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Buffeting forecasting of a long-span bridge based on wind field monitoring data and twin LSTM recurrent neural network method

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SUMMARY:
Buffeting analysis of long-span bridges induced by strong wind has received attention recently due to traffic service requirements. However, the essential question is whether the bridge's response can be preliminarily estimated in advance before landing strong winds. In this work, a buffeting response early forecasting framework based on meteorological weather prediction is proposed. The Weather Research and Forecasting (WRF) model provided short-term predictions of future weather at the meteorological site because historical wind data can be utilized to calibrate the prediction. The high-resolution wind environment at the bridge site is predicted by LSTM neural network and super-resolution (SR) technology from wind forecasting at the nearby station. Then, the buffeting response regression model is built based on the LSTM seq2seq method under different wind types.

Keywords: wind characteristic forecasting, long short-term memory (LSTM) network, buffeting response prediction

1. INTRODUCTION

In recent year, the buffeting responses of long-span suspension bridges induced by strong winds has attracted the attention of many researchers because extensive vibration can interrupt normal road traffic and even force the bridge to be closed. Facing the calculation of buffeting response in bridge engineering, two issues have been reported that strong wind characteristics at bridge site (Liu et al., 2022) and the method of estimating bridge buffeting response (Laima et al., 2023) at specific wind characteristic are difficult to be done. This paper proposes a solution to estimate the buffeting response long-span bridges based on LSTM seq2seq method.

In this work, a pure data-based buffeting response early forecasting framework based on meteorological weather prediction is proposed. The LSTM neural network is firstly employed to build the wind characteristic mapping from meteorological station to bridge site at deck elevation and the buffeting response prediction from wind characteristics to structural acceleration root-mean-square (RMS) response, respectively. Meanwhile, the time interval of wind recorded by meteorological station is about three hours, which is higher than the time interval required by wind-induced vibration analysis, and the SR technique (Kuleshov et al., 2017) is employed to predict the wind environment at 10-min interval. Combining the above two parts together, the buffeting response of long-span bridges can be evaluated in advance under the effect of extreme weather patterns (like strong monsoon wind and typhoon).

2. METHODOLOGY

According to the Davenport's wind load chain, to forecast the wind-induced response of a bridge under extreme winds, it is necessary to obtain the wind information in the future period near the bridge site, and then the wind-induced response can be calculated based on theoretical method, even a pure data-driven model. In this work, the research objectives are divided into two parts, namely wind speed series prediction (Task 1) and wind-induced structural response prediction (Task 2), and the twin LSTM seq2seq regression method is employed to build the regression model.

2.1. Data preparation and preprocessing

The wind sequence recorded by meteorological station, namely raw wind sequence, the wind sequence at bridge site, namely target wind sequence, and synchronous bridge acceleration response recorded by structural health monitoring system installed in Xihoumen Bridge (Zhoushan, Zhejiang province in China) are obtained (shown in Figure 1). The time interval of raw wind sequence and target wind sequence are 3 hours and 10 minutes, respectively. All the wind environment and structural response data of Xihoumen Bridge from 2010 to 2020 are obtained, as well as corresponding wind data at two meteorological stations.

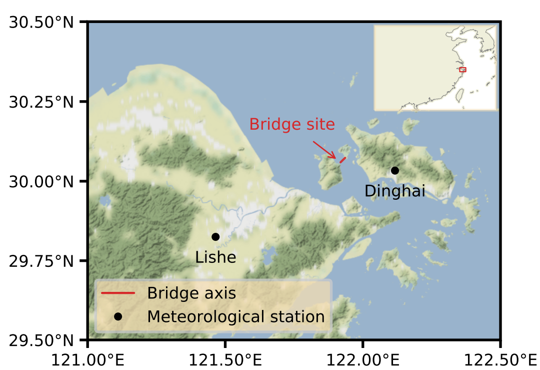

Figure 1. Location of bridge site and meteorological station nearby bridge

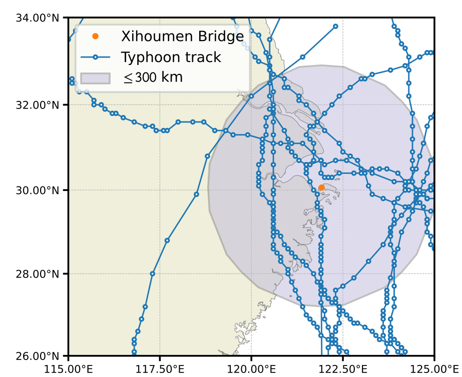

Figure 2. Typhoon path affected Xihoumen Bridge from 2010 to 2020

For monsoon, the time series segments with wind speeds greater than 8 m/s are selected as the dataset. From 2010 to 2020, there are 11 records of typhoons affecting Xihoumen Bridge (Figure 2), so the data set by changing the starting point of time series (data augmentation) is extended.

2.2. Description of LSTM seq2seq model

LSTM, as a variant of the RNN, has the characteristics of lateral information exchange, which helps to mine the relationship between time series wind data at different locations. Seq2Seq models consist of an Encoder and a Decoder. By introducing seq2seq model into LSTM network, the prediction from raw wind sequence to target wind sequence and from wind sequence to response sequence can be realized. The LSTM seq2seq network used in this work contains an input layer, a LSTM layer, a linear full connection layer, an activation layer and a output layer. The number of intermediate nodes varies by task.

2.3. Loss function for training and model evaluation

The loss function is the optimization objective function for model training. The model was trained with a time-domain loss function. Here, the mean square error (MSE) loss was adopted. To quantify the estimation accuracy of model, the root mean square error (RMSE) between prediction value $s_T(n)$ and real value $\hat{s}_T(n)$ was adopted.

3. APPLICATION

An engineering application of Xihoumen Bridge was performed to access the effectiveness of the proposed framework to achieve the buffeting response early forecasting. Introducing the wind mapping between wind speed at meteorological station and wind speed at bridge site, the SR technique between low resolution wind speed and high resolution wind speed at bridge site, and the buffeting response regression between wind characteristics and bridge response, the flow chart is shown in Figure 3.

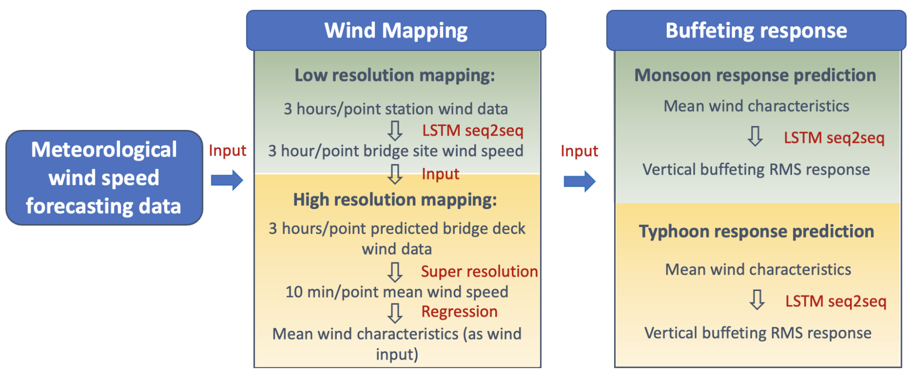

Figure 3. Framework Flowchart

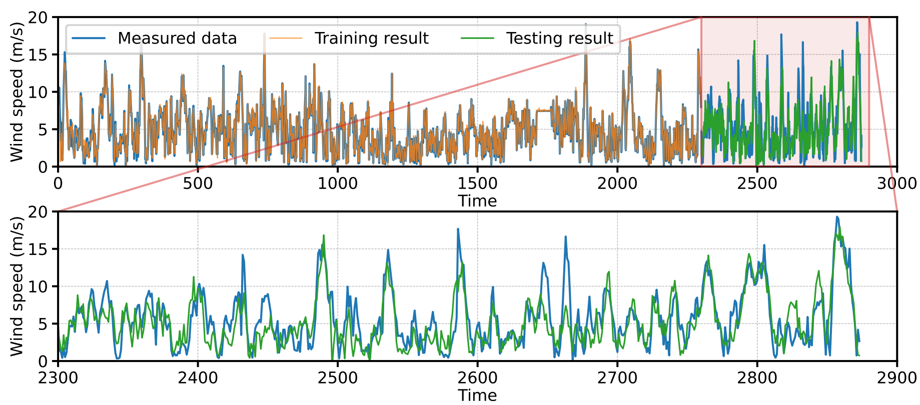

Figure 4. Wind mapping between meteorological station and bridge site

The wind mapping between meteorological station and Xihoumen Bridge site in Task 1 is shown in Figure 4, and the model evaluation index is RMSE = 2.68 m/s. According to the SR method proposed by Kuleshov et al. (2017), the short-time Fourier transform of SR from 3 hours interval to 10 minutes interval in Task 1 is shown in Figure 5. The buffeting response prediction validation of test set under monsoon and typhoon climates in Task 2 are shown in Figure 6 and Figure 7, and the

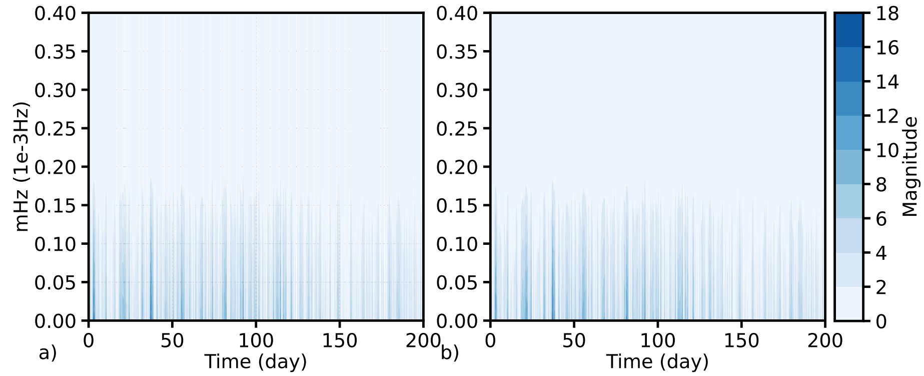

Figure 5. STFT of SR regression, a) actual high resolution series, b) predicted high resolution series

model evaluation indexes are RMSE $= 0.43$ $\mathrm{cm/s^2}$ (monsoon), RMSE $= 1.17$ $\mathrm{cm/s^2}$ (typhoon). The less accurate prediction under typhoon may be due to the small amount of training set samples.

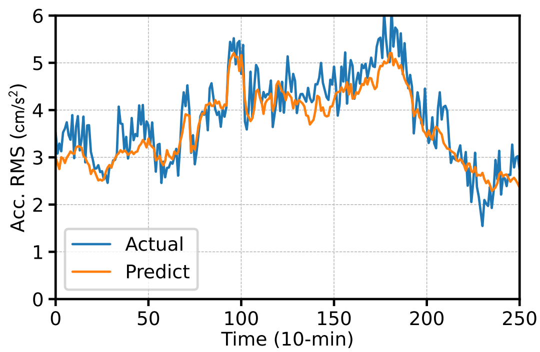

Figure 6. Buffeting response validation of proposed forecasting model when monsoon

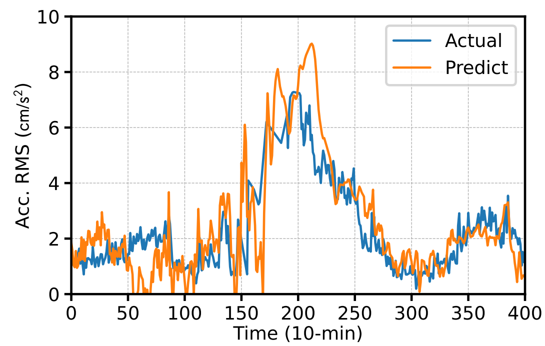

Figure 7. Buffeting response validation of proposed forecasting model when typhoon

4. CONCLUSION

In this paper, a buffeting response early forecasting solution based on LSTM and SR technique is proposed, which can implement the wind-induced vibration prediction in advance under monsoon and typhoon climate.

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