where the
 mapping relationship between the data input and output is presented when the forecast time is
 5 s. Therefore, the response at $t + 5$ is predicted based on the response from $t-10$ to t .

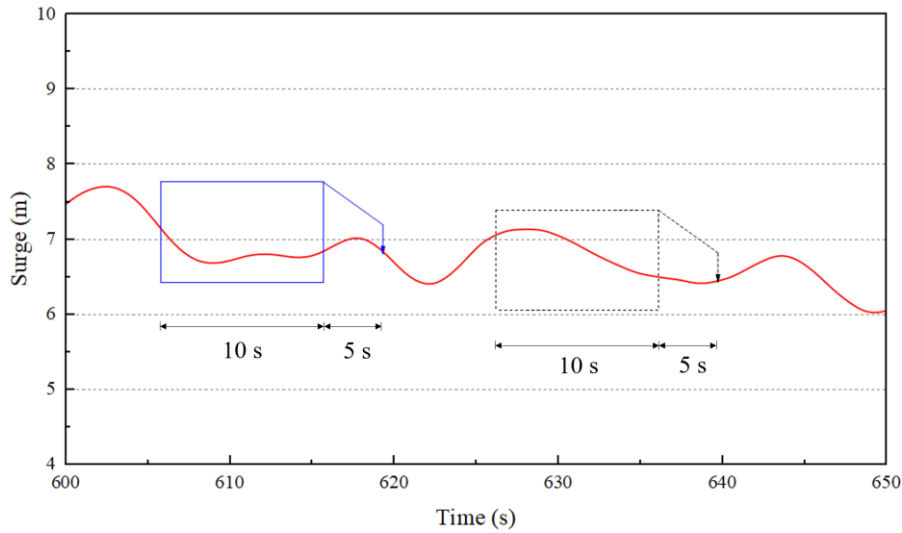


Figure 4. Sliding windows for data input and output

2.3. LSTM Model Structure

The LSTM network model established in this paper has three hidden layers and one fully connected output layer, shown in **Figure 5**. The data sampling frequency is 20 Hz. The input time step of the LSTM network contains 200 time series points with a motion response of 10s. The batch size is set to 256 sample sets, which are also the input for training and updating internal parameters. The number of neurons is set to 200. These two parameters are hyperparameters and can be adjusted according to the performance of the actual test.

Input layer: input time series with a window of 200 data points, representing the motion response of 10s. The input dimension of the single-input model is 1, and that of the multi-input model is 3.

Hidden layer: The hidden layer has 200 nodes.

Output layer: The output layer is dense, the activation function is linear, and the output result is the motion response at the target time.

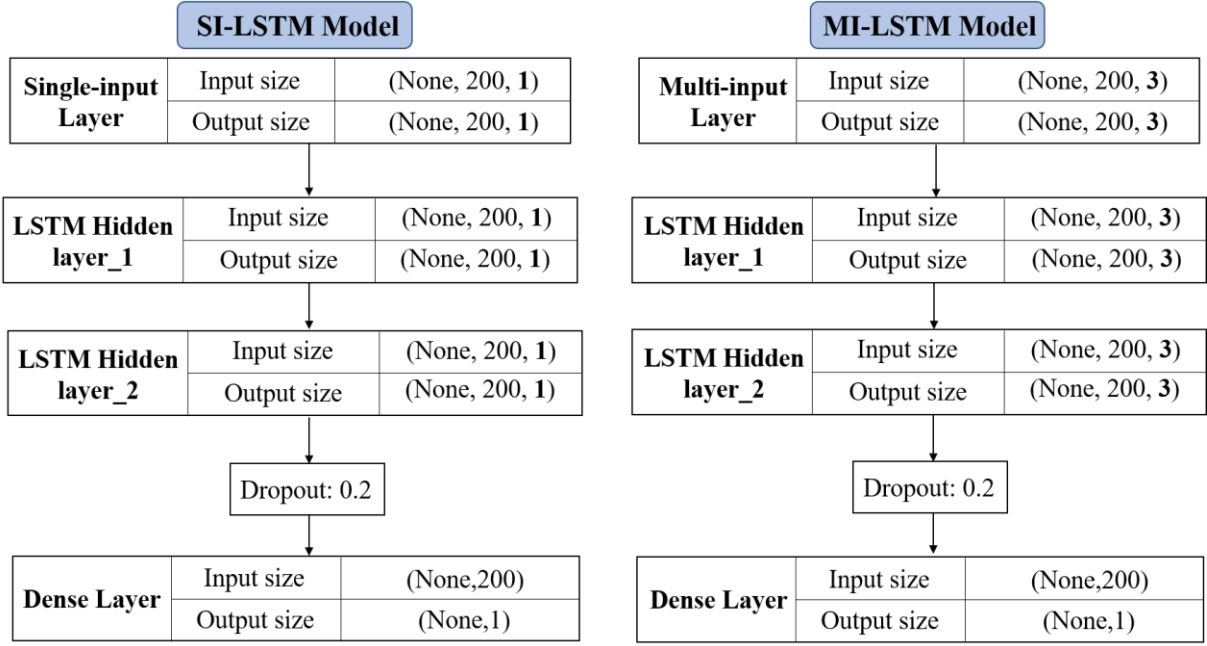


Figure 5. LSTM network model structure and data transfer format

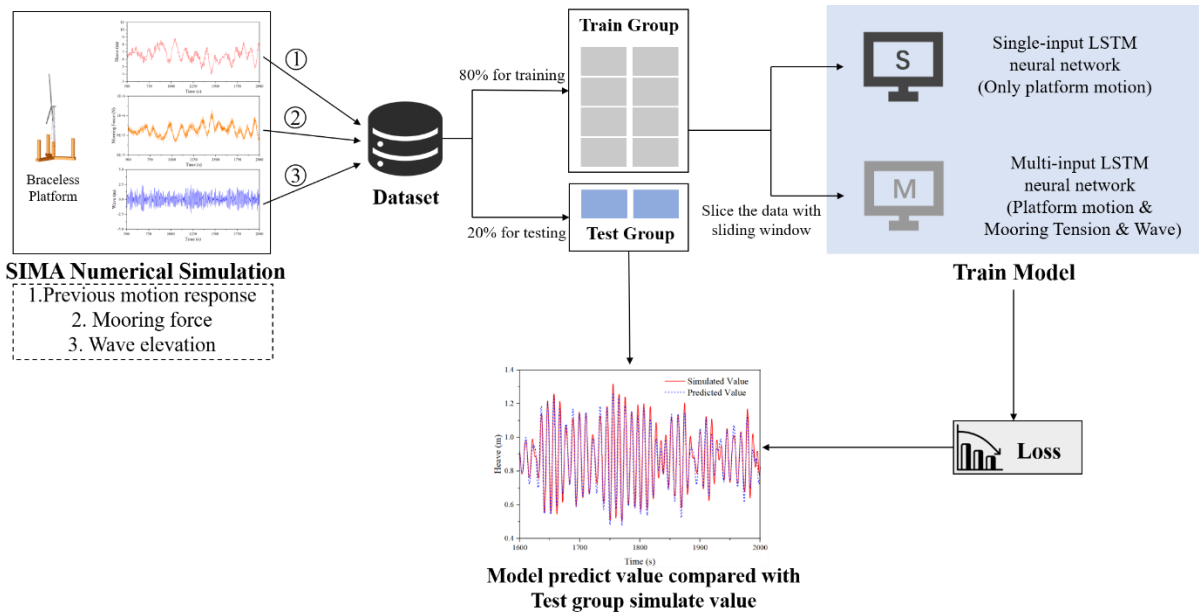
The Adam algorithm is configured for the LSTM network [30]. Adam algorithm is an advanced Stochastic Gradient Descent (SGD) algorithm, which introduces an adaptive learning rate for each parameter. The adaptive learning method and the Momentum method are combined. The learning rate is dynamically adjusted by the first and second moment estimation of the gradient. The gradient descent process is relatively stable and suitable for most non-convex optimization problems in large data sets and high-dimensional space.

Simultaneously, the Dropout layer is added after the input layer and the hidden layer to prevent overfitting [31-[32], and the Dropout_1 and Dropout_2 are set to 0.2. Overfitting may occur due to a large number of unknown network parameters or training times. The principle of dropout is that during the neural network training, some neurons are randomly discarded and not used for training at this round to avoid overfitting and accelerate loss convergence.

In this paper, the LSTM neural network is constructed, and the input data consists of three parts, including time series of previous motion response, mooring force, and wave elevation. And the current motion response is set as the output data. The process of using the LSTM neural network model to predict the motion response is shown in **Figure 6**. The process of predicting

240 motion response by LSTM neural network.

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242

243 **Figure 6.** The process of predicting motion response by LSTM neural network

244 **3. Braceless Platform model**

245 The 5 MW Braceless model is established by SIMA, and the time domain response is
 246 obtained by numerical simulation. SIMA is developed for the analysis of flexible marine riser
 247 systems, but it is also suited for any slender structures, such as mooring lines, umbilicals, steel
 248 pipelines, and conventional risers. The data used in training in this paper came from the FOWT
 249 model of a 5 MW Braceless semi-submersible platform in the water depth of 100 m. The
 250 Braceless platform consists of one central column, three side columns, and three pontoons,
 251 shown in **Figure 7**.

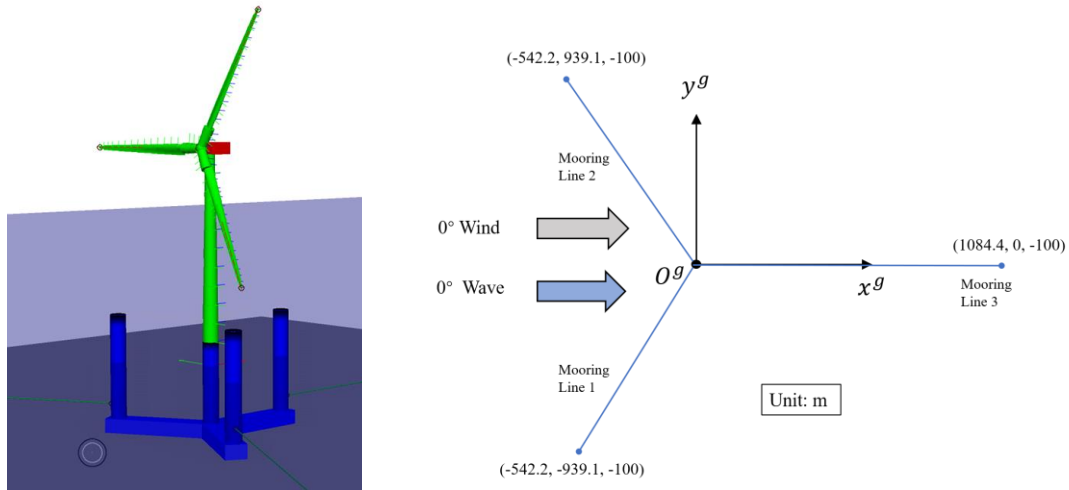


Figure 7. Schematic of 5-MW Braceless platform

Three side columns are evenly distributed around the central column at 120° . They are connected to the bottom of the central column by a floating buoy to form a Braceless semi-submersible platform. The three-point mooring system is adopted, and the anchor chain is set at the bottom of the side column. 0° wave-wind misalignment is considered in the simulation. The main parameters of the Braceless platform are shown in **Table 1**. Parameters of the 5 MW Braceless Platform:

Table 1. Parameters of the 5 MW Braceless Platform

Parameter	Value
Central column diameter (m)	6.5
Side column diameter (m)	6.5
Buoy height (m)	6
Buoy bottom width (m)	9
Buoy short radius (m)	41
Buoy long radius (m)	45.5
Depth of the draft (m)	30
Displacement (t)	10555
Steel weight (t)	1804

Based on the data given in Ref. [33], site 5 in Norway was selected as a representative site for the simulation. In the following cases, the water depth is 100 m. The average wind speed V_t , effective wave height H_s , and spectrum peak period T_p at the selected cabin height are listed. The JONSWAP spectrum is used to describe random ocean waves, and the JONSWAP spectrum is shown in Equations 9-1 to 9-3. The Kaimal wind speed spectrum is used to describe the offshore wind conditions.

$$S_{(f)} = \alpha \frac{H_s^2}{T_p^4 f^5} \exp \left[-\frac{5}{4} (T_p f)^{-4} \right] \gamma \exp \left[-\frac{(T_p f - 1)}{2\sigma^2} \right] \quad (9-1)$$

where f is the wave frequency, γ is the shape parameter, and σ and α are shown below,

$$\sigma = \begin{cases} 0.09 & f \geq f_p \\ 0.07 & f < f_p \end{cases} \quad (9-2)$$

$$\alpha = \frac{0.0624}{0.230 + 0.0336\gamma - 0.185/(1.9 + \gamma)} \quad (9-3)$$

Table 2. Environment matrix

Case	V_t (m/s)	γ	H_s (m)	T_p (s)
EC 1	9.8	3.3	2.9	9.98
EC 2	14.8	3.3	4.5	11.81
EC 3	16	3.3	5.3	12.81

4. Single-input and Multi-input

4.1. Data Partitioning and Error Measurement

The sampling frequency of the Braceless platform simulation test is 20 Hz. The total sampling length of motion response (surge, pitch, and sway) is 2000 s. The collected time series

279 contains 40000 data points. In the training model, the first 32000 points of response data are
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2 280 the training groups and the last 8000 points of response data are the test groups. Three test cases
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4 281 (EC1, EC2, and EC3) are selected, and each test case contained 2000 s surge, pitch, and sway
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7 282 motion data.

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9 283 The training group data is used to train and obtain the neural network model. The
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12 284 relationship between training Epochs and Loss is observed through the Loss function. Then the
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14 285 test group data is imported into the trained neural network model to verify the accuracy and
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17 286 performance of the trained model.

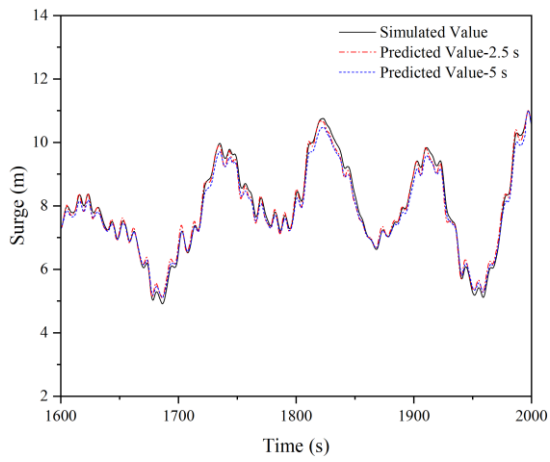
18
19 287 The Loss function adopted in this paper is the Mean Squared Error (MSE), which is the
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21
22 288 averaged squared difference between the predicted value and the measured value as shown in
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24 289 Equation 10:

$$27 \text{ 290} \quad MSE = \frac{\sum (y'_t - y_t)^2}{n} \quad (10)$$

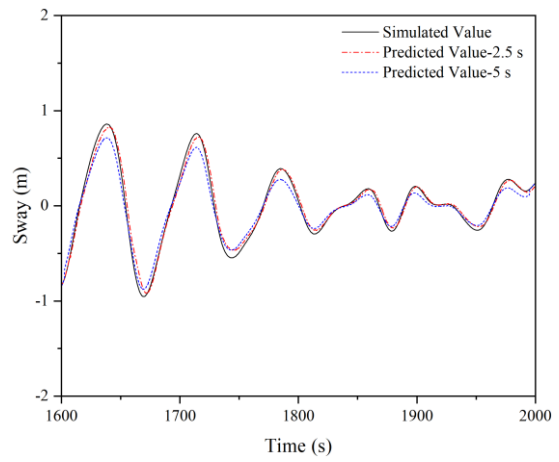
28
29 291 where y'_t is the predicted value of the motion response at time t , y_t is the measured value
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32 292 of the motion response at time t , and n is the total number of predicted values 8000 in this
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34 293 study.

35 36 37 38 294 4.2. Single-input Predicted Results

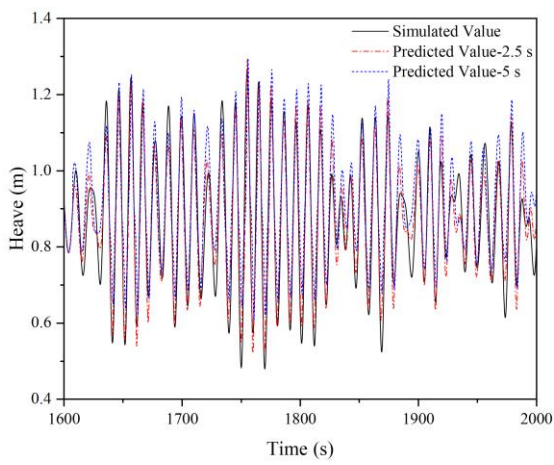
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41 295 Single-input LSTM (SI-LSTM) model is used to train the motion response data in the
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43
44 296 training group in terms of the heave, surge, sway, and pitch. The training input of the model is
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46 297 only based on the previous motions. The output of the model is compared and analyzed with
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48
49 298 the data of the test group. The predicted advance time is set as 2.5 s and 5 s respectively. The
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51 299 actual and predicted values are shown in **Figures 8-10**.



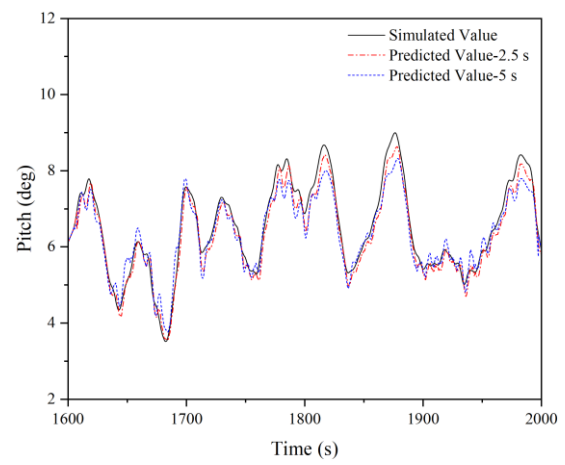
(a)



(b)



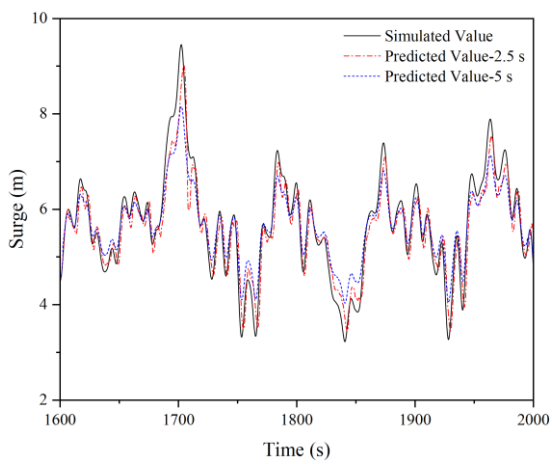
(c)



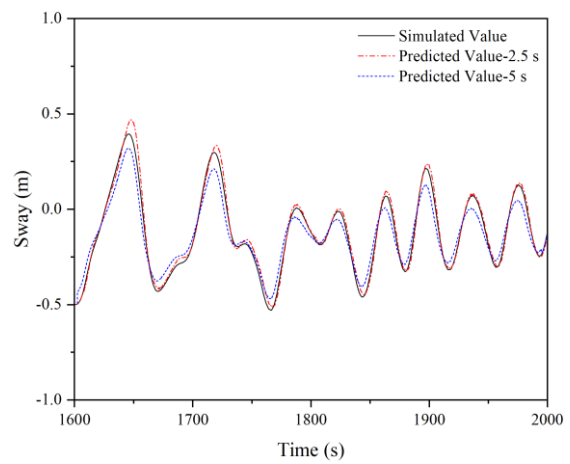
(d)

Figure 8. Simulated and predicted values of EC 1 at 2.5 s and 5 s :

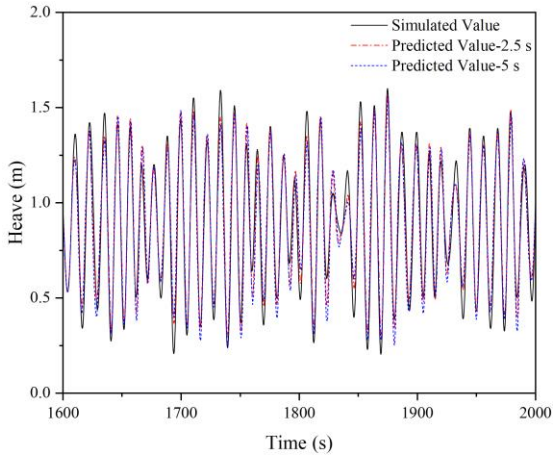
(a) Surge; (b) Sway; (c) Heave; (d) Pitch



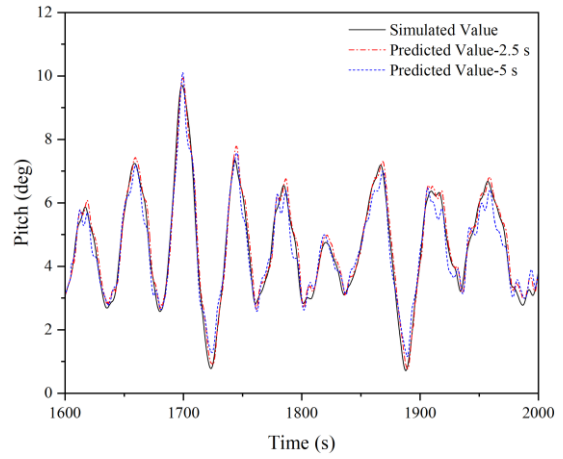
(a)



(b)



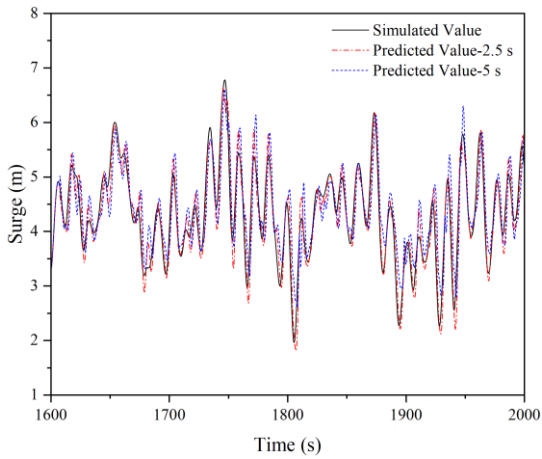
(c)



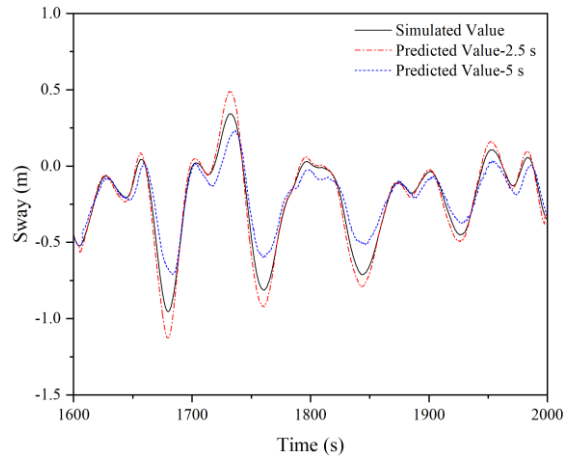
(d)

Figure 9. Simulated and predicted values of EC 2 at 2.5 s and 5 s:

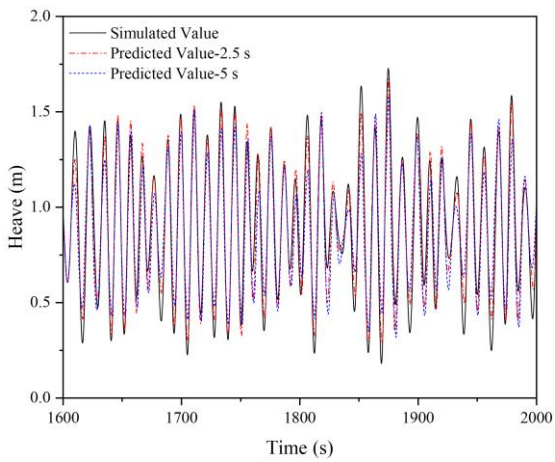
(a) Surge; (b) Sway; (c) Heave; (d) Pitch



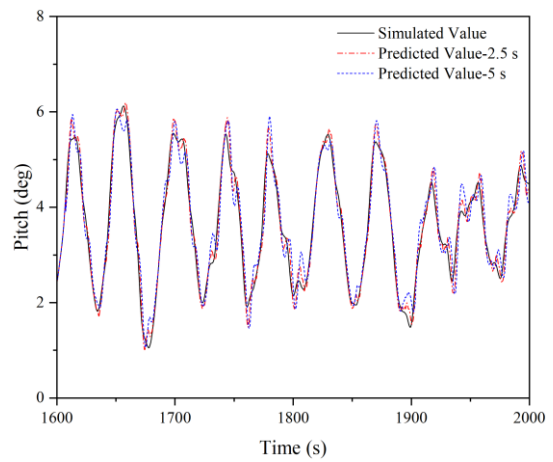
(a)



(b)



(c)



(d)

316 **Figure 10.** Simulated and predicted values of EC 3 at 2.5 s and 5 s:

317 (a) Surge; (b) Sway; (c) Heave; (d) Pitch

318 It can be seen from **Figures 8-10** that when the previous motion response is used as the
319 single input, the predicted value at PAT of 2.5 s is closer to the simulated value. Due to the large
320 amplitude of motion in the surge, the predicted results in **Figure 8(a)** agree well with the
321 simulation results, apart from the minor discrepancy at the peak of the surge in **Figures 9-10(a)**.
322 Due to the small amplitude in sway, the predicted results under the two PATs generally agree
323 with simulated results compared to the agreement between predicted and simulated surge.
324 Similarly, there is also a minor discrepancy at the peak. The amplitude of heave motion is the
325 smallest among the three motions, but it contains higher frequency components. The predicted
326 heave motion in three test cases in **Figures 8-10** presents better agreement with simulated
327 results at PAT of 2.5 s, but a minor discrepancy can be noted at the peak and trough at PAT of 5
328 s. The peak value of pitch in **Figures 8-10(d)** is also large, but there is higher-order fluctuation
329 at the peak and trough due to the nonlinear motion induced by wind and waves. Single-input
330 LSTM model learned the nonlinear features from the training data group, so the predicted value
331 agrees well with the simulated results.

332 In summary, compared with the simulated values, the predicted values in all motions have
333 very minor discrepancies at peak and trough, but a fairly good agreement has been presented.
334 The discrepancy at peak and trough can be attributed to the limited input factors to train the
335 neural network. To unravel this, the multi-input network structure is investigated in detail in
336 Section 4.3.

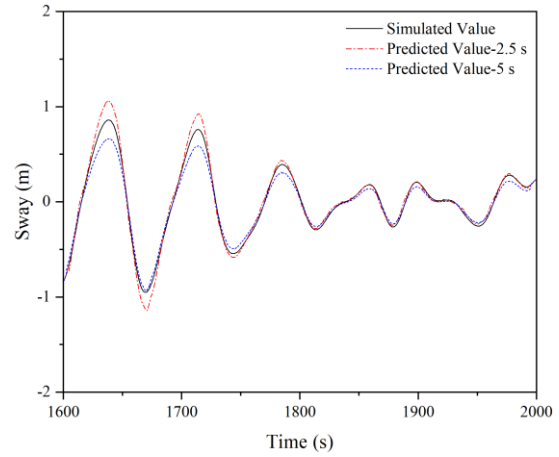
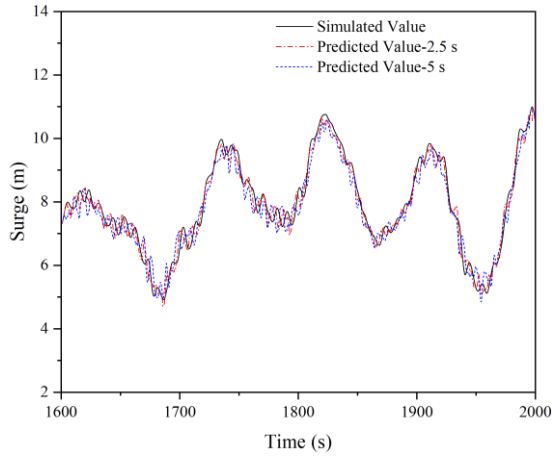
337 4.3. Muti-input Predicted Results

338 A multi-input model is trained to explore the effects of multiple factors as input conditions
339 on the predicted results. Unlike the single-input model, the training input of the multi-input
340 LSTM (MI-LSTM) model is based on the previous motions, mooring forces, and wave

341 elevation. The output of the model is compared and analyzed with the data of the test group.

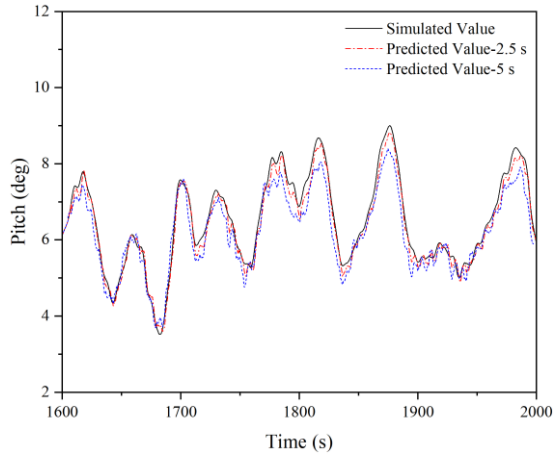
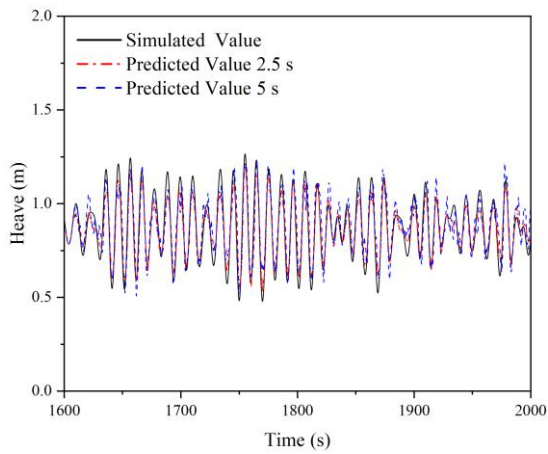
342 The predicted advance time is set as 2.5 s and 5 s respectively. The test and predicted results

343 are shown in **Figures 11-13**:



344 (a)

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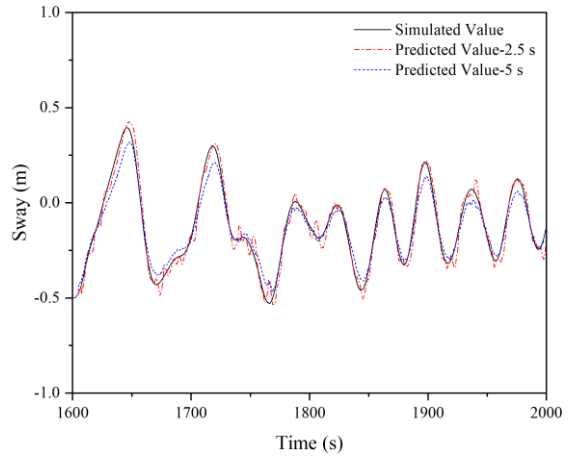
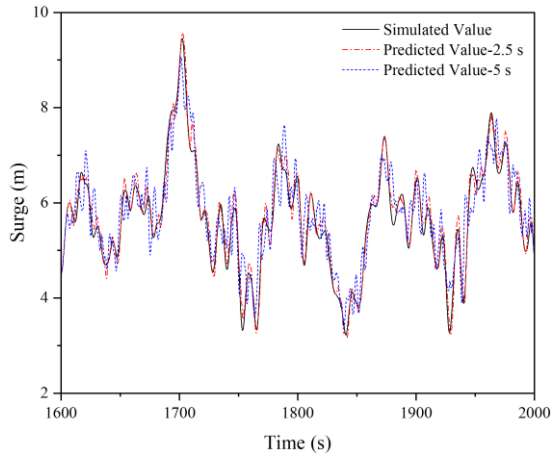


346 (c)

347 (d)

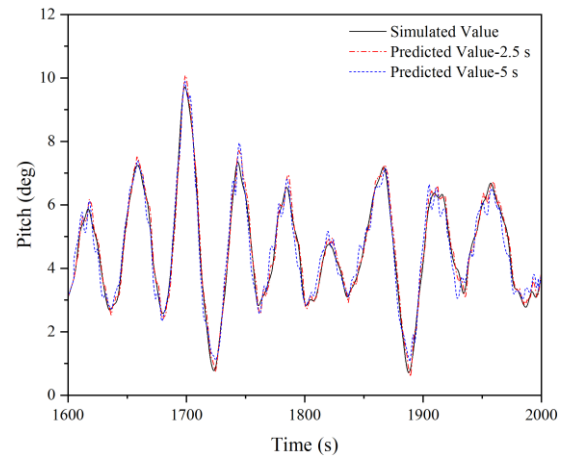
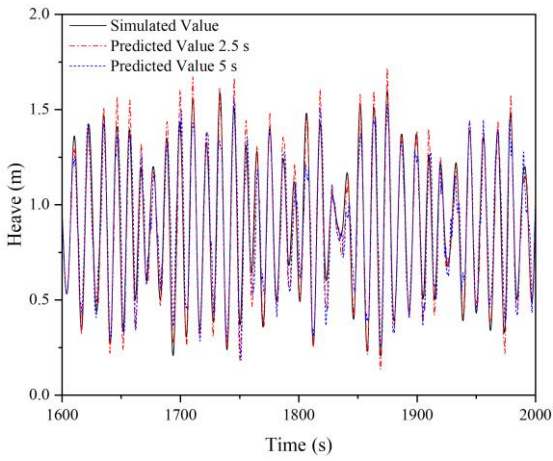
348 **Figure 11.** Simulated and predicted values of EC 1 at 2.5 s and 5 s:

349 (a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)

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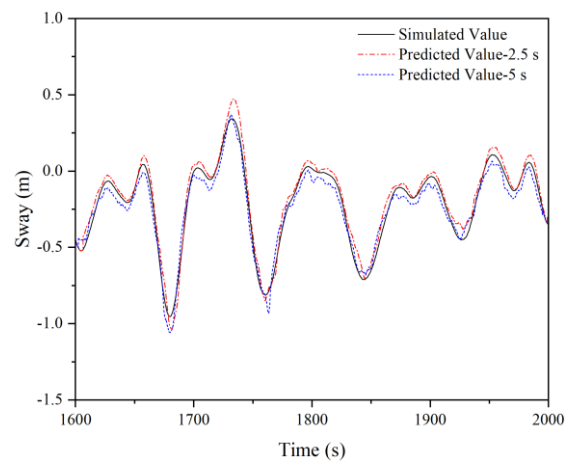
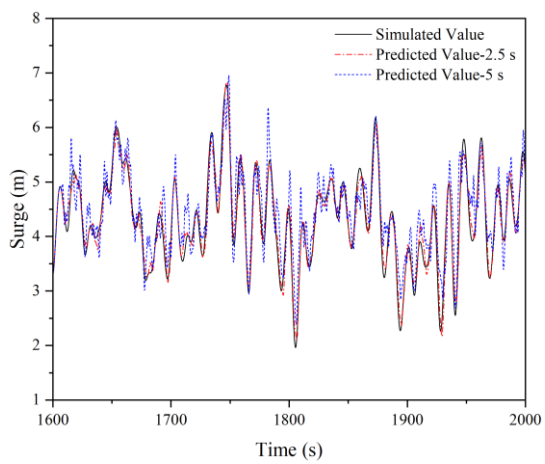


(c)

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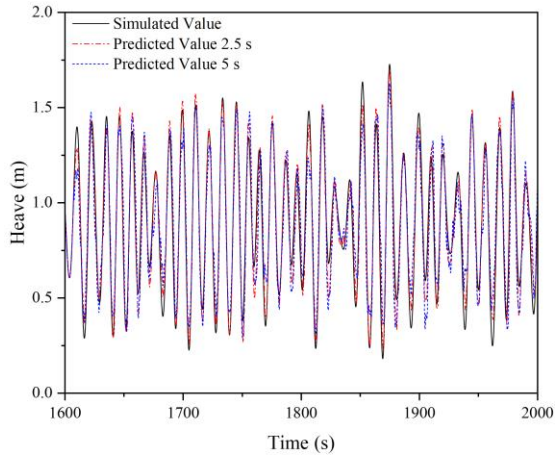
Figure 12. Simulated and predicted values of EC 2 at 2.5 s and 5 s:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

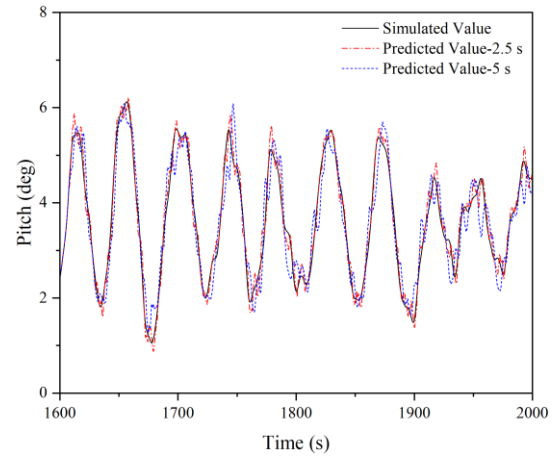


(a)

(b)



(c)



(d)

Figure 13. Simulated and predicted values of EC 3 at 2.5 s and 5 s:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

When the model input factors become multiple, i.e., adding mooring force and wave elevation, a better agreement between the predicted value and the simulated value is obtained compared with the single input case. Improved agreement of surge prediction at peak in **Figure 12(a)** is presented compared to **Figure 9(a)**. But in the case of multiple inputs, the fluctuations can also be noticed from the predicted surge. Sway and heave are not significantly improved due to their less sensitivity to mooring force. With the additional input factors, the accuracy of the predicted pitch has been improved significantly as pitch motion is sensitive to mooring forces, comparing **Figure 9(d)** and **12(d)**. It can be found that in the period 1900s-2000s, the discrepancy of the single-input model can be found, while the multi-input model presented better performance with additional input data sets. Similar to the pitch, better agreements have been achieved for the predicted surge.

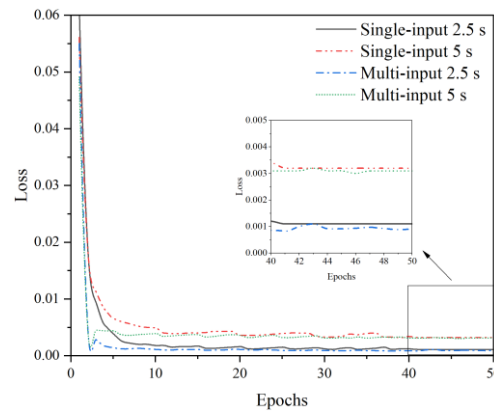
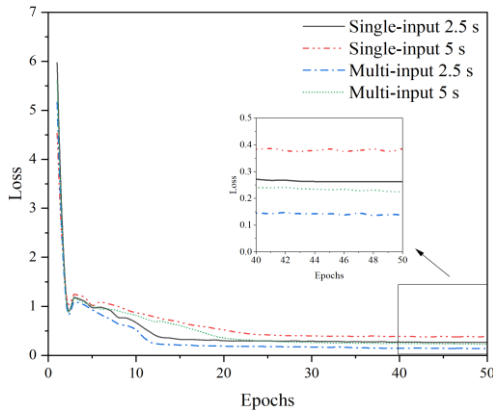
In a word, after adding the additional input factors to train the multi-input model, better performance in predicting the FOWT motion response has been demonstrated. However, the saw-tooth effect of the MI-LSTM model is more obvious, caused by the deep learning of the additional input information. The saw tooth effect is further analyzed after analyzing the scatterplot of discrete situations in Section 4.4.

378 4.4 Error Analysis

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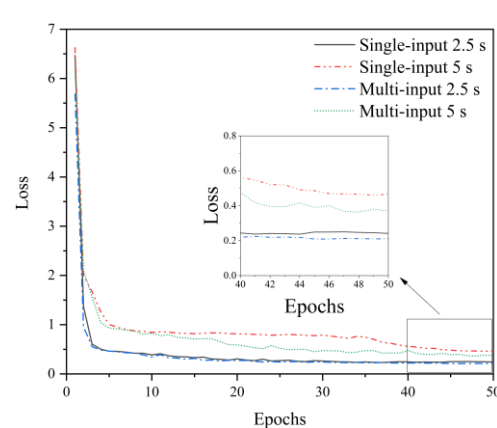
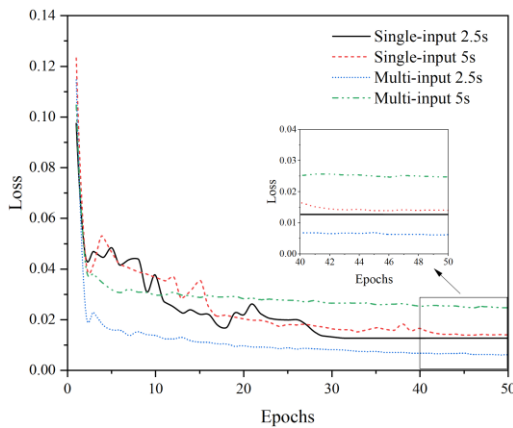
In this study, the number of Epochs is set to 50 rounds. It is shown in **Figure 14** the trend of the Loss function changing with the Epochs is generated and recorded during the training. It can be noted that with the increment of Epochs, Loss decreases rapidly in the beginning. Then after the rapid decrease stage, Loss finally tended to be stable. After the Epochs reaches 50, Loss remains unchanged. It can be concluded that the network training effect will not be further improved after 50 rounds and a neural network model with good accuracy is generated. The model has completed learning about the relationship between the input and output data.

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(a) (b)



(c) (d)

Figure 14. The curve of Loss affected by Epochs for different directions:

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(a) Surge; (b) Sway; (c) Heave; (d) Pitch

At the same time, the Loss of the MI-LSTM model is found to be lower than that of the

393 SI-LSTM model both in 2.5 s and 5 s. It can be considered that the learning ability of the model
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2 394 is improved after additional factors are added to the training. The predicted results are shown
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4 395 in sections 4.2 and 4.3 and compared with simulation data. It is difficult to observe their overall
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7 396 discretization, so a scatter plot of the prediction results in different input modes is plotted in
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10 397 this section, as shown in **Figure 15**.

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12 398 According to **Figure 15**, comparing the SI-LSTM model with the MI-LSTM model under
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14 399 the different cases, it can be found that after adding two additional input factors, the discrete
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16 400 situation of the MI-LSTM model prediction results is significantly smaller than that of the SI-
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19 401 LSTM model prediction results. This phenomenon is more evident in the sway and heave of
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22 402 EC1, surge and sway of EC2, and sway and heave of EC3. The use of the MI-LSTM model is
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24 403 beneficial in reducing the discrete nature of predicted results.
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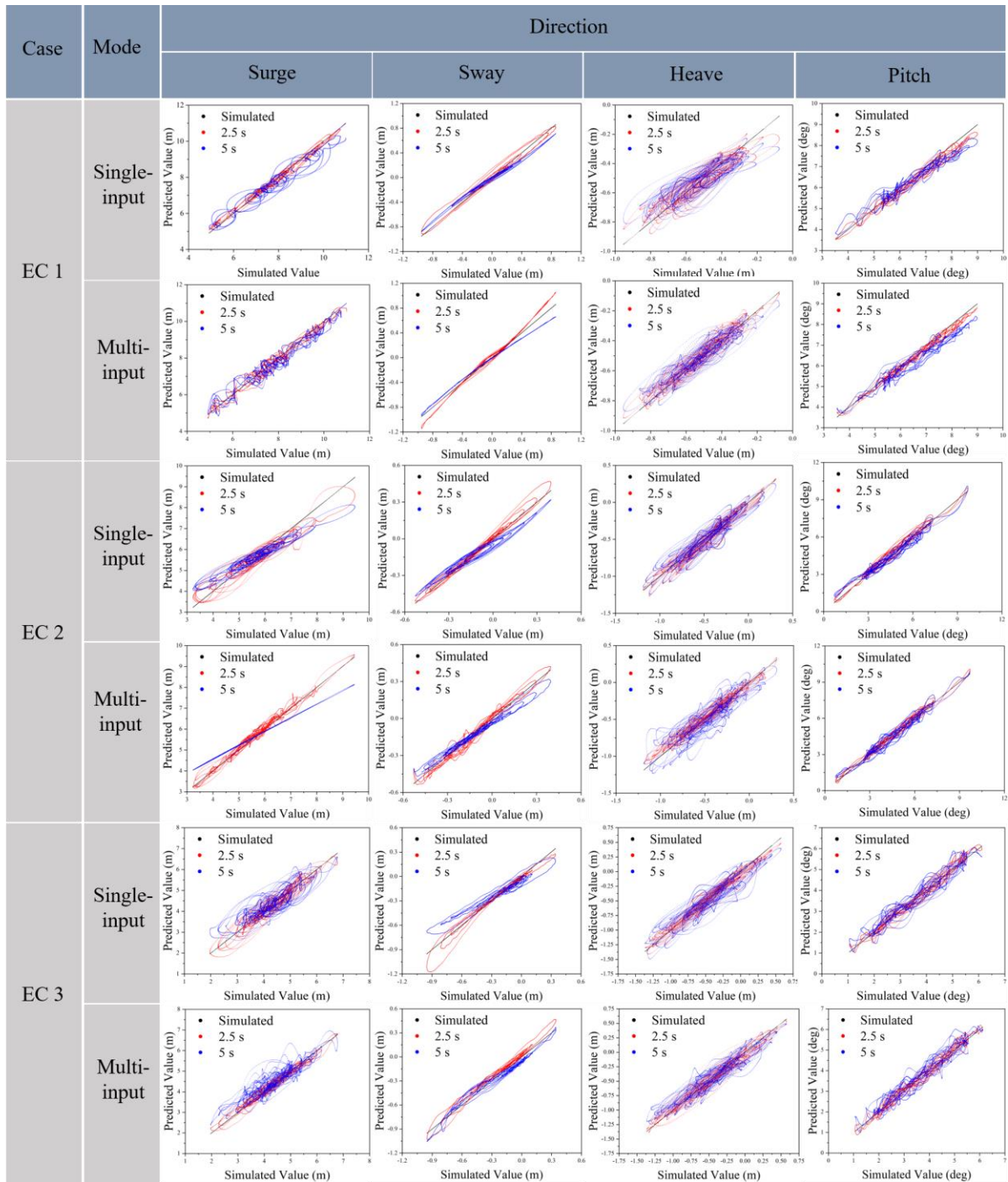
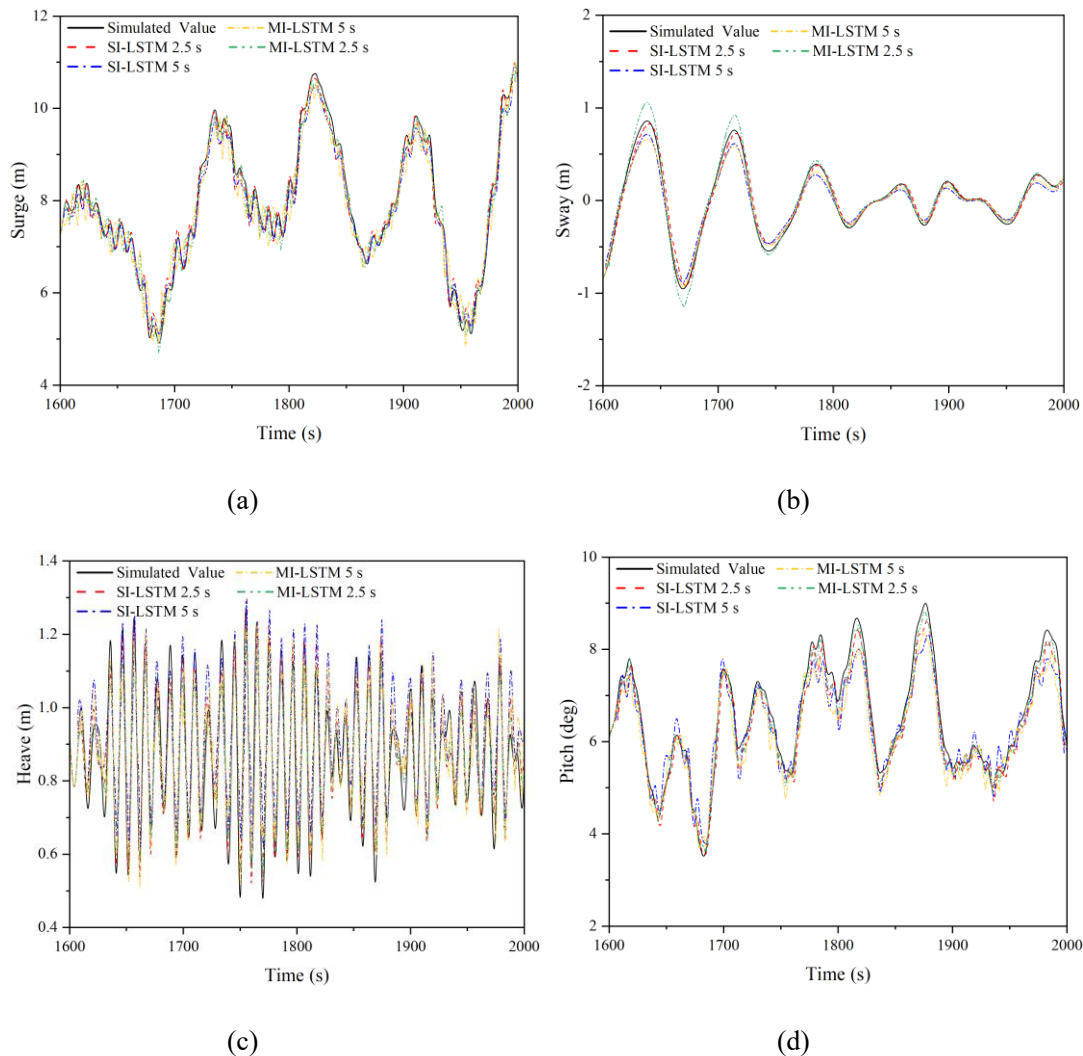


Figure 15. The discrete scatter plot of prediction results with two models

Comparing the prediction results of the SI-LSTM model with the MI-LSTM model on the same image, the comparison results for EC 1 are shown in **Figure 16**. From the figure, one can find that the prediction results of both SI-LSTM model and MI-LSTM model have high accuracy. For the surge motion, both models have the best results and have a good fit in both

411 peak and trough positions as well. For the sway motion, the MI-LSTM model predicts a certain
 412 absolute value bias at the response extremes, while the SI-LSTM model predicts a certain
 413 absolute value bias at the response extremes. For the heave motion, since the SI-LSTM model
 414 does not take into account the effect of wave elevation, and the response in the heave direction
 415 happens to be most affected by the wave, the accuracy of the SI-LSTM model in this direction
 416 is not as good as that of the MI-LSTM model. For the pitch motion, the results of both models
 417 are similar to those of the surge direction, but the predicted values are smaller at the peak, which
 418 is more obvious in the SI-LSTM model.



423 **Figure 16.** Comparison of 1st-order and 2nd-order hydrodynamic prediction results:

424 (a) Surge; (b) Sway; (c) Heave; (d) Pitch

426 In addition to the impact of discrete situations, the overall accuracy of the MI-LSTM
 427 model and the single-input model is also important. The individual statistics for predicting the
 428 final result of the FOWT motion response using both models are listed in Table 3. The overall
 429 accuracy of both models is presented in **Figure 17**.

430 Based on Table 3 and Figure 16, the results at PAT of 2.5 s present better agreements than
 431 at PAT of 5 s. After adopting the MI-LSTM model, the accuracy of the prediction results in
 432 pitch and heave has been significantly improved. With the increment of PAT, the period between
 433 input and output becomes larger, so the time correlation between the two decreases and the
 434 uncertainty increases. The upper limit of learning ability decreases as the correlation between
 435 input and output information decreases. Therefore, the accuracy at PAT of 5 s is lower than that
 436 of 2.5 s.

Mode	Statistics	EC 1				EC 2				EC 3			
		Heave	Pitch	Surge	Sway	Heave	Pitch	Surge	Sway	Heave	Pitch	Surge	Sway
Single- input 2.5 s	Max	73.2%	95.9%	99.9%	96.7%	96.2%	92.6%	95.3%	81.2%	84.3%	98.8%	97.8%	81.0%
	Min	92.3%	99.0%	96.2%	96.2%	93.4%	92.4%	93.0%	97.1%	96.8%	96.2%	92.4%	76.9%
	Average	99.7%	97.2%	99.8%	88.6%	95.6%	92.4%	98.5%	90.6%	96.9%	93.3%	96.5%	94.9%
	STD	87.5%	93.7%	94.3%	94.0%	97.7%	98.9%	83.7%	90.6%	96.0%	92.1%	93.5%	97.7%
	Overall	88.2%	96.4%	97.6%	93.9%	95.7%	94.1%	92.6%	89.9%	93.5%	95.1%	95.0%	87.6%
Multi- input 2.5 s	Max	73.2%	98.0%	97.6%	97.1%	97.4%	96.1%	96.8%	92.5%	95.8%	98.5%	99.4%	82.9%
	Min	96.0%	97.8%	95.8%	89.6%	93.3%	93.9%	98.2%	98.7%	98.3%	93.5%	96.6%	91.9%
	Average	97.5%	98.2%	99.4%	88.6%	96.0%	98.5%	98.9%	96.6%	99.2%	98.2%	99.0%	92.4%
	STD	97.3%	95.3%	96.8%	97.9%	97.8%	98.8%	95.6%	95.5%	96.6%	98.1%	94.9%	96.6%
	Overall	91.0%	97.3%	97.4%	93.3%	96.1%	96.8%	97.4%	95.8%	97.5%	97.1%	97.5%	91.0%
Single- input 5 s	Max	73.2%	92.5%	98.7%	83.2%	82.9%	95.9%	86.1%	81.1%	69.7%	88.9%	97.4%	67.9%
	Min	89.3%	93.0%	96.7%	92.2%	91.4%	80.1%	74.9%	94.4%	90.8%	89.5%	67.2%	74.3%
	Average	98.9%	97.7%	97.8%	75.0%	93.0%	89.0%	89.8%	91.7%	92.3%	93.5%	98.3%	92.9%
	STD	75.6%	81.5%	88.3%	82.6%	93.3%	89.8%	76.2%	78.7%	90.4%	87.3%	85.3%	70.2%
	Overall	84.3%	91.2%	95.4%	83.3%	90.1%	88.7%	81.8%	86.5%	85.8%	89.8%	87.1%	76.3%
Multi- input 5 s	Max	73.2%	93.3%	98.1%	76.8%	82.5%	98.2%	87.8%	80.8%	85.3%	89.1%	97.4%	82.1%
	Min	91.3%	95.1%	98.5%	98.4%	96.0%	76.5%	85.7%	94.4%	91.0%	94.3%	78.4%	89.0%
	Average	97.7%	95.5%	98.6%	83.7%	96.9%	89.8%	88.4%	91.9%	98.0%	97.5%	96.4%	89.3%
	STD	89.7%	86.2%	91.3%	85.3%	97.0%	98.0%	90.8%	81.0%	88.8%	91.6%	87.2%	93.2%
	Overall	88.0%	92.5%	96.7%	86.1%	93.1%	90.6%	88.2%	87.0%	90.8%	93.1%	89.8%	88.4%

437 **Table 3.** The accuracy of each statistic under the different input model

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At the same time, the overall prediction result of the MI-LSTM model is better than the SI-LSTM model. The additional input factors increase the dimension of information, which enables the MI-LSTM model to explore more relationships between different input factors and the motion response of the target output. MI-LSTM model also adds more details to the final prediction results, improving the overall accuracy of the prediction results. In other words, there is a positive correlation between mooring force, wave elevation, and the motion response of the platform.

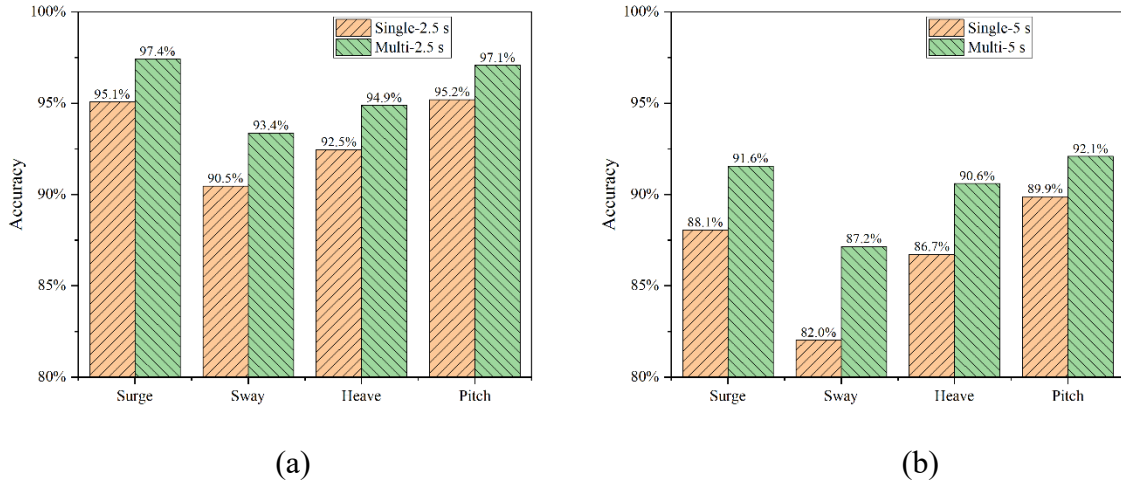
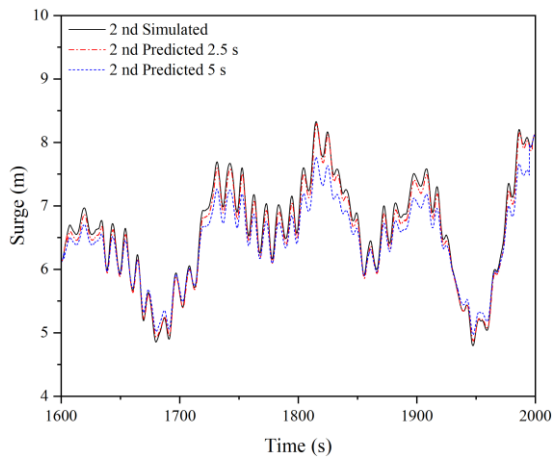


Figure 17. Overall accuracy under different PATs: (a) 2.5 s; (b) 5 s

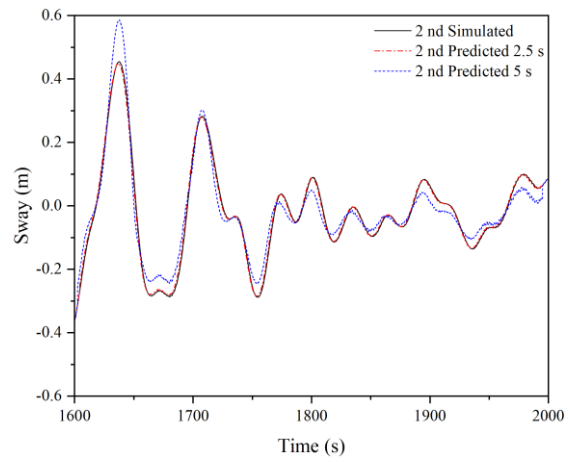
5. Second-order Hydrodynamic Effects

5.1 Prediction results under the influence of second-order hydrodynamic effects

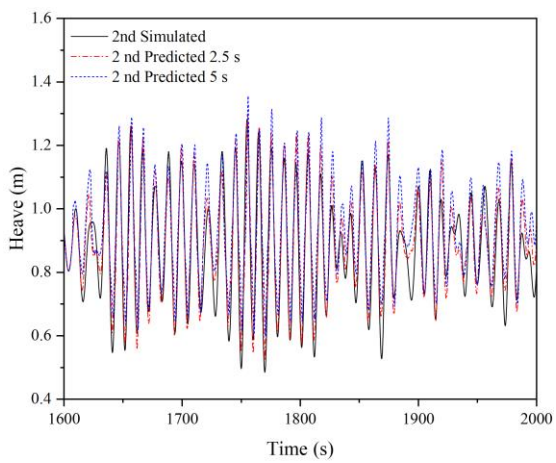
The influence of second-order hydrodynamics is significant for the load prediction of a FOWT [34]. EC1-EC3 are again simulated considering second-order hydrodynamic effects, the simulation data is imported into the MI-LSTM model for training. The prediction results under the second-order hydrodynamic force are obtained after the training, shown in **Figures 18-20**.



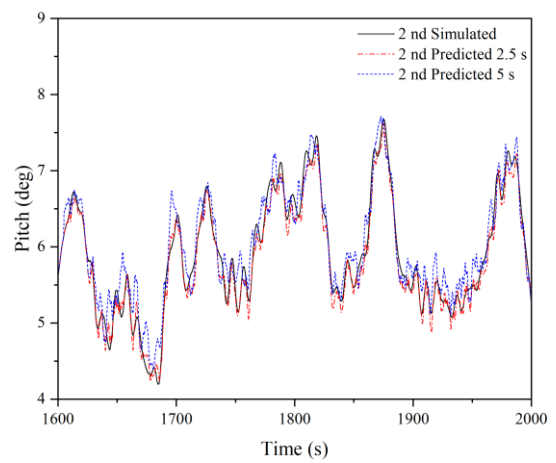
(a)



(b)



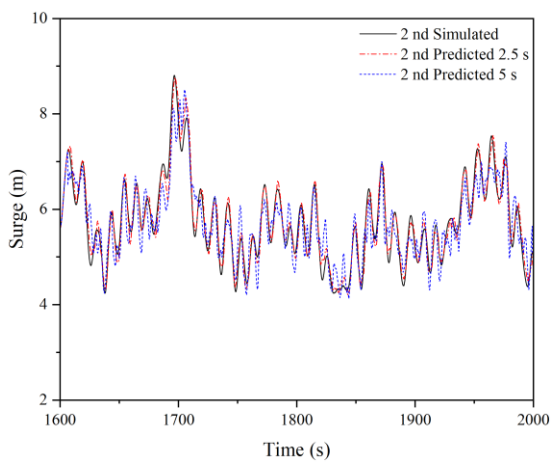
(c)



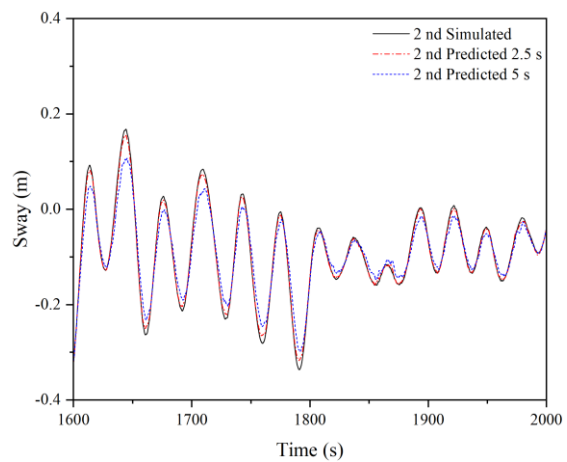
(d)

Figure 18. Simulated and predicted values of EC 1 at 2.5 s and 5 s:

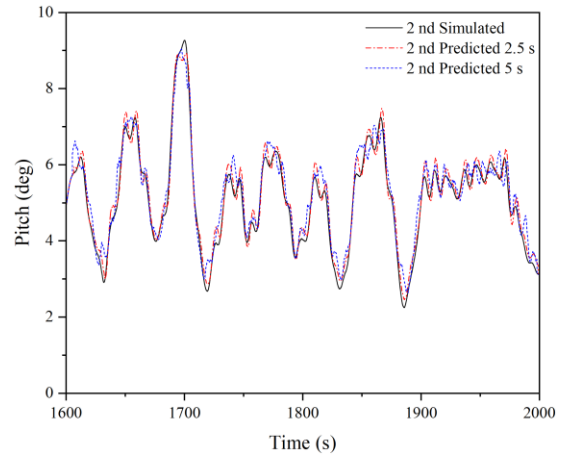
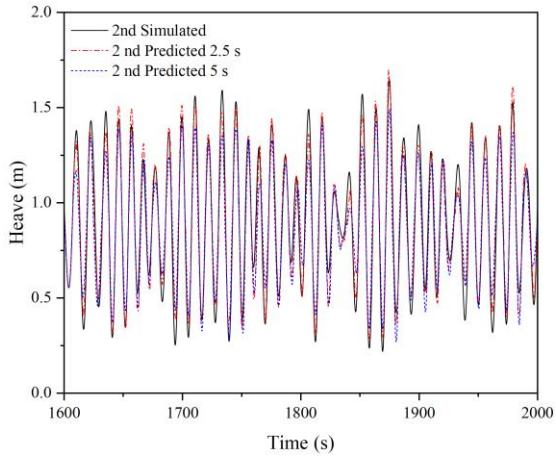
(a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)



(b)

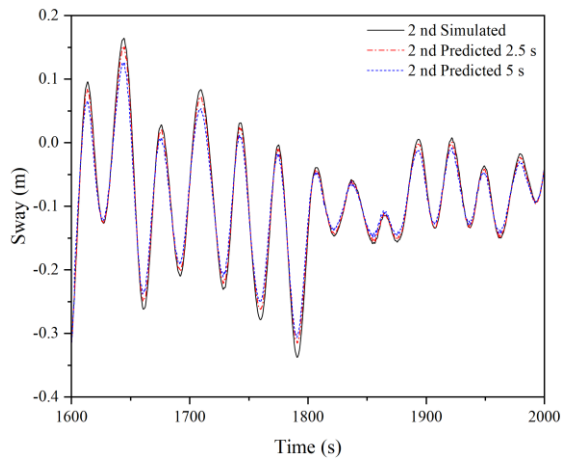
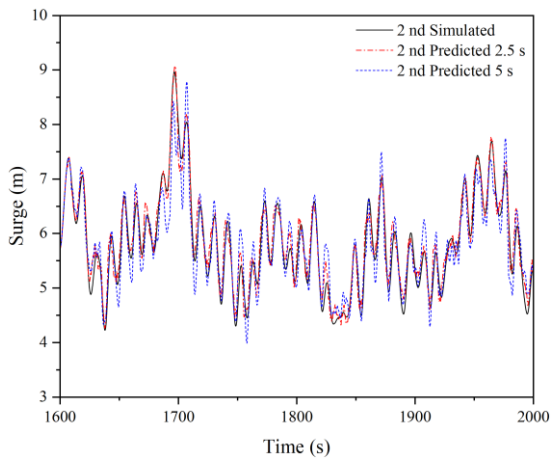


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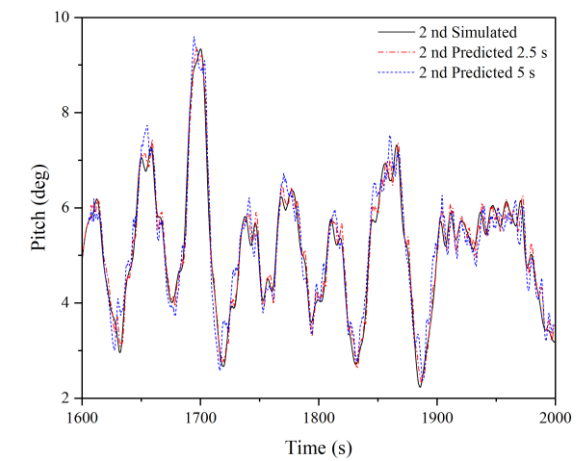
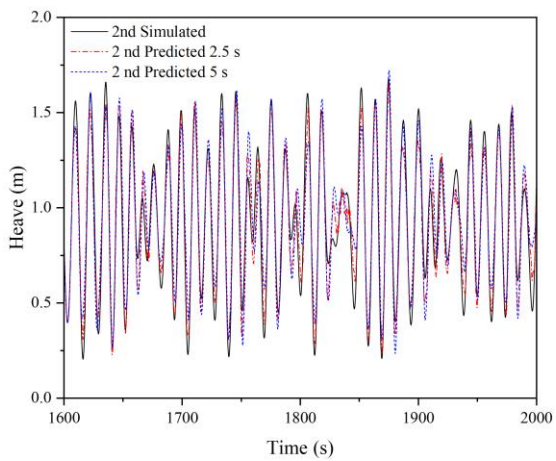
Figure 19. Simulated and predicted values of EC 2 at 2.5 s and 5 s:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch



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(b)



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(c)

(d)

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Figure 20. Simulated and predicted values of EC 3 at 2.5 s and 5 s:

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(a) Surge; (b) Sway; (c) Heave; (d) Pitch

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Figures 18-20 show that the peak fitting in all directions at 5 s is weaker than that of 2.5

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s, similar to the case when the platform model is affected by first-order hydrodynamic forces.

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Compared with the first-order hydrodynamic influence, the prediction results under the second-

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order hydrodynamics show smaller fluctuations in both surge and pitch. On the other hand, the

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predicted value of sway is smooth, and there is no slight fluctuation. The error of prediction

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results in heave mainly occurs in peaks and troughs, but it is not obvious. The statistical

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accuracy in each direction, as well as the overall accuracy, is further analyzed in section 5.2.

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5.2. Error Analysis

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To compare the short-term prediction effect of the MI-LSTM model in both first-order

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hydrodynamics and second-order hydrodynamics cases, the results of the PAT of 2.5 s under

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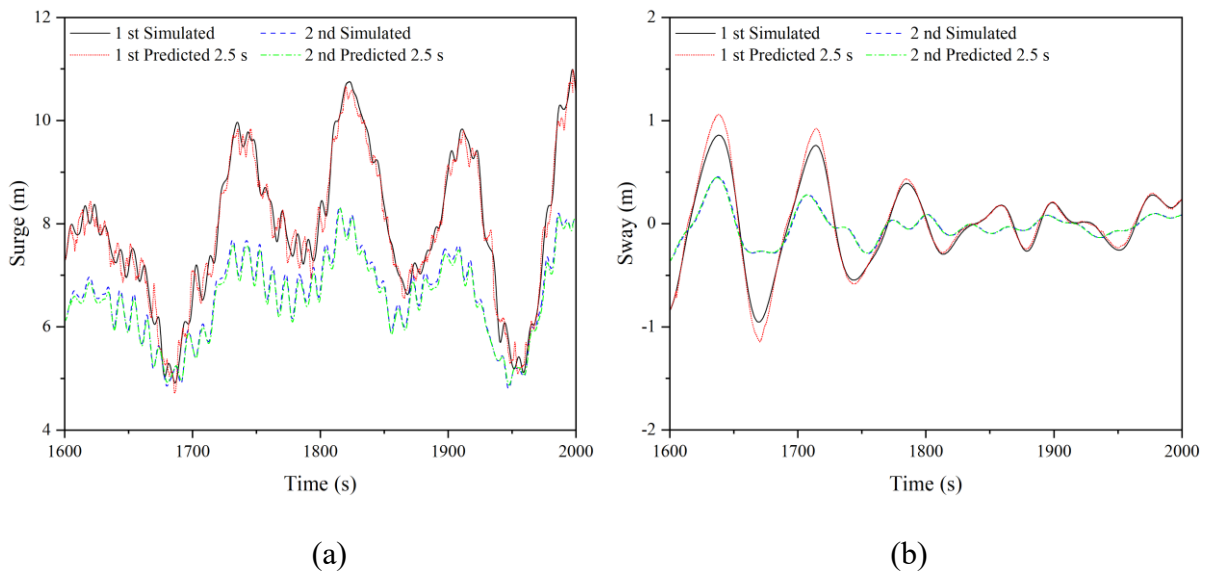
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EC 1 are selected for comparison, shown in **Figure 21**.

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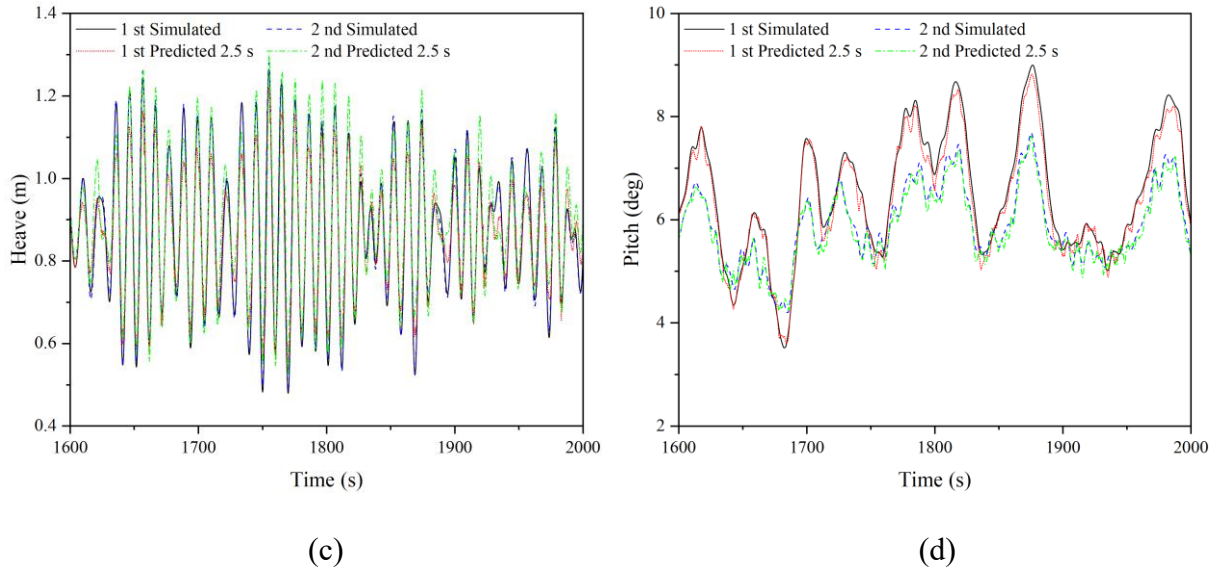


Figure 21. Comparison of 1st-order and 2nd-order hydrodynamic prediction results:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

According to **Figure 21**, it is observed that the motion response exhibits a stronger nonlinear characteristic under the influence of second-order hydrodynamic forces. This phenomenon is particularly evident in the surge, pitch, and sway directions, where more nonlinear fluctuations appear at the extremes of the kinematic response in all three directions. The effect of second-order hydrodynamic forces did not have much influence in the heave direction.

At the same time, in the surge, sway and pitch directions, there are significant deviations in the predicted values at the extremes of the motion response for the first-order hydrodynamics case. While in the second-order hydrodynamics case, the MI-LSTM model has better prediction at both peak and trough values. In the heave direction, the motion response of the platform in the two cases does not differ much and does not have the nonlinear characteristics in the other three directions. Therefore, the prediction effect of the MI-LSTM model in the heave direction under the influence of second-order hydrodynamics is not significantly improved.

The response spectrum analysis of the platform under the influence of second-order hydrodynamics are supplemented and chose EC 1 to plot the power spectrum density (PSD), as

508 shown in **Figure 22**. There is a common phenomenon in all four directions, the predicted value
 509 of 2.5s is better than 5s in the performance of PSD, and both of them fit better with the PSD
 510 results of simulation values. The difference between the predicted and simulated values is
 511 mainly in the low-frequency peak of the response spectrum, while the PSD performance of the
 512 model predictions is better at the off-peak.

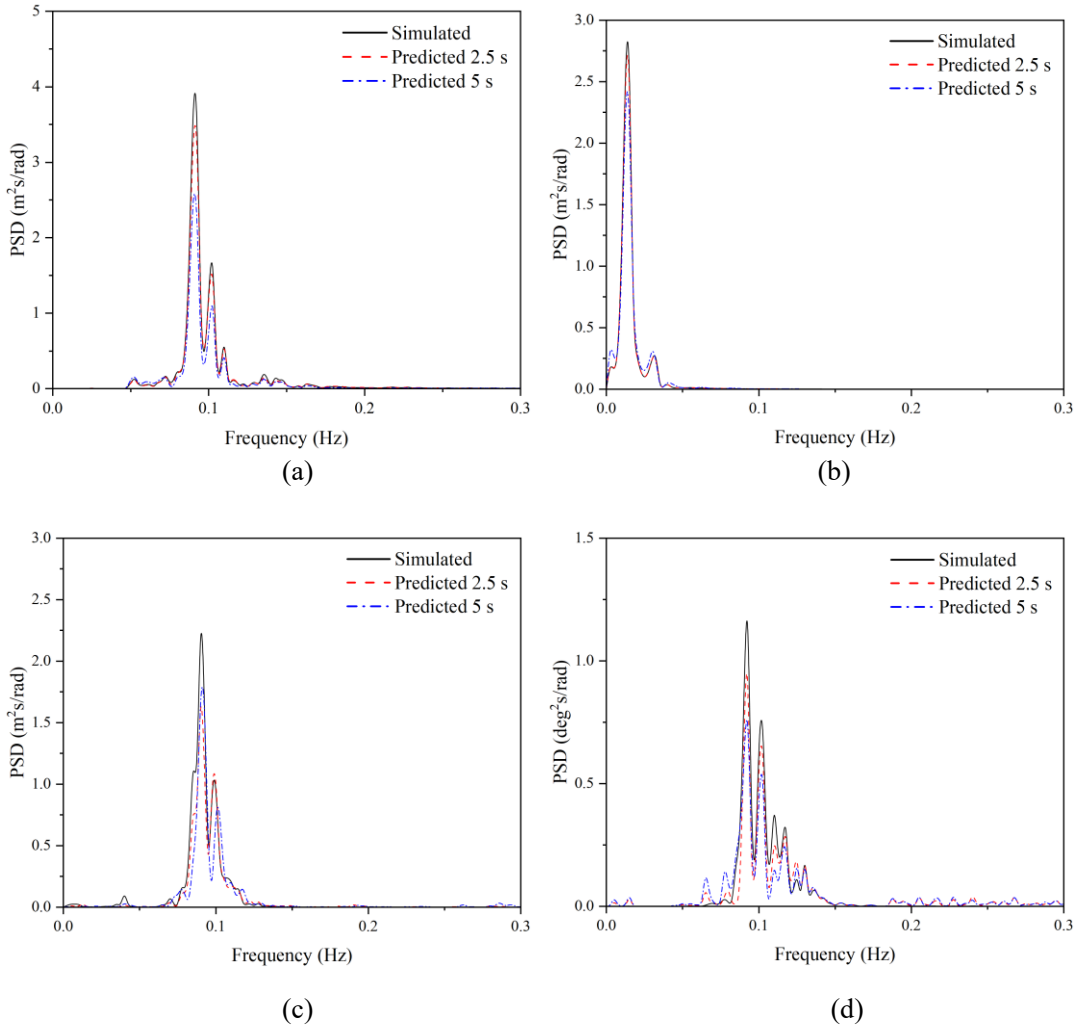


Figure 22. Power spectral density of motion response in different directions

(a) Surge; (b) Sway; (c) Heave; (d) Pitch

520 Under the influence of second-order hydrodynamics, this section also analyzes the
 521 individual statistics of the prediction results and calculates the overall accuracy of each
 522 direction of motion response, shown in **Table 4**.

Table 4. The accuracy of each statistic under the influence of second-order hydrodynamics

Mode	Statistics	EC 1				EC 2				EC 3			
		Heave	Pitch	Surge	Sway	Heave	Pitch	Surge	Sway	Heave	Pitch	Surge	Sway
Multi- input 2.5 s	Max	96.5%	99.4%	99.6%	98.7%	92.6%	96.3%	99.5%	92.2%	98.0%	98.9%	98.8%	91.8%
	Min	88.5%	99.2%	98.5%	99.1%	90.9%	90.7%	99.2%	97.0%	90.2%	96.2%	99.1%	94.9%
	Average	98.8%	98.8%	98.9%	96.5%	98.0%	97.6%	99.7%	99.0%	99.9%	99.0%	98.9%	99.2%
	STD	89.9%	96.2%	96.1%	98.6%	95.8%	96.5%	99.6%	94.6%	98.6%	99.2%	96.7%	92.8%
	Overall	93.4%	98.4%	98.3%	98.2%	94.3%	95.3%	99.5%	95.7%	96.7%	98.3%	98.4%	94.7%
Multi- input 5 s	Max	87.0%	99.5%	97.6%	71.0%	97.1%	97.5%	96.6%	63.4%	94.2%	97.2%	97.8%	77.1%
	Min	94.3%	95.5%	96.5%	97.5%	89.5%	82.5%	97.4%	97.0%	94.3%	93.4%	94.4%	94.9%
	Average	98.6%	98.1%	97.3%	80.7%	94.6%	96.5%	99.3%	98.2%	94.5%	98.8%	99.6%	99.0%
	STD	87.9%	92.3%	91.4%	98.1%	93.1%	92.5%	90.9%	80.4%	92.6%	98.0%	91.3%	84.1%
	Overall	92.0%	96.3%	95.7%	86.8%	93.6%	92.3%	96.0%	84.8%	93.9%	96.9%	95.8%	88.8%

524

525 According to the results given in **Table 4**, it can be seen that the accuracy of the predicted
526 results in all directions under the influence of second-order hydrodynamics is still at a high
527 level, overall accuracy exceeds 90% at PAT of 2.5 s and 85% at PAT of 5 s. This phenomenon
528 verifies the conclusions of Section 4 and confirms that an increase in PAT leads to a decrease
529 in prediction accuracy.

530 The overall accuracy of the 4 degrees of freedom directions calculated from **Table 4** is
531 shown in **Figure 23**. At PAT of 2.5 s, the difference in prediction accuracy between the second-
532 order hydrodynamics and the first-order hydrodynamics is more obvious in surge and sway. At
533 PAT of 5 s, in the direction of surge, heave, and pitch, the prediction accuracy in the second-
534 order hydrodynamics case is about 3% higher than that in the first-order hydrodynamics.

535 By comparing with the results in the first-order hydrodynamics in Section 4, it can be
536 found that the MI-LSTM model in the second-order hydrodynamics case not only has a good
537 ability to learn multi-factor relationships and platform response prediction but also has a higher
538 prediction accuracy than the first-order hydrodynamics case.

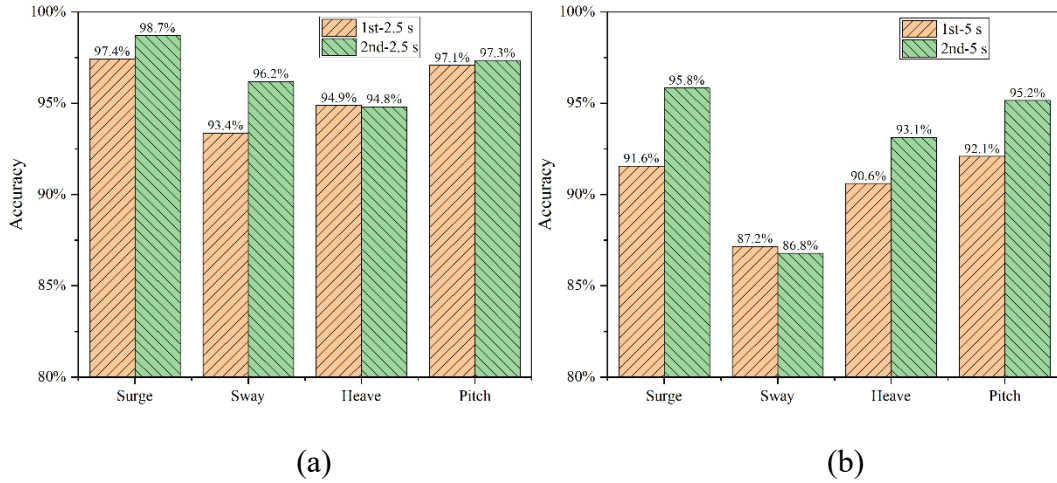


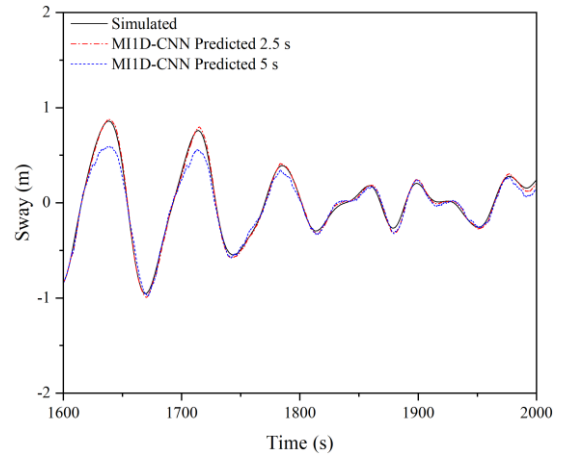
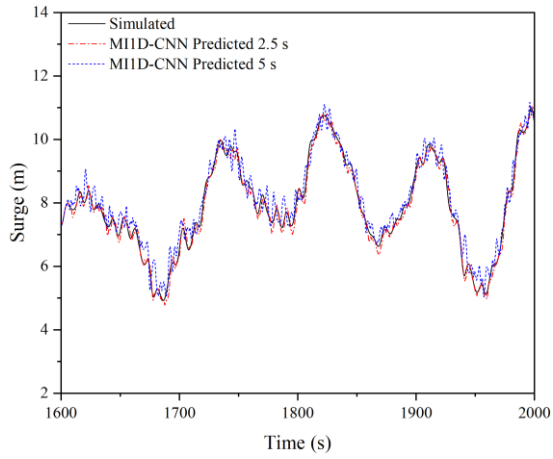
Figure 23. Overall accuracy under different PATs: (a) 2.5 s; (b) 5 s

6. Comparison with the MI1D-CNN model

6.1 Predicted results with MI1D-CNN model

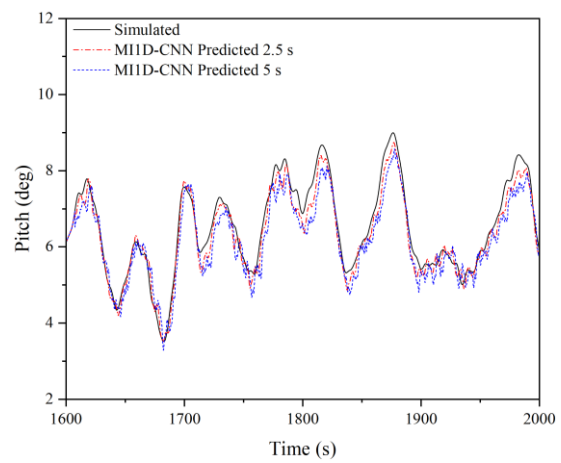
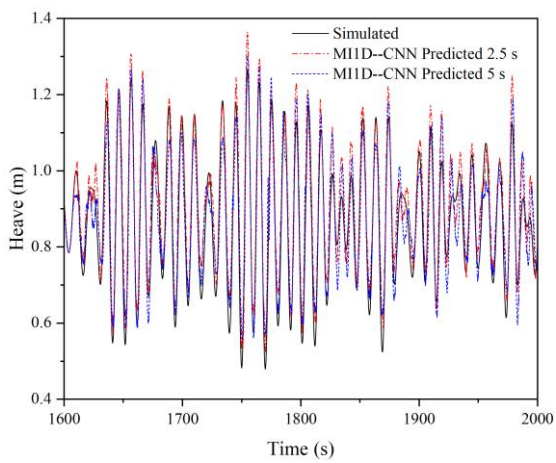
Currently, the mainstream deep learning methods mainly include the CNN method and the RNN method, and the MI-LSTM model established in Section 4 belongs to the RNN method. CNN methods are mostly used in image recognition and text recognition. As a representative method to deal with time series problems in CNN, a one-dimensional convolutional neural network (1D-CNN) has a certain effect on short-term prediction by adding a pooling layer.

In this section, a multi-input one-dimensional convolutional neural network (MI1D-CNN) is built to compare the CNN method with the LSTM method for the motion response prediction problem, using the same training data as in Section 4. The training of the MI1D-CNN model is completed, and the results obtained from the multi-input LSTM model are compared in Section 6.2 in terms of training time and overall accuracy. The prediction results obtained by the MI1D-CNN model are shown in **Figures 24-26**.



(a)

(b)

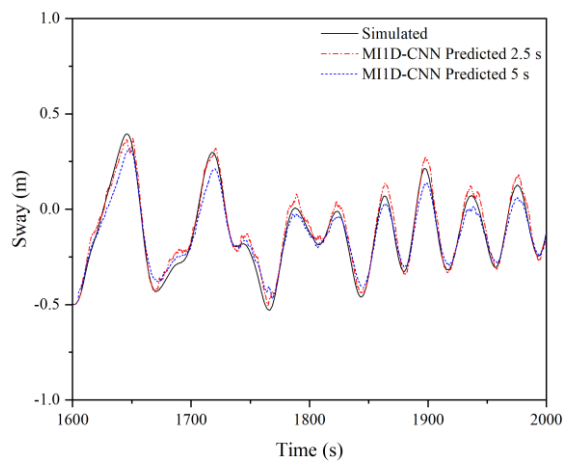
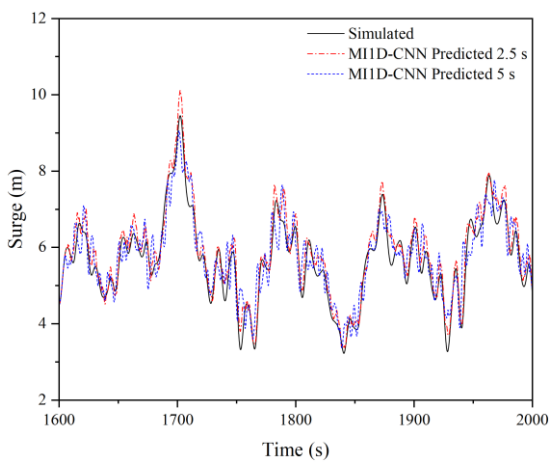


(c)

(d)

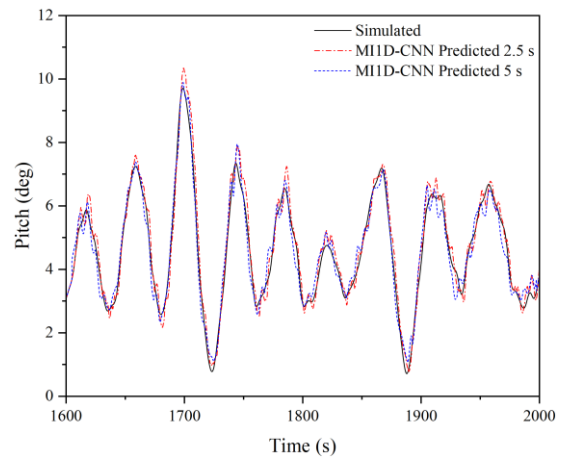
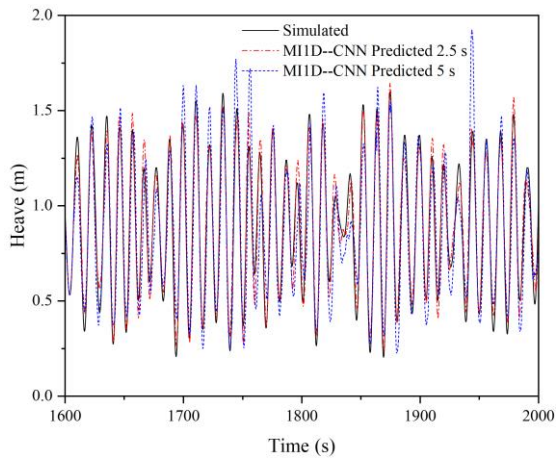
Figure 24. Simulated and predicted values of EC 1 at 2.5 s and 5 s:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)

(b)

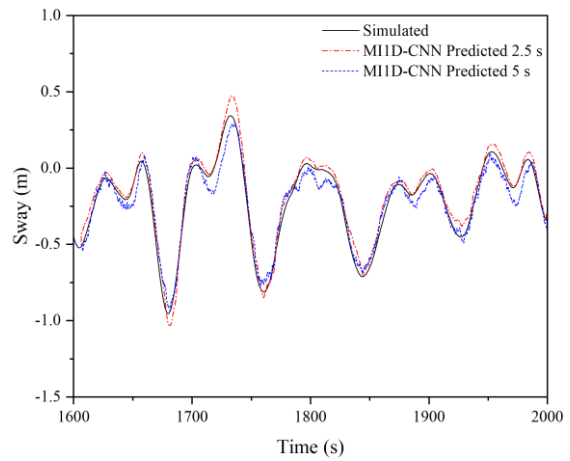
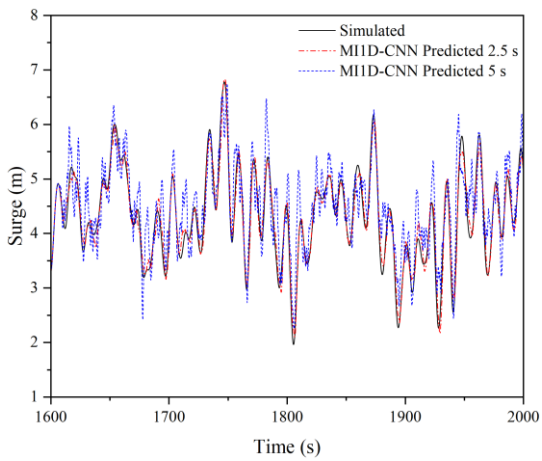


(c)

(d)

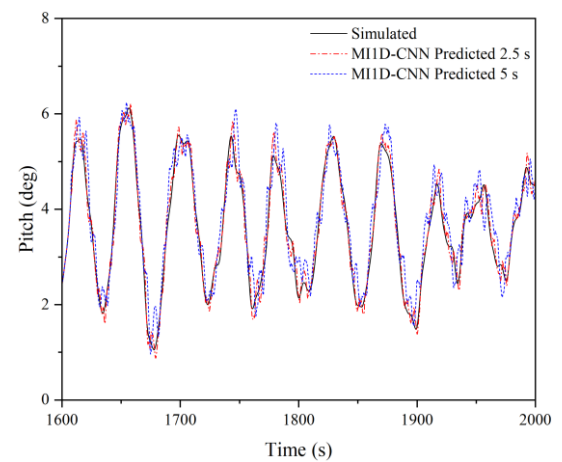
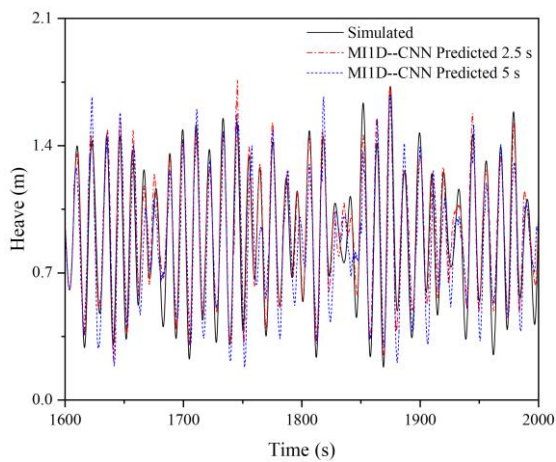
Figure 25. Simulated and predicted values of EC 2 at 2.5 s and 5 s :

(a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)

(b)



(c)

(d)

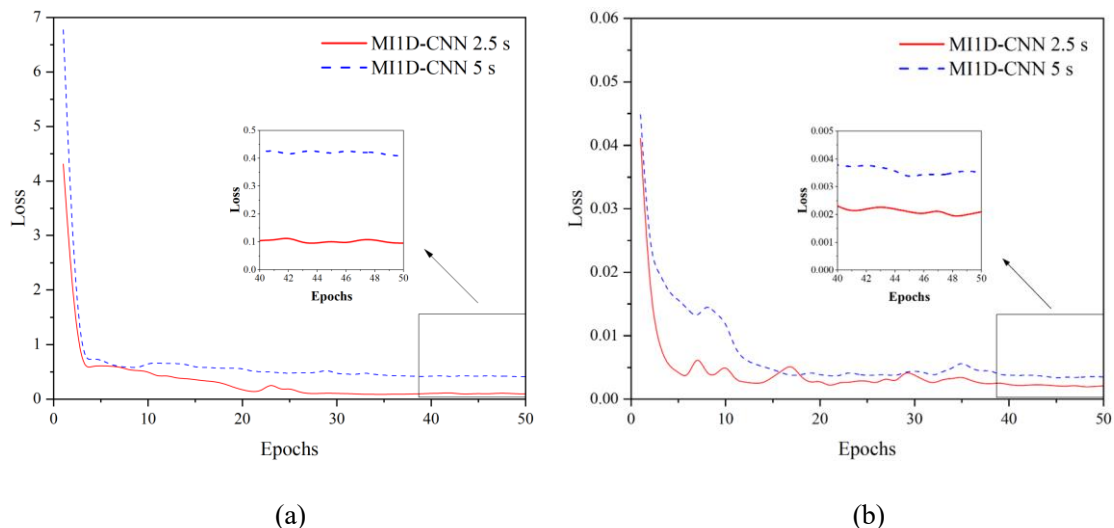
572 **Figure 26.** Simulated and predicted values of EC 3 at 2.5 s and 5 s:

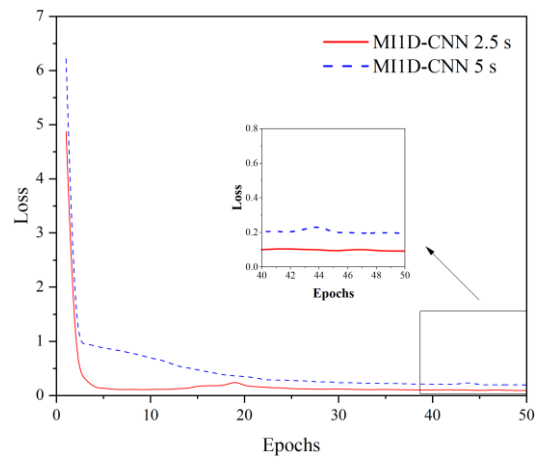
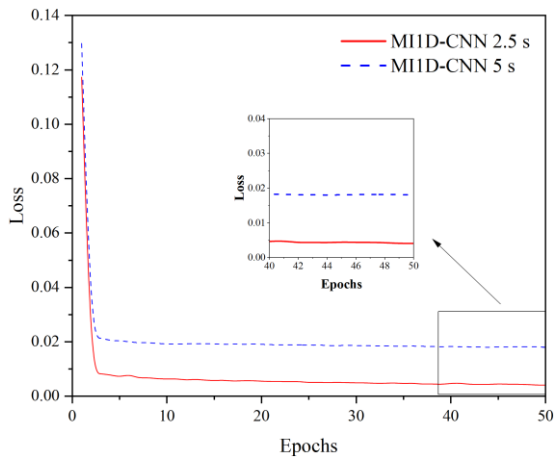
573 (a) Surge; (b) Sway; (c) Heave; (d) Pitch

574 According to **Figures 24-26**, and compared with **Figures 11-13** in Section 4.3, it can be
575 found that the motion response predicted by the MI1D-CNN model produces a large number of
576 serrations in surge and pitch of each environmental condition, especially at PAT of 2.5 s. At the
577 same time, the prediction result at PAT of 5 s in sway does not fit well with the simulation
578 results. To further compare the results of the MI-LSTM model with the MI1D-CNN model, it
579 is further explained from the aspects of training time and overall accuracy in Section 6.2.

580 6.2 Comparison with Multi-input LSTM Model

581 By counting the Loss values during the training of the MI1D-CNN model, we show the
582 decrease of the model training Loss for EC 1, shown in **Figure 27**. One can observe that, unlike
583 the change process of the MI-LSTM model's Loss value, the oscillation phase of the MI1D-
584 CNN model's Loss value is not obvious in the decreasing process. the MI1D-CNN model's Loss
585 value stops changing when the number of training rounds reaches 50 rounds, which indicates
586 that the model training has been completed and the performance is satisfactory. To further
587 observe the imitative effect between the predicted values obtained by the two models and the
588 simulated values, EC1 is selected and the results are summarized as shown in **Figure 28**.



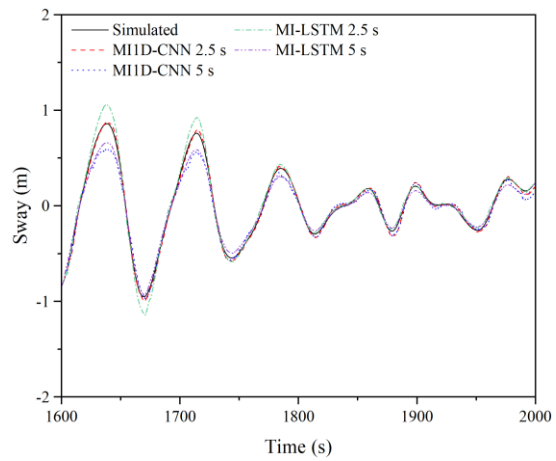
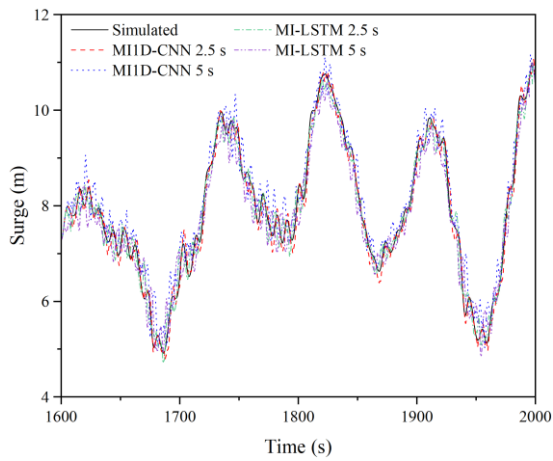


(c)

(d)

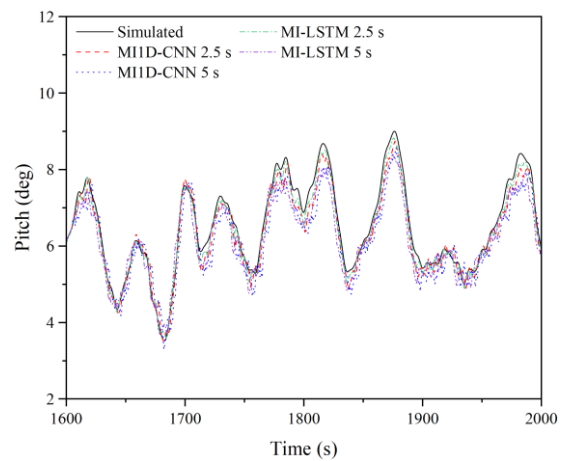
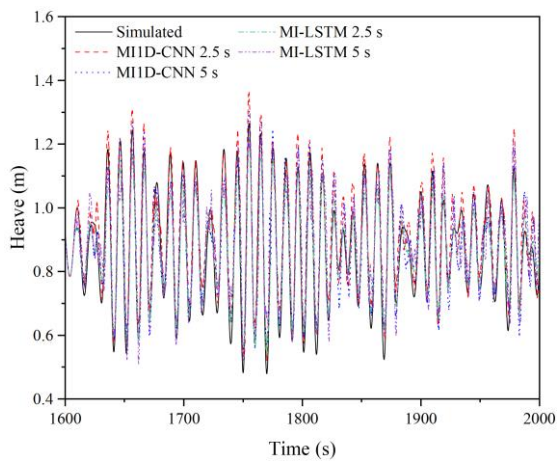
Figure 27. The curve of Loss affected by Epochs for different directions:

(a) Surge; (b) Sway; (c) Heave; (d) Pitch



(a)

(b)



(c)

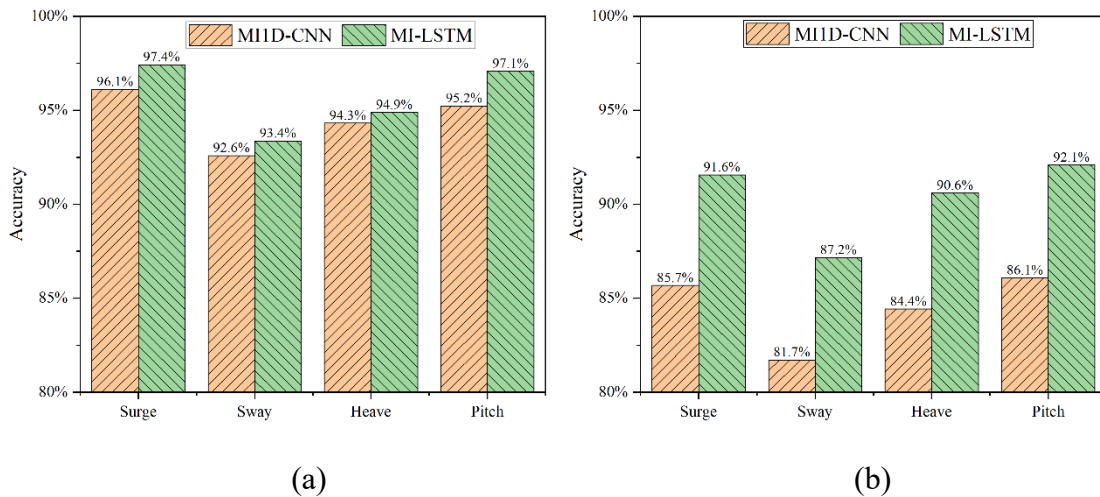
(d)

600 **Figure 28.** The results of the MI1D-CNN model and the MI-LSTM model are compared:

601 (a) Surge; (b) Sway; (c) Heave; (d) Pitch

602 According to **Figure 28**, from the overall imitative effect of the time series curve, the
 603 prediction results of both models fit well with the simulation results at PAT of 2.5 s. However,
 604 at PAT of 5 s, the result of the MI1D-CNN model is slightly inferior to the MI-LSTM model
 605 result, and when the PAT is at 5 s, the predicted value of the former has a large fluctuation. This
 606 volatility does not exist in the simulation value, particularly in **Figures 28(a)** and **(d)**. The time
 607 series of the platform response has a certain smoothness in sway, so both models' imitative
 608 effects are good. While the time series of the platform response itself is more volatile in heave,
 609 the imitative effects of the peak are not as good as in other directions.

610 To find out the difference between the MI1D-CNN model and the MI-LSTM model, the
 611 overall accuracy of the MI1D-CNN model is calculated by combining each operating condition.
 612 Then compare the overall accuracy of the MI1D-CNN model with the MI-LSTM model
 613 proposed in Section 4 and the result is shown in **Figure 29**.



614 **Figure 29.** Comparison of the overall accuracy of different models in each direction:

615 (a) 2.5 s; (b) 5s

616 According to **Figure 29**, it can be found that there is no significant difference between the
 617 results of the two models when PAT is at 2.5 s, the overall effect of the MI-LSTM model is
 618
 619

620 slightly better than the MI1D-CNN model, and the accuracy of the former is 1%-2% higher
 621 than the latter in all directions. But at PAT of 5 s, the situation is very different, the MI-LSTM
 622 model performs much better than the MI1D-CNN model, and the accuracy of the former is
 623 about 5% higher than the latter in all directions.

624 It can be seen that when the corresponding period of the prediction platform becomes
 625 longer, the traditional CNN model is not satisfactory, while the MI-LSTM model proposed in
 626 this paper performs well. Since 1D-CNN only performs convolution operations on time series
 627 information within the length of a convolution, heritability in time series information is only
 628 reflected in a single convolutional neuron. Therefore, when PAT is small, the effect on the
 629 MI1D-CNN model and the MI-LSTM model is insignificant. However, with the increase of
 630 PAT, the disadvantage of the MI1D-CNN model in processing temporal genetic information
 631 will become significant.

632 In addition, the training time of the two models is also recorded, as shown in **Table 5**.
 633 According to **Table 5**, the training time of the MI1D-CNN model is much shorter than that of
 634 the MI-LSTM model, which is related to the learning and calculation method of the model itself.
 635 The training time of the MI1D-CNN model is short, but it sacrifices a part of the accuracy, and
 636 the training time of the MI-LSTM model is relatively long, but the accuracy is greatly improved.

Table 5. Statistics on the training duration of the two models

Modes	PAT (s)	Epochs	Time (s)
MI-LSTM	2.5	50	912
	5	50	1053
MI1D-CNN	2.5	50	108
	5	50	157

639
 640 In summary, balancing training time and accuracy has always been an important issue in
 641 deep learning. If the goal is ultra-short-term forecasting of the FOWT motion response and the

642 accuracy requirement is relatively low, the MI1D-CNN model can be chosen. However, to
1
2 643 increase the time span of motion response forecasting and maintain prediction accuracy, the
3
4
5 644 MI-LSTM model is a better choice.
6
7

8 645 7. Conclusion

9
10 646 Based on the motion response data of the Braceless platform, the MI-LSTM prediction
11
12 647 model is established by the RNN deep learning method and is trained for different degrees of
13
14
15 648 freedom under different environmental conditions. The accuracy of prediction results under
16
17 649 different PAT and input methods are determined and compared using statistics. Based on the
18
19
20 650 analysis and discussions, the conclusion can be made as follows:
21

22 651 (1) Taking the previous data of platform motion response, mooring force, and wave
23
24 652 elevation as input, after 50 rounds of training with two LSTM models, the Loss no longer
25
26
27 653 decreases, resulting in accurate prediction results. The Loss of the MI-LSTM model is slightly
28
29 654 better than the SI-LSTM model. The MI-LSTM model more comprehensively learns the
30
31
32 655 relationship between multiple factors and the target output.
33

34 656 (2) Based on the established and trained LSTM neural network model, the prediction
35
36
37 657 results of the model fit well with the simulated value. The prediction accuracy with PAT at 2.5
38
39 658 s is slightly higher than the accuracy with PAT at 5 s and the overall performance of the MI-
40
41
42 659 LSTM model is better than the SI-LSTM model. The additional two factors can positively
43
44 660 improve the accuracy of the final prediction result.
45

46 661 (3) The established MI-LSTM model is applied to the situation where the platform is
47
48
49 662 affected by second-order hydrodynamics, and it is found that the model has a better predictive
50
51
52 663 effect on the response of the Braceless platform affected by second-order hydrodynamics. The
53
54 664 MI-LSTM model has a better performance for the case where the nonlinearity phenomenon is
55
56 665 more pronounced.
57

58
59 666 (4) The MI-LSTM model established in this paper is compared with the traditional MI1D-
60
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667 CNN model, and the advantages and disadvantages of the two models are clarified from the
668 aspects of training time and overall accuracy. When the PAT is small, the difference between
669 the results of the two models is not significant, while when the PAT increases, the results
670 obtained by the MI-LSTM model are better than those obtained by the MIID-CNN model.

671

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677 Development (PKLHD202003). The last author is now supported by the National Natural
678 Science Foundation of China (Grant No. 52201379).

679

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