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Data-driven modeling of bridge vortex-induced vibration via a physics-guided machine/deep learning framework

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SUMMARY:
In this work, we propose a physics-guided machine/deep learning framework for data-driven modeling of bridge vortex-induced vibrations (VIVs). This framework includes full-scale measurements of structural vibrations and wind fields of a prototype long-span bridge and machine/deep learning algorithms for data-driven modeling of bridge VIVs. We leverage full-scale measurements to address the challenges in conventional wind-tunnel-based methods of bridge VIV modeling, e.g., high Reynolds number effects, non-stationary and non-uniform wind fields, and uncertainties in prototype bridge structural dynamics. However, unlike wind-tunnel-based methods, the obtained data of full-scale measurements are often restricted because the real wind field is natural (i.e., uncontrolled). To address this challenge, we propose machine/deep learning-based methods to derive data-driven models of bridge VIVs from such uncontrolled full-scale measurement data. A case study on a real suspension bridge shows that the proposed method is effective and accurate for bridge VIV response prediction under real natural winds. Further, the critical VIV wind speed range of the suspension bridge is obtained based on the derived data-driven model.

Keywords: bridge vortex-induced vibration, full-scale measurements, machine/deep learning

1. INTRODUCTION

Vortex-induced vibration (VIV) modeling is quite important for flexible structures (here, modeling refers to the model of aerodynamic forces acting on bridges). Rigorous mathematical-physical modeling of VIV requires simultaneously solving the Navier-Stokes (N-S) equation and motion of equation of the structure. However, because of the strong nonlinearity of the N-S equation, this has proved to be mathematically intractable (Basu and Vickery, 1983). As a less-than-ideal alternative, simplified semi-empirical models are proposed based on wind tunnel experiments. Simiu and Scanlan (1986) proposed a single ordinary differential equation to model VIV, and the parameter identification approach was then proposed by Ehsan and Scanlan (1990). The semi-empirical models are highly dependent on wind tunnel experiments. However, the discrepancy between the wind tunnel experiments and prototype bridge results in the inability of these models to accurately predict VIV responses for a prototype bridge: (1) the section model in the wind tunnel cannot reflect the three-dimensional aeroelastic characteristics for the VIV of the full-scale bridge; (2) the above models assume that wind is uniform and steady-flow, whereas the wind flow at the bridge site may be nonuniform in the spanwise direction and unsteady during a VIV event; (3) the Reynolds number of a section model is generally one to two orders of magnitude smaller than that of a full-scale bridge. Structural Health Monitoring systems (including wind and wind effects monitoring) on many long-span bridges worldwide (Ko and Ni, 2005; Li et al., 2006; Azarbayejani, et al., 2009) collect a large amount of data and provide an opportunity to investigate the wind effects on prototype bridges. However, the wind and wind effects for prototype bridges are much more complicated than those in wind tunnel experiments and numerical simulations. Additional challenges appear with the uncertainty associated with bridges and measurement noise. Fortunately, in recent years, machine learning (ML) which is a branch of artificial intelligence (AI) has shown much ability to deal with strong nonlinearity, high dimension, and complicated and noisy data. To address the above-mentioned challenges in wind-tunnel-based methods for bridge VIV modeling, this work proposes a physics-guided machine/deep leaning framework to identify the predictive model of a prototype bridge VIV from full-scale measurements. The derived data-driven model is required to perform VIV response prediction in the time domain given any real natural wind fields histories.

2. LONG-TERM FULL-SCALE MEASUREMENTS

The long-span suspension bridge investigated in this study has a 1650 m central main span and a 578 m side span. It is noted that the existence of a hill on the south island close to the 3/4 center span location leads to the nonuniform flow of natural wind. Wind speed at the site is monitored with Young Model 81000 three-dimensional ultrasonic anemometers at a sampling frequency of 32 Hz. The vertical acceleration of the bridge deck is monitored by GT02 force-balance triaxial accelerometers at a sampling frequency of either 100 Hz (in 2010 and 2011) or 50 Hz (after 2012). The anemometers and accelerometers are installed on both the upriver and downriver sides of the sections at the 1/4, 1/2 and 3/4 center span, as shown in **Fig. 1**. Note that the anemometers are installed on lighting columns at a height 6 m above the bridge deck surface. All the wind data analyzed in this study are obtained from the inflow anemometers, which can measure natural winds without interference from bridge components. 90° and 270° are defined as the wind directions perpendicular to the bridge axis.

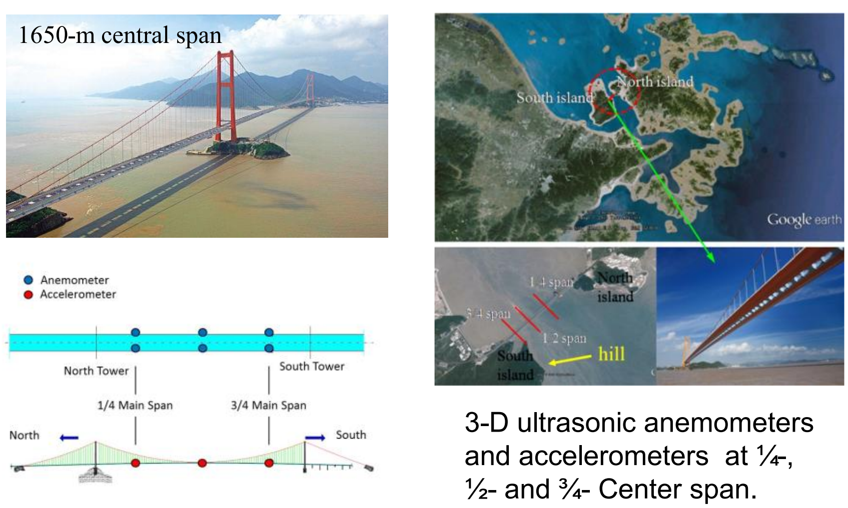

Figure 1. The studied long-span bridge and full-scale measurements of bridge vibrations and wind fields.

3. A PHYSICS-GUIDED MACHINE/DEEP LEARNING FRAMEWORKF FOR BRIDGE VIV MODELING

The proposed machine/deep learning framework includes a support vector regression (SVR)-based method for coarse-time-scale modeling and a recurrent neural network (RNN)-based method for fine-time-scale modeling. Based on the prior knowledge of the bridge VIV, the bridge response amplitude at time step t can be represented as follows

$$A^{t} = f_{\text{VIV}}\left(A^{t-1}, U_{1/4}^{t}, U_{1/2}^{t}, U_{3/4}^{t}, \theta_{1/4}^{t}, \theta_{1/4}^{t}, \theta_{1/4}^{t}\right) \tag{1}$$

where, A denotes the VIV response amplitude (1-minute RMS of displacement or instantaneous amplitude of displacement), U the corresponding wind speed, θ the corresponding wind direction angle. The subscript denotes the location. The specific goal in the data-driven modeling is to identify the model function f_{VIV}.

3.1. SVR-based coarse-time-scale modeling

The schematic of the SVR-based coarse-time-scale modeling is shown in **Fig. 2**(a). The time step size is 1 minute. The bridge response and the wind conditions are based on 1-minute statistics. The obtained model is required to perform time-domain prediction of bridge VIV response given real natural winds, as shown in **Fig. 2**(b). It is observed that the predicted bridge VIV response process is consistent with the measured. Further, we perform parametric study the bridge VIV response using the obtained SVR-based model. The critical VIV wind speed range is identified as shown in **Fig. 3**(a) while the influence of the non-uniformity of the wind field is shown in **Fig. 3**(b). It is observed that the critical VIV wind speed range is about [10 m/s, 12 m/s]; the non-uniformity of the wind speed has a significant influence when level of nonuniformity approach some critical value because wind speeds at some locations along the span are outside the critical VIV wind speed range.

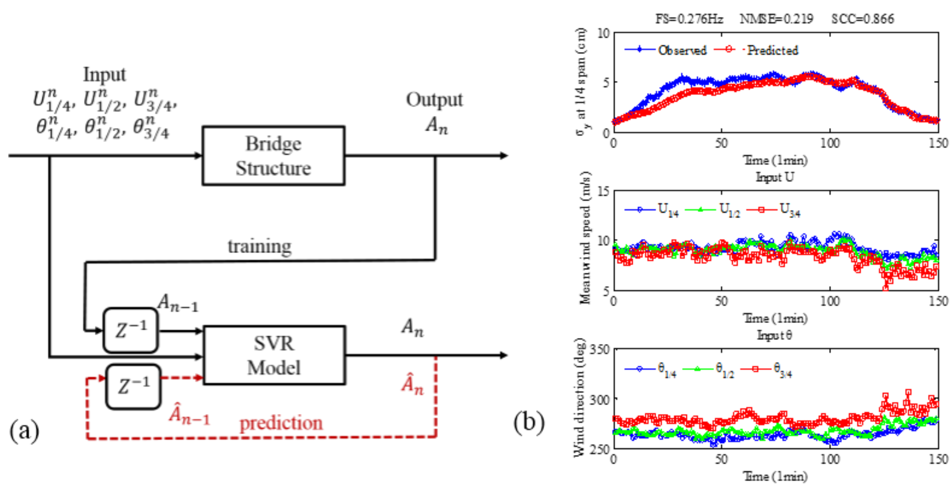

Figure 2. The schematic of the SVR-based method and the bridge VIV response prediction for a real VIV event.

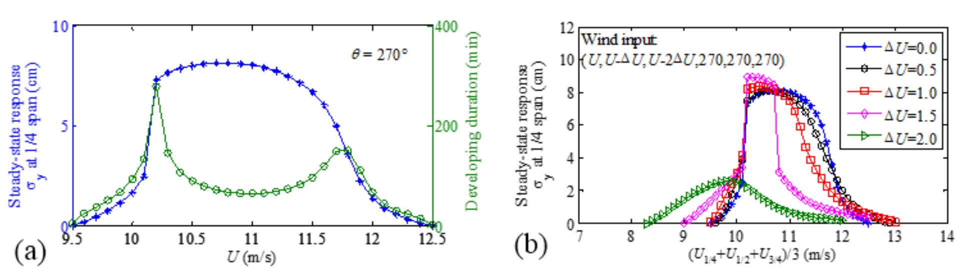

Figure 3. Parametric study of the bridge VIV using the obtained SVR-based model.

3.2. RNN-based fine-time-scale modeling

The schematic of the RNN-based fine-time-scale method is shown in **Fig. 4**(a). The time step size is around 3 seconds. The bridge response amplitude is obtained by extracting the envelop of vibrational displacements. The time varying mean wind speeds are calculated using low-pass filters. The obtained model is required to perform time-domain prediction of bridge VIV response given real natural winds, as shown in **Fig. 4**(b). It is observed that the predicted bridge VIV response process is consistent with the measured.

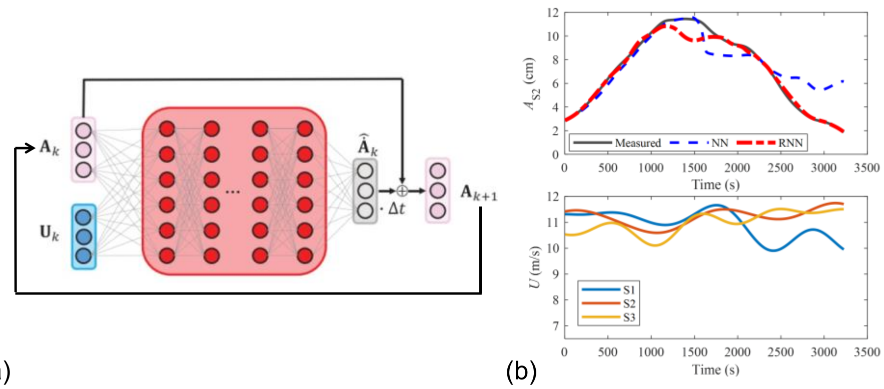

Figure 4. The schematic of the RNN-based method and the bridge VIV response prediction for a real VIV event.

4. CONCLUSION

This work proposes a machine/deep learning framework for data-driven modeling of bridge VIVs using full-scale measurement data of a prototype bridge. The obtained data-driven models are used to predict bridge VIV response under real natural winds that are non-stationary and non-uniform. It is observed that the obtained data-driven models are accurate. Further, the critical VIV wind speed range of the studied bridge is identified based on the obtained data-driven model.

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