Development of a Novel Wave-force Prediction Model based on Deep Machine Learning Algorithms

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ABSTRACT

The future knowledge of the waves and force is indispensable for the model identification and the real-time control of ocean engineering devices. In order to effectively control the motion of the offshore structures in a real-time manner, it is required to have an accurate and efficient prediction of the waves. Machine learning has been widely applied in ocean engineering field as it offers compromise between prediction accuracy and computational cost. The present study focuses on wave-force prediction of offshore structures based on deep machine learning algorithms. A novel wave-force prediction model is proposed, which makes full use of the efficient processing characteristics of Long Short-Term Memory Recurrent Neural Network (LSTM RNN) and Nonlinear Autoregressive Exogenous Feedback Neural Network (NARX FNN) for time series data processing. The relationship between the wave height and the wave height is non-causal and nonlinear which need future wave height knowledge for current wave excitation force. Therefore, The LSTM RNN is firstly utilized for multi-step prediction of the time series of wave elevation. The NARX FNN is used to address the model system identification between the wave heights and the wave force. Then, the LSTM RNN is further applied to predict the future force of offshore structures for the real-time control of the structure motions. After that, the proposed deep machine learning algorithm is utilized for wave-force prediction based on the experimental data obtained in Kelvin Hydrodynamic Laboratory and the optimal horizon can be specified for the test model by comparing the performance of different prediction horizons. The results indicate that LSTM-NARX model can successfully predict the time series of the waves and force.

KEY WORDS: wave-force prediction, deep machine learning, LSTM RNN, NARX FNN.

1 INTRODUCTION

Wave energy as a dense and stable renewable energy resource is forecast to have the potential to supply 10% of European electricity needs or to generate the equivalent of up to 20% of UK electricity; about half today's total renewable generation. WECs convert the oscillation of kinetic and potential energy carried by ocean gravity waves to electrical energy that can be delivered to the electrical grid through a mechanism known as power take-off system (PTO) (Anderlini,2019) . Wave energy drives two or more parts move relatively then energy is captured by hydraulic mechanic or direct drive. However, there is no wave energy converter reaching commercial stage due to its high levelised cost of energy (LCOE). There is one of the ways to move a step forward by improving the power absorption efficiency under real-time control. By controlling the force exerted from PTO system, such as latching control, it is possible to tune the velocity of WEC with the excitation force of incoming wave for achieving the maximum energy absorption. The wave excitation force is regarded as the combination of incident component and diffraction component from the view of linear potential theory (LPT).

There are myriad reasons to explain why predicting wave is important, from surfer and swimmers to shipping route planning, from offshore structure protection in extreme condition to stabilising renewable energy electrical grid. There are also reasons for wave prediction in WECs operation: as illustrated in (Garcia-Abril, 2017), for implementation of many energy maximising control strategies, there are two processes requiring future knowledge of the incoming wave experienced by WEC. Falnes(Falnes, 1995) described the non-causal characteristic of wave excitation force deduced by wave elevation, and future wave elevation is necessary information as well. It is a open problem to predict wave excitation force for decades. Fusco and Ringwood (Fusco, 2012) assumed that in-coming wave elevation is known fully or in the near future, as well as Son and Yeung (Son, 2017). Also there are researchers realise wave force predcition in alternative methods, for example linear superposition (Li, 2012), Kalman Filter (Ling, 2015) and Artificial Neural Network (Li, 2018) and these mentioned prediction methods have been used in control implement of WEC. These methods are based on physical foundamation or processing statastics. Because of the complicate nonliear relation between wave height and wave excitation force, data extroplation performance of existed prediction tools is not accurate enough for a long short-term prediction of Model Predictive Control (MPC). The accuracy of the model of the body dynamics strongly affected the performance of real-time control methods (Anderlini, 2017). Only if an accurate wave prediction is obtained, the real-time control makes sense. The predicted wave force with unsatisfactory performance may cause negative effects with control commands. As wave force predction plays an important role in real-time MPC control of WEC, a prediction algorithm with high accuracy and low computuation cost is necessary to be developed, calibrated, and validated with the rapid development of wave energy engineering.

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As the explosive development of Artificial Intelligence and Machine Learning appliacation in last decade, more and more research field (image processing, speech regnition, medicine, power grid and automatic control) introduce some ‘pop-stars’ of machine learning to solve tradtional problems in an untraditional way. ANN is one of the most widely used machine learning tools for interdisciplinary research. As a tool for time series prediction and modelling, artificial neural networks (ANNs) have been successfully used in a variety of application domains, including financial time series prediction (Zhang, 2014), significant wave forecasting (Deo, 1998), and traffic prediction (Duan, 2016). There are some attempts using ANN to optimize power asorption with control strategy. In (Valério, 2008), ANN models for the Archimedes Wave Swing (AWS) prototype are developed. ANNs are then used together with proven control strategies (phase and amplitude control, internal model control and switching control) to maximise energy production. Li (Li, 2018) has applied ANN to predict MPC wave force to improve power efficiency of a heaving point absorber WEC. With the complexity of application problems increases, the vanilla feedforward neural network cannot meet the demand of so many types of specific applications. Aiming at different technical challenges, types of ANN, including LSTM RNN and NARX FNN, have been developed for these applications. Using these advanced machine learning tools is a novel approach to solve wave force prediction problem in WECs real-time control.

2 PROBLEM STATEMENT

Model Predictive Control is one of the most commonly used control strategies in which prediction of excitation force is necessary. No matter which method, either linear or non-linear one, is used to approximate the actual behaviour of wave force, the nonlinearity and non-causality are not eliminated. The computational cost is also crucial factor in the prediction model which has potential in real-time control. These three factors are discussed below.

Non-linearity

Models based on linear wave theory have many desirable advantages in hydrodynamic calculation, like linear component superposition or transfer function in frequency domain. However, they are based on the assumption of ideal fluid, small amplitude of wave and body motion. Normally as we know, none of the systems is completely linearity in reality. All systems have some kind of nonlinear behaviour more or less. If this behaviour is significant enough, white box mathematical models are hard to obtain (Valério, 2008). That is why other techniques, like grey or black box models, should be given attention and used as alternatives.

Most WECs consider non-linear effects in operation mode. As WECs is designed to achieve a maximum motion, the linear relationship is not totally suitable for the devices. The larger amplitude of motions become exaggerated to gain wave energy, the more predominant nonlinear components will be. Fortunately, nonlinear effects are only an issue under the operation conditions. Beyond the operation limitation, the main target is normally to keep WECs safe and integrated. WECs will change into a survival mode, which limits the motion and allows wave force exerted on the device to be tolerated. In (Giorgi, 2015), it is shown that two kinds of nonlinear relation between incident wave and excitation force as indication to introduce nonlinearity into the hydrodynamic models. Nonlinear effects in operation state, which is between linear region and highly non-linear region, is considered when analysing WECs motions and forces caused by wave elevations.

Non-causality

Non-causality is a relationship for input-output variable. Causality is that current value of output is related to current and history value of input, as well as history output. Non-causality means that current output is not only related to the values mentioned in causality, but also the value of future input. The non-causality between wave elevation and structure motion and its reason is explained, although the wave propagation is a causal process (Falnes, 1995). To explain the concept of non-causality concretely, for example, a wave maker in the wave tank laboratory is the cause of the wave height of a certain position, but an upstream wave elevation is not the real cause of a downstream wave elevation. However, the two elevations of different locations are relevant. From the view of non-linear system identification (Nelles, 2002), the relationship between wave height and wave excitation force is a non-linear dynamic system with external input. Besides, it also has nature of non-causality.

Compromise between accuracy and computation cost

As an engineering issue, especially real-time manner control, computation cost is one of the most important factors which should be taken into account as accuracy of the algorithm. There are two traditional methodologies, linear potential theory (LPT) and Computational Fluid Dynamics (CFD) to simulate the structure response induced by wave. As linear potential assumption with non-viscosity and non-rotation assumption, LPT based on Boundary Element Method (BEM) has have high computation speed, but non-linear items is not totally included with added dynamic storing force, dynamic pressure, and viscous damping. Linear assumption which never exists in the actual world makes the simulation accuracy stay at a low level. On the other hand, if fully non-linear CFD is applied to solve hydrodynamic problem, for example OpenFOAM software package, accuracy is better than former one. However, the accuracy brings such extremely high computation cost. Typical computation time can be up to 1000 times the simulation time (Giorgi, 2017). However, sometimes the accuracy and the computation cost are almost contradictory in the simulation process. The computation cost will rise when we are chasing high quality of prediction performance, vice versa. Thus, it is desirable to develop hydrodynamic models with characteristics that overcome computational-accuracy contradiction lain between the LPT and CFD; ideally, a good compromise able to describe the most important nonlinear components of the real system, without requiring excessive computational time cost. Deep machine learning is one of the suitable tools to balance the trade-off between these two major factors. Deep learning architecture of ANN guarantees that the system model envelops enough nonlinear components with its nonlinear information transformation among perceptual neurons. The testing or predicting process is a straightforward multiplication of an input vector mapping by well-trained machine learning model. As the multiplication is an extreme rapid numerical operation and the characteristics of the system is contained in the weight and bias matrices which is well-trained by history data in advance, therefore the simulation lead no much computational time with comparable accuracy to a first-principle model while there is a relative long time for the network training process to learn the system.

Except the selected method of prediction model, the prediction horizon (PH) is a factor to control the balance between computational cost and accuracy. In nonlinear time series prediction, ANN models are commonly used as one-step-ahead predictors, estimating only the next value of a time series without feeding the predicted value back to the input of model. If the user is interested in a wider prediction horizon, a procedure known as multi-step-ahead prediction, the model’s output should be fed back to the input set for a fixed but finite number of time steps. In this case, the input set components, previously composed of real sample points of the time series, are gradually replaced by predicted values as feedback. One of the advantages of multi-step prediction is the faster speed than one-step prediction. However, it was found that the longer the forecasting time horizon, the less accurate was the prediction. We can explain this in two aspects. If prediction outputs do not feedback the model, the previous input characteristics have little influence on the output. On the other hand, as the output feedback the prediction system, the error of prediction output will be accumulated with this process. In a more actual view, the computation cost ~~include~~includes not only the simulation of wave prediction, but also the digital signal transmission and control command implement process and it should be shorter than the prediction horizon which proves the effectiveness on the real-time manner.

Form both the view of existing simulation methods and the requirement of control strategies, we proposed machine learning techniques to predict wave height and wave force with the goal of replacing these computationally intensive or low-level accurate physics-based model for improving power efficiency of WEC in real-time manner. As the non-causality between the wave height and the wave excitation force shown above, the wave height will be predicted by LSTM RNN. The length of prediction time duration in an iterative loop is called prediction horizon. At current time step t_k, with the information of history and future of wave height $(\eta_{k-n},\ldots,\eta_k,\ldots,\eta_{k+h})$ as external input signal, as well as history structure motion information $(x_{k-n},\ldots,)$, the current structure motion x_k is calculated by NARX FNN with theory of nonlinear system identification.

3 MACHINE LEARNING MODEL FOR WAVE-FORCE PREDICTION

Long Short-Term Memory Recurrent Neural Network

Although conventional RNN can solve time-series problems better than the vanilla ANN due to recurrent weight parameter sharing, however, with the limited ability of memory in hidden layers, it is difficult to transmit information over long distances in conventional RNN, namely gradient explosive and gradient vanishing. As a branch of RNN architecture used in the field of deep learning (Hochreiter, 1997), LSTM RNN is first proposed in 1997 which outperforms against the conventional one. Because of introducing memory block into the network architecture, gradient explosive and gradient vanishing problems can be solved successfully (Greff, 2017), just like the model can learn how to forget useless information and keep long-term memory from the recorded data. As wonderful performances of LSTM RNN in time series issues, it have been applied to tasks such as unsegmented, connected handwriting recognition, speech recognition, and so on. There are fresh progress for LSTM in recent years, like Gated recurrent unit (GRU) (Cho, 2014) and now it has been used in the design of intelligent assistants and translate software by major technology companies, such as Google (Wu, 2016).

The memory block in Fig. 1~~Fig. 1~~ is the basic unit as the core of LSTM RNN, which including input gate, output gate, forget gate and state cell. These gates and cells exchange information through Constant Error Carousel with equations shown below in order to 'keep memory' of characteristics in the time series. The gates control information flow and transmit information between short-term memory and long-term memory and state cell stores the long-term time-series memory. LSTM RNN is regarded as a deep learning architecture because of existing of memory block.

$$f_t=\sigma(y_f)=\sigma(\omega_f\cdot x+b_f) \tag{1}$$

$$i_t=\sigma(y_i)=\sigma(\omega_i\cdot x+b_i) \tag{2}$$

$$o_t=\sigma(y_o)=\sigma(\omega_o\cdot x+b_o) \tag{3}$$

$$\tilde{c}_t=\tanh(y_{\tilde{c}})=\tanh(\omega_c\cdot x+b_c) \tag{4}$$

$$c_t=f_t\times c_{t-1}+i_t\times\tilde{c}_t \tag{5}$$

$$h_t=o_t\times\tanh(c_t) \tag{6}$$

in equation (1)~~(1)~~-(6)~~(6)~~, the subtitles, f,i,o represent the forget gate, input gate and output gate separately. σ is the sigmoid function as the most used activation function in different types of neural network and tanh is the mathematical operator of hyperbolic tangent. The operator $\times$ is defined as a multiple operation of matrices (Zhao, 2019).

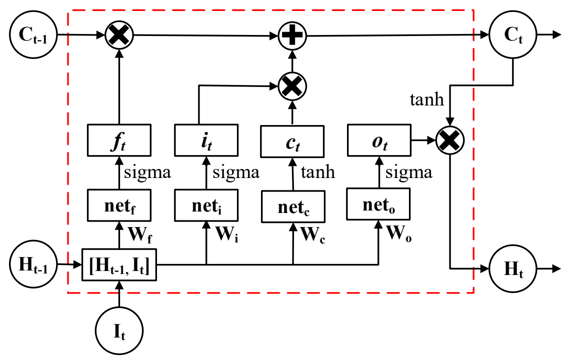

Fig. 1 The architecture of LSTM memory block

Nonlinear Autoregressive Exogenous Feedback Neural Network

The Nonlinear Autoregressive model with eXogenous input (NARX model) is an important class if discrete-time nonlinear dynamic system that can be represented as a mathematic reflection,

$$y_{k+1}=f(y_k,\ldots,y_{k-p+1};u_{k+q},\ldots,u_k,\ldots,u_{k-r+q+1}) \tag{7}$$

in which y and u denote input and output of the model. p and r are the quantity of input and output. q is the forward step duo to the non-causal relation. f shows the nonlinear reflection relation between input and output. The reflection f can be expressed as a function or a black-box ANN. If the latter way is chosen, it is regards as NARX FNN, so NARX network is a special type ANN based on NARX model. From the view of non-linear system identification, NARX FNN is one of powerful class which is suitable for nonlinear dynamic system, especially for time series nonlinear system control as a principle application, like our wave-motion model. As a tool of nonlinear system identification, the NARX network has been successfully applied to a number of real world input-output modelling problems, such as heat exchangers (Yassin, 2010), waste water treatment plants (Zounemat-Kermani, 2019).

Fig. 2~~Fig. 2~~ and Fig. 3~~Fig. 3~~ are the two types of architecture of NARX FNN network. Series-parallel model is used in training process in which there is no feedback of output. And in a multi-step prediction, predicted output of kth step, y_k, will be used as input of network to predict output of $(k+1)$th step, y_{k+1}.this model for multi-step prediction is so called parallel model of NARX FNN. Series-parallel mode is expressed in Equation (8)~~(8)~~,

$$\hat{y}_{k+1}=f(y_k,\ldots,y_{k-p+1};u_{k+q},\ldots,u_k,\ldots,u_{k-r+q+1}) \tag{8}$$

in which p and q represent history steps of input and output. r represents the amount of non-causal information needed in the system. And parallel mode is shown in Equation (9)~~(9)~~,

$$\hat{y}_{k+1} = f(y_k,\ldots,\hat{y}_{k-m}, y_{k-m-1},\ldots,y_{k-p+1}; u_{k+q},\ldots,u_k,\ldots,u_{k-r+q+1}) \tag{9}$$

in which $\hat{y}_{k+1}$ means predicted value, so as other variable with the same supertitle. The subtitle m is feedback output simulated by the NARX network. Considering the non-causal effect, external input, namely wave height data series, need to be offset with the same distance as the considered future horizon.

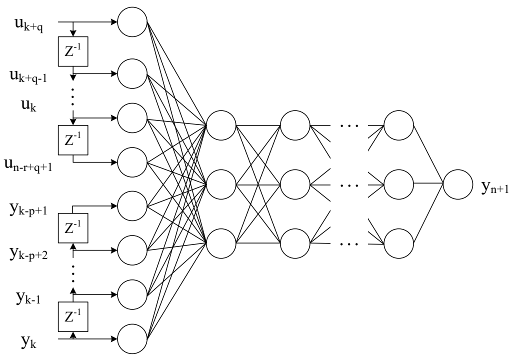

Fig. 2 The architecture of LSTM memory block Series-parallel mode of NARX FNN

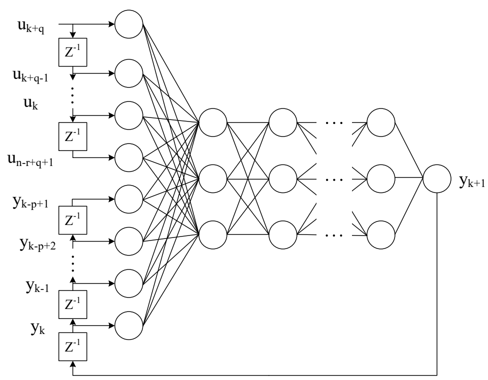

Fig. 3 The architecture of LSTM memory block Parallel mode of NARX FNN

Architecture of LSTM-NARX network

Combining the function of LSTM RNN and NARX FNN, a wave-force prediction model can be established. LTSM RNN is first used to predict the future wave height information. It is straightforward that the PH of LSTM RNN is the maximum time limitation which is considered for non-causal wave-force relationship. And PH for wave force LSTM model restricts the future wave force knowledge we can applied in MPC optimization of WEC motion control. There are three prediction processes in total, two by LSTM RNN, one by NARX FNN. The flowchart in Fig. 4~~Fig. 4~~ illustrates to describe how the wave information and machine learning algorithms are used in the prediction process.

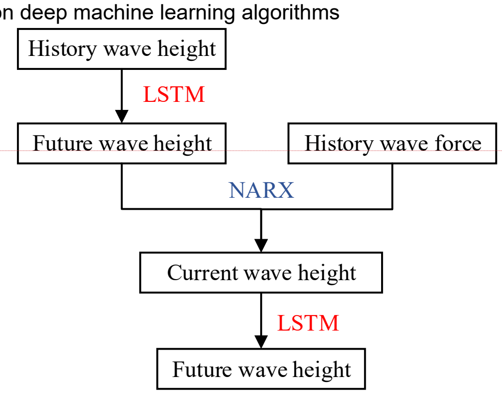

Fig. 4 The architecture of LSTM memory block The LSTM-NARX network architecture

These two ML algorithms are more computationally expensive in training process than BPNN actually because there are more weights and biases to optimize in the training loop. But the time consumption of testing/prediction of BPNN and LSTM RNN are almost the same, because whichever network, there is only a matrix operation in every prediction step. The proposed model trains the prediction model offline and predicts online, so the training time is not an explicit disadvantage of the proposed approach comparing with conventional densely connected ANN.

4 EXPERIMENTAL MODEL AND DATA PROCESSING

Experimental model

There are mainly two ways to obtain the data - experimental test and numerical simulation. These methods have their own pros and cons. Numerical simulation is flexible to change the scale of model to get results in different cases. Numerical simulation cannot conclude all interaction effect accurately, such as high nonlinear interaction and viscous effect in the realistic world. The experimental test reflects the real relation between wave and motion. But model scale effect sometimes is a big trouble. Wave heights and wave excitation force of an offshore structure model tested in Kelvin Hydrodynamics Laboratory (KHL), University of Strathclyde is used to prove the proposed wave-force prediction algorithm. The KHL towing tank has a dimensional of 76 m × 4.6m × 2.5 m, in the length, width and depth direction.

For the purpose of validation and verification of the proposed methodology, fixed type wave structure interaction is first investigated in the present study. Floating wave structure interaction will normally introduce a spatial synchronization between the wave and the corresponding response due to the structure drift motion, e.g. the wave measured by wave probes may not necessarily be the wave that exert onto the model. For the above reason, a classic wave and surface piercing vertical cylinder interaction problem is chosen, where the bottom extend cylinder was rigidly connected to two load cells at both ends. The total horizontal wave force acting on the cylinder was calculated by summation of the horizontal force measured by the two load cells. The cylinder tested has a diameter of 0.3 m and draft of 1.8 m, and was physically deployed in the middle of the towing tank.

Taking the advantage of the excellent precession of the wave maker. The wave time history was first collected without the presence of the device, at the exact position where the device was later installed. Same wave was then tested on the device to acquire the force response. In this way, the effect of reflection and diffraction due to the presence of the cylinder will not affect the incident wave measurement. The tested Johnswap spectrum with gamma 3.3 has a Hs of 25 mm and Tp of 0.8 s, both at model scale.

For the sake of simplicity, the wave generated in wave tank is single directional instead of multi-directional wave. As the wave heights are recorded as system input, wave excitation represents system output. It is a single-input/single-output (SISO) system, but the proposed algorithm is also suitable to analyse multi-input/multi-output (MIMO) system for solving multi-body motions or coupled MDOF motion problems.

Data processing

Data pre-process is necessary before training the network. Normalization as shown in Equation (10)~~(10)~~ is not only beneficial to network training as the weight gradient is in the same magnitude to eliminate the errors caused by different dimensions and ranges, but also it is available to compare results from different methods or resources. Each sequence after normalized is in the range of [0, 1]. High-frequency filtering is also used to reduce non-sense noise signal if necessary.

$$y = \frac{Y - Y_{\min}}{Y_{\max} - Y_{\min}} \tag{10}$$

Although prediction results which are shown in the same magnitude with original data will be obtained by an inverse normalization, here the normalized data is used for results and discussion in a straightforward way. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are selected to evaluate the accuracy of the prediction results. The former reflects the absolute deviation between actual data and predicted one, and the latter is the variance,

$$\text{MAE} = \frac{1}{N}\sum_{1}^{N}\left|y - \hat{y}\right| \tag{11}$$

$$\text{RMSE}=\sqrt{\frac{\sum_{1}^{N}(y-\hat{y})^2}{N}} \tag{12}$$

in which y is the predicted value, $\hat{y}$ is the actual data value, and N is the quantity of the prediction data.

In all, after the normalization process, results of different cases can be compared together, as the variable is only distributed between a certain region, between 0 and 1. Then the errors of mathematical analysis can be discussed in the same magnitude.

5 RESULT AND DISCUSSION

Analysis of LSTM RNN prediction result of wave height

For LSTM RNN the most important parameter is the quantity of hidden units, namely the number of memory blocks in hidden layers. There is no intension to discuss the sensitivities of learning rate and different gradient descent methods in this paper. Therefore, the fixed initial learning rate, learning rate drop and gradient descent methods are all fixed. The parameters of the fixed network are listed below in Table 1~~Table 1~~. The unmentioned details, for example cost function, are set as defaulted value in the MATLAB Deep Learning Toolbox. The principle of using defaulted values is suitable for next section when discuss NARX FNN.

Table 1 Training parameters of LSTM network

Fixed network parameter	value
Initial learning rate	0.9
Learning rate drop period	100
Learning rate drop factor	0.5
Hidden units	100

When the parameters of network training is specific after the optimization process, it means that nothing can change the performance of the network except for random initialization of weight matrices. Therefore, the next step is to decide the PH which also has impact on the accuracy and computational cost of the prediction process. As shown in Table 2~~Table 2~~, the MAE of one-step prediction (PH=0.01) is 0.0013 and RMSE is 0.0019 which are very small. Since the one-step prediction horizon guarantees no error is accumulated in the feedback cycles, the real weight and the predicted one are almost overlapped. As the predicted information of wave height will be regarded as the input of force prediction, so the one-step prediction is not long enough to meet the requirement of future wave in the NARX network model, and one-step prediction is very time-consuming as well. The quantity of the predicted time steps needs to be determined in order to get the best machine learning model, considering the part of NARX prediction model. As the performances of these three cases are quite small, one cannot see significant differences among three time-series curves comparing with the real wave height in Fig. 5~~Fig. 5~~.

Analysis of NARX FNN prediction result of wave force

In the NARX FNN prediction model there are two types of variables required in the training model. The first type is the wave height which consists two parts. The history height the real data of experiment cases and the future information. Different from the LSTM RNN, the NARX FNN network has more parameters to optimize, e.g. the value of layers, input delay, output delay, and future horizon. The input delay is the time length of input history data (history wave height) used in the NARX FNN. For example, the input delay is 0.1s in the case 1 of Table 3. As the sampling frequency is 100Hz, the history input data is 10 steps backwards. The output delay is time length of output history data (history wave force). The future horizon is the time length of future input information (future wave height) which is predicted by LSTM RNN. These 3 types of data are all the inputs and the future wave force is the predicted output for the NARX FNN. But the optimization process is not discussed in details in this paper. We compare several cases to give out a straightforward way to choose the optimized parameter, although the chosen parameters may not be the optimal ones. The input delay and future horizon are equal in length as the symmetrical effect of the history height and future height.

Table 2 Prediction performance of LSTM network with different prediction horizons

Case No.	PH/s	MAE	RMSE
1	0.01	0.0013	0.0019
2	0.25	0.0131	0.0225
3	1	0.0526	0.0731

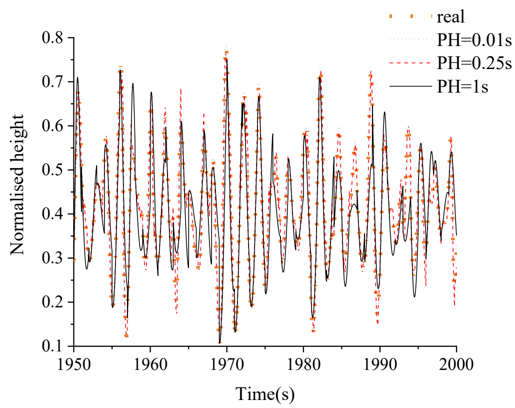

Fig. 5 LSTM one-step prediction of wave height (PH =0.01s, 0.25s, 1s)

Table 3 Prediction performances of NARX network with different prediction inputs

	Layer	Input delay/s	Output delay/s	Future horizon/s	PH /s	MAE	RMSE
1	1	0.1	0.1	0.1	50	0.0415	0.0543
2	2	0.1	0.1	0.1	50	0.0448	0.0580
3	1	0.9	1	0.1	50	0.0393	0.0499
4	1	1	2	1	50	0.0205	0.0254
5	1	0.5	1	0.5	50	0.0233	0.0297
6	5	0.5	1	0.5	50	0.0213	0.0280
7	1	0.25	0.1	0.25	50	0.0300	0.0405
8	1	0.1	0.5	0.1	50	0.0320	0.0412
9	5	1	2	1	50	0.0195	0.0238

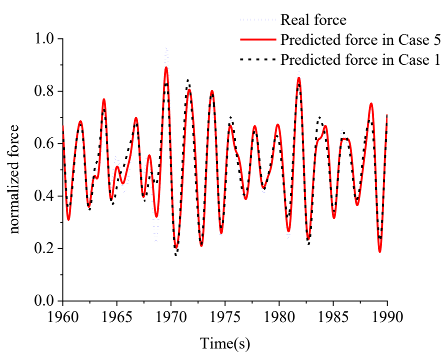

Fig. 6 Wave force prediction of NARX FNN in Case 1 and 5

When other parameters are not initialised well, increase of the layer number has negative effect for network training in case 1 and 2, as shown in Table 3~~Table 3~~. Keeping the layer number invariable, as the input delay (as the same as future horizon) and output delay increase, the performances are decreased simultaneously. When the delays are risen, the influence of the layer number is reversely positive towards the network performance. If the values of network parameters are set too large, the computational cost of training process increases dramatically with insignificant performance improvement. As shown in Fig. 6, when these parameters of NARX network increases, the time series prediction becomes more accurate.

The accuracy of prediction improves as the prediction process is implemented by iterative sub-loop. Namely neither all the information is not predicted in a single loop nor frequent information updating like one-step prediction. A trade-off PH of NARX network output, namely wave force, need to be determined in specific issues.

Analysis of LSTM-NARX prediction result of wave force

The aim of wave-force prediction based on machine learning is to forecast the future wave force which can be used in the real-time control of the WEC motion. Although the wave force can be calculated by NARX FNN, it is not sufficiently long to optimize the WEC motion with MPC. So prediction based on LSTM algorithm need to be implement again for predict wave force information. As shown in Fig. 7, when the prediction horizon is 0.02s, the accuracy of the predicted result is quite high so that there is almost no difference between two curves. Although the accuracy of predicted wave force decreases when the prediction horizon increases, the predicted wave force is also in phase with the real force, which is one of the most important ~~feature~~features of the real-time MPC.

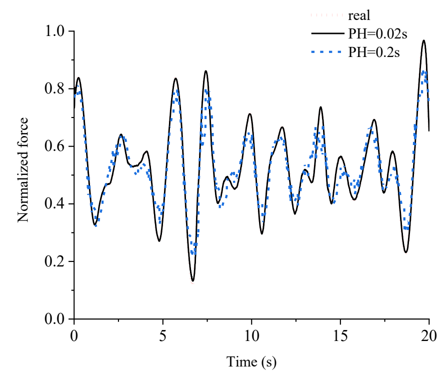

Fig. 7 Wave force prediction of LSTM-NARX network

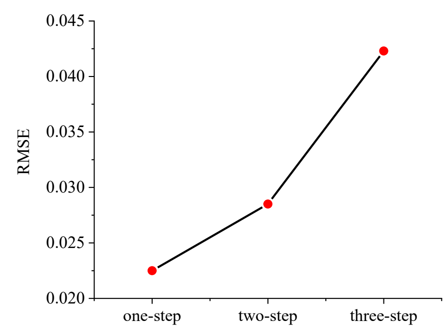

Fig. 8 Accumulated over-all performances of wave-force prediction

In each stage of wave prediction, no matter what wave height or wave force is applied, there is an inevitable error since any methods can predict the future information perfectly. If there is an error propagating from one stage to another one, the error will accumulate with a higher speed. Because the input of the following prediction model is not real data, but the approximate simulation result of previous stage. The predicted wave height will be used as the input in the machine learning algorithm at the stage of the wave force prediction based on NARX FNN. Also, the result of NARX FNN will be used in the LSTM RNN prediction of wave force. As shown Fig. 8, at first the accuracy of the first step stays at a low level. As the prediction process is implemented, the performance of the over-all process becomes worse, and the increase of error in the third step is much more obvious than the former step. It is because that the accuracy is lower so that the predicted result cannot reflect the nature of the real data. In order to simulate a satisfied predicted wave force, the accuracy of the former step needs to be promised.

6 CONCLUSIONS

In order to effectively control the motion of the offshore structures in a real-time manner, it is required to have an accurate and efficient prediction method of the waves. In this paper, a LSTM-NARX machine leaning prediction model is proposed to realise wave-force prediction which is suitable for non-linearity and non-causality. To verify the machine learning prediction model, an experimental dataset collected from Kelvin Hydrodynamic Laboratory is used in this study. The optimal horizon can be specified for the test model by comparing the performance of the cases with different network parameters. According to the work done above, the following conclusions can be drawn:

1. A novel wave-force prediction model based on machine learning algorithms is proposed in this paper which can be used to effectively control the motion of the offshore structures in a real-time manner. Owing to the novel architecture of LSTM RNN and NARX FNN, non-linearity and non-causality of wave height and wave force can be simulated successfully in time-series process.

2. The LSTM RNN is used to implement wave height prediction with history data of wave height as the input. Then, the NARX FNN is used to predict the future wave force when the wave height and wave forces predicted by LSTM are treated as the network inputs. The prediction results accurately match the experimental data collected from Kelvin Hydrodynamic Laboratory with different prediction horizons.

3. The LSTM-NARX prediction algorithm has a good performance when predicting the future wave force. The LSTM RNN is used twice and NARX FNN is used once in the framework of the complex prediction algorithm. The performance of network decreases when the prediction horizon increases. The error is accumulated from the former step to the latter step in the prediction process.

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