Data-driven model to forecast dynamic motion of a platform

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Abstract. The prediction of platform motion is important for offshore activities, as it can provide helpful early warning information and improve the motion compensation system. In this work, we proposed a data-driven model based on machine learning to predict the dynamic motion of a platform excited by irregular waves. The dataset for training and testing came from a model test carried out in the deep-water wave basin. Without prior knowledge of underlying physics, the data-driven model could study features from the data directly. It is found that the trained model can extend the predictions of the platform dynamic motions tens of seconds into the future with high accuracy, which are validated by the experimental measurements. This work shows the potential of the data-driven model to predict the dynamic motion of offshore platforms.

Introduction

The dynamic motion responses of offshore platforms usually move in six degrees of freedom, which are excited by environmental factors like ocean wave, wind, or current. The dynamic motion would lead to great challenges to perform offshore activities and limit lots of motion-sensitive works. Thus, it is important to predict the dynamic motions of platforms as it can provide helpful early warning information and improve the motion compensation system. From the traditional analysis, dynamic motion is normally illustrated by the response spectra and the response amplitude operator in the frequency domain. The statistical values are used as features to describe dynamic motions and these results are helpful for the design of platforms. However, the dynamic motion of platform is not described in the following short term. In recent decades, machine learning [1] is one of the popular topics and it has been widely applied to the field of nonlinear dynamics. The machine learning model could study features from the data directly without much prior knowledge of underlying physics. The reservoir computing model [2, 3, 4] has been successfully used to model and predict many nonlinear dynamical systems. Thus, in this work, we propose the strategy to make the predictions of dynamic motion of a platform excited by the irregular wave based on the reservoir computing model as shown in Fig. 1.

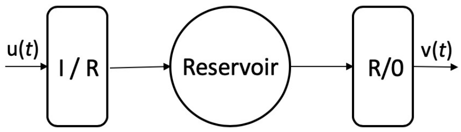

Figure 1: The framework of reservoir computing model

Results and Discussions

The dataset for the machine learning model came from an experiment carried out in the deep water wave basin. A platform is tested in the irregular wave environment. The dataset is separated into the training set, validation set and test set. The training set is applied to train the model and the validation set is used to choose the optimal hyper-parameter of the machine learning model. The performance of the data-driven model is evaluated by the predictions in the test set. It is found that the trained model can predict the dynamic surge, heave, and pitch motions of the platform tens of seconds into the future with high accuracy, which is evaluated by the corresponding experimental results. Without prior knowledge of underlying physics, the data-driven model based on the reservoir computing technique can give us a framework to study the features directly from the data. This work presents the potential of using the machine learning model to forecast the dynamic motion of offshore platforms.

References

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