DEVELOPMENT OF A DEEP-LEARNING BASED WAVE FORECASTING MODEL USING LSTM NETWORK

Thit Oo Kyaw, Waseda University, thit_oo_kyaw@toki.waseda.jp
Tomoya Shibayama, Waseda University, shibayama@waseda.jp
Yoko Shibutani, Toyo Construction, shibutani-yoko@toyo-const.co.jp
Yasuo Kotake, Toyo Construction, kotake-yasuo@toyo-const.co.jp

INTRODUCTION

Forecasting of wave conditions plays an essential role for offshore construction and maintenance. At present, the real-time wave forecasting is mainly conducted by traditional numerical wave modelling, which can be computationally expensive and time consuming. Recently, machine learning-based wave forecasting models have been developed and their integrated usage with physics-based numerical models has become popular (O'Donncha et al. 2018). These studies mostly apply Feed Forward Neural Networks (FFNNs) with an emphasis on prediction of time-series of waves, tides and storm surges (Kim et al. 2016). However, FFNNs are related with varnishing and exploding gradient problems. As a particularly advanced approach, we develop a deep learning-based wave forecasting model using Long Short-Term Memory (LSTM) network under Recurrent Neural Networks. As a case study, the model will be utilized to predict the wave conditions (low or high) near the Tottori Port, Japan. The accurate prediction of low wave conditions is important for decision-making process of offshore and nearshore construction work. Therefore, the present model can be a practical tool to reduce the potential waste of resources in those projects.

METHODOLOGY

General framework of the model (Figure 1) includes input layer (to pass initial features from datasets), network layers (to conduct training/testing simulations) and output layer (to provide final classified forecast).

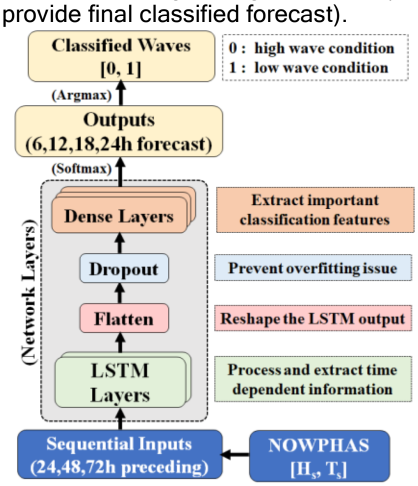

Figure 1 - Network for Wave Condition Forecasting

The input wave data is obtained from the Nationwide Ocean Wave information network for Ports and HArbourS (NOWPHAS) under the Port and Airport Research Institute, Japan. Hypothetically, the wave conditions are considered preferably low for working offshore if the values of significant wave height (H_s) and significant wave period (T_s) are smaller than 0.8 m and 9 s, respectively. Therefore, sequential information of H_s and T_s parameters are defined as input features. The output is the predicted wave classification results. Thus, the forecasted wave condition results can assist to determine whether it will be advisable or not to conduct work on the next day.

RESULTS AND DISSCUSSION

The model simulations were conducted using input wave parameters (H_s and T_s) of i) one preceding day (24 h), and ii) two preceding days (48 h). Subsequently, the wave condition for i) 4 h, ii) 12 h, and iii) 24 h lead times were predicted. It was found that training and validation of the model with 48 h preceding input wave data results in higher accuracy than 24 h for forecasting of all lead times. The overall performance of the model for 48 h lead time is depicted in Figure 2, showing high validation accuracy (over 90 %) with error (loss) values of around 0.12. Since the model counts as 1 for low wave condition and 0 for other, the confusion matrix shows the agreement of the predicted results with NOWPHAS observed data.

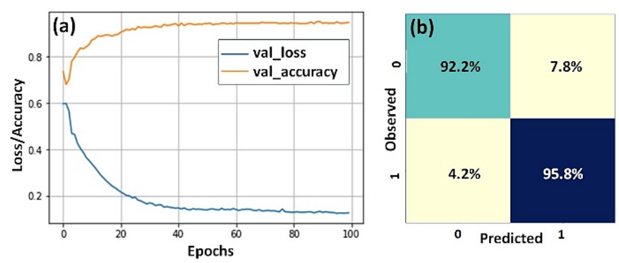

Figure 2 - Accuracy of LSTM Forecasting Model, (a) Validation Performance, (b) Confusion Matrix between Observed and Predicted Wave Conditions

In summary, the results suggest that if the sequential wave data for at least 48 h is known, the wave condition (low or high) for 24 h lead time can be well predicted using the present model. Therefore, the present model can be used as an advanced tool to assist the planning of possible working days at offshore construction sites.

REFERENCES

O'Donncha, Zhang, Chen, and James (2018): An integrated framework that combines machine learning and numerical models to improve wave-condition forecasts, Journal of Marine Systems, 186, pp. 29-36.
Kim, Matsumi, Pan, and Mase (2016): A real-time forecast model using artificial neural network for after-runner storm surges on the Tottori Coast, Japan, Ocean Engineering,

122, pp. 44-53.