LONG-TERM VIBRATION AND TEMPERATURE MONITORING ON A STEEL PLATE GIRDER BRIDGE

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1. INTRODUCTION

For reliable performance of vibration-based damage detection, it is important to distinguish abnormal changes in modal parameters caused by structural damage from environmental-induced fluctuation[1]. In this study, the temperature effect on modal frequencies of a steel plate-girder bridge is studied through its long-term structural health monitoring (SHM).

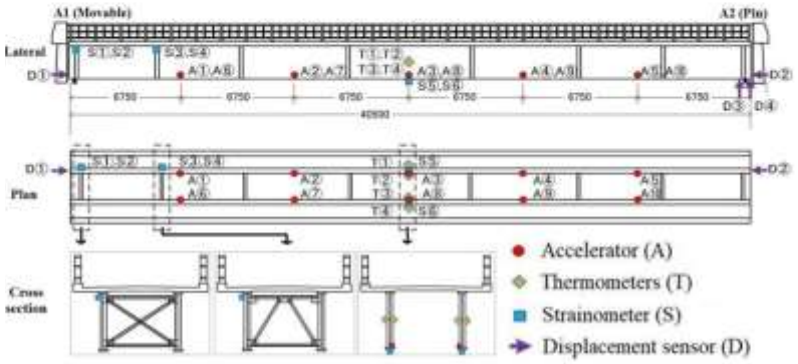

Fig. 1 Bridge sensor deploying map.

2. OBSERVATION BRIDGE AND SYSTEM IDENTIFICATION

The observation bridge, a steel plate-girder bridge with a span of 40.5 m long as shown in **Fig. 1**, had been monitored for almost one year from September 1, 2016 till August 28, 2017. The monitoring system includes 10 accelerometers and 5 thermometers that consider spatial temperature distribution. The accelerations were sampled at 200Hz, and the sampling time of other sensors was every 30 minutes. This study focuses on the frequencies of the first three bending modes, which were identified by means of a Fast Bayesian FFT (Fast Fourier Transform) method[2] and separated into two groups, one for training the model to quantify the temperature effect on modal frequencies and the other to validate it.

Table 1 MLR results.

1st bending mode ($w_0 = 3.1619$)		2nd bending mode ($w_0 = 9.5978$)		3rd bending mode ($w_0 = 21.9230$)	
Input	w	Input	w	Input	w
T_{01}	0.0046	T_{01}	0.0032	T_{11}	0.0026
T_{05}	0.0362	T_{03}	0.0094	T_{25}	-0.0036
T_{15}	-0.0371	T_{05}	0.0248		
T_{25}	-0.0067	T_{15}	-0.0471		
		T_{21}	0.0015		

3. REGRESSION MODELS

The frequencies were firstly assumed linearly correlated with temperature readings from the bridge and a linear model is built by multiple linear regression (MLR) as following in Eq. (1):

$$\mathrm{y} = w_0 + \mathbf{x}\mathbf{w} + \epsilon \tag{1}$$

where w_0 is the model offset, $\mathbf{x}$ is the temperature inputs and $\mathbf{w}$ is a column vector of the weight to be multiplied by each input, and the result is shown in **Table 1**. Therein, the subscript of input T_{ij} indicates its time and spatial information. The i stands for the time corresponding to temperature reading: the beginning (0), mid (1) or end (2) of the time interval (an hour). For the j, T_{i1} and T_{i2} are the temperature recorded outside and inside the left wing at the mid span, T_{i4} and T_{i3} are their equivalence on the right wing, and T_{i5} is the temperature in the box of the data acquisition system installed on the road beside the bridge to record the monitoring environment. It was found that the temperature recorded on the road beside the bridge at the mid of the sampling time (T_{15}) influences the modal frequency significantly and the temperature gradient across the midspan resulted in very limited contribution to the modal frequency variation.

Table 2 Statistics of MLR and GPR.

Mode	MLR		GPR	
	RMSE	R^2	RMSE	R^2
1st bending	0.1000	0.1348	0.0834	0.3980
2nd bending	0.1002	0.3109	0.0866	0.4843
3rd bending	0.0964	0.0131	0.0847	0.2372

A model based on Gaussian process (GP) was built and the target frequency y is assumed to follow Gaussian distribution as:

$$y \sim \mathcal{N}(m, k) \tag{2}$$

where the mean m and variance k are functions of the temperature inputs $\mathbf{x}$ governed by a series of hyper-parameters, which are determined by Gaussian process regression (GPR)[3] based on training data, and that relation is employed to correlate temperature data $\mathbf{x}$ and the corresponding modal frequency y. It can be found in **Table 2** that the GPR can better explain the variation of modal frequencies.

Keywords: Actual bridge, correlation analysis, Gaussian process regression, long-term monitoring, temperature effect
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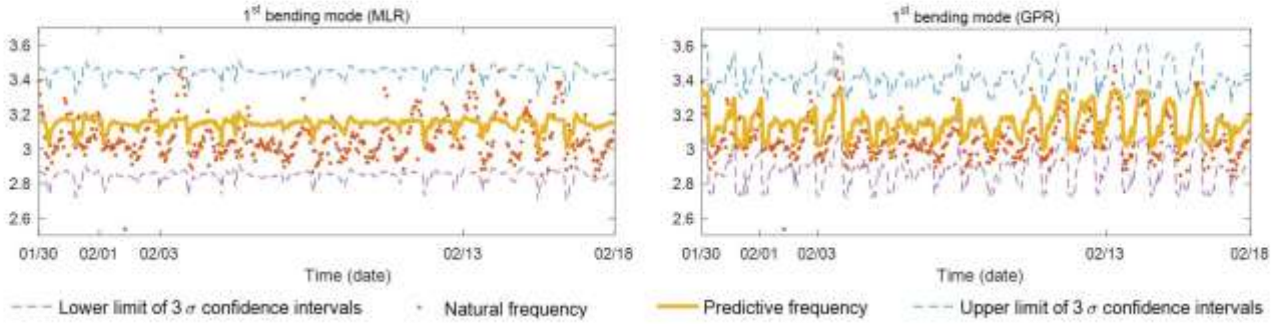

Fig. 2 Identified natural frequency and predictive frequency by MLR and GPR of first bending mode. (unit: Hz)

4. MODEL VALIDATION

The regression models established in the previous section were used to predict the modal frequency of the bridge from January 30 to February 18 in 2017. Based on temperature input from test data set, the predictions made by both models are shown in **Fig. 2** for the 1st bending mode. Those for the 2nd and 3rd bending modes were omitted for the page limitation. It showed that the GPR model made fairly accurate predictions, where the predictive confidence interval basically covered all the observations, while the MLR model failed to predict the fluctuations on February 3 and February 13.

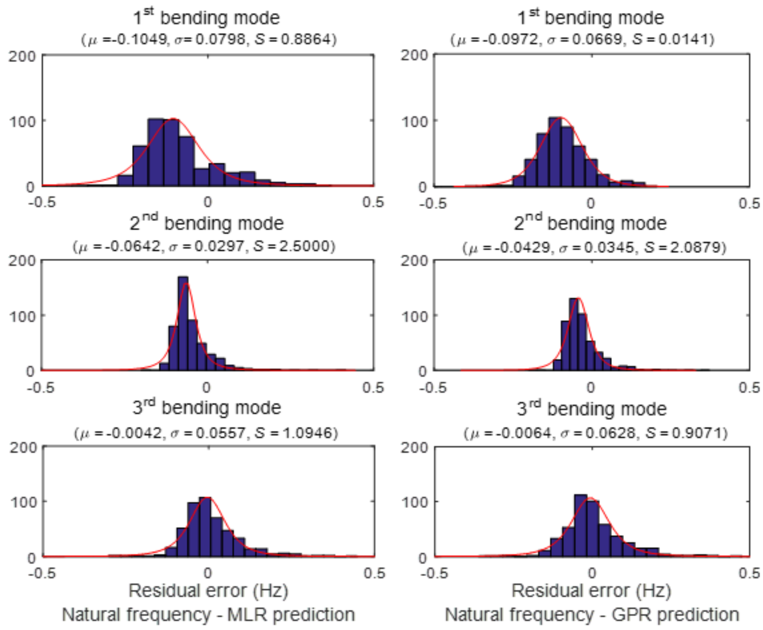

Fig. 3 Residual error histogram fitted by *t* location-scale distribution.

It was found that both models led to accurate predictions of the second bending mode most of the time. For the third bending mode, as shown in **Table 1**, the MLR model extracted very limited correlation feature from the training data and resulted in an uninformative prediction. Meanwhile, even though the GPR can sometimes trace the variation trend, the number of the frequency located outside the confidence interval is no less than that of the MLR. Besides the uncertainties in higher order mode identification, such phenomenon can be partially explained by the fact that the standard error of the MLR (RMSE in Table 1) is usually higher than that of the GPR.

5. RESIDUAL ANALAYIS

The residual error corresponding to prediction made by both methods is presented in **Fig. 3**, through which it can be found that: compared with the MLR, the utilization of the GPR can alleviate the bias in prediction, reflected by the generally smaller absolute value of the mean (μ) of the fitted distributions; also, the residual error of the GPR shows significantly lower level of skewness (S), which means it is more asymmetrically distributed around the sample mean.

6. CONCLUSION

Observation demonstrated that the temperature change can influence modal frequency variation significantly, especially the temperature change recorded on the road beside the bridge at the mid of the sampling time. In addition, compared with linear model, the predictor based on GPR can better trace the variation of modal frequencies due to environmental temperature change and make less biased prediction.

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