Machine Learning-based Prediction of Crosswind Vibrations of Rectangular Cylinders

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ABSTRACT

In order to evaluate crosswind vibrations of rectangular cylinders, machine learning method was used to build an efficient and effective prediction model for supplementing wind tunnel tests and numerical simulation. 5 machine learning models were trained based on the existing high-quality and reliable wind tunnel test datasets. 4 types of crosswind vibration phenomena, including over-coupled, coupled, semi-coupled and decoupled, were predicted. It was found that the gradient boosting regression tree model is capable of predicting crosswind responses of rectangular cylinders at side ratios from 0.75 to 3 and Scruton numbers from 0 to 150 under wind flow with turbulence intensities from 0 to 16%. Evidently, GBRT model can be an effective and economical method to study crosswind vibrations of rectangular cylinders and hence supplement traditional wind tunnel tests and numerical simulation.

1. Introduction

Crosswind vibration, due to its potential large oscillation amplitudes, is one of the key issues in the wind-resistant design of such structures. Rectangle is one of the typical shapes for the cross section of such structures, which are usually prone to vortex-induced vibration (VIV) and galloping. Furthermore, VIV and galloping are possibly coupled with each other to result in unexpected large amplitudes, which would increase the possibility to destroy structures.

To date, a complete and accurate theory to explain coupled and decoupled phenomenon of VIV and galloping of rectangular cylinders is still unavailable. Although the theoretical analysis model of VIV has been continuously improved in recent years (Mannini, 2020; Mortveit Ellingsen and Amandolese, 2020). However, these methods are still based on empirical or semi-empirical models, and experiments are preconditions of the analysis process. Den Hartog (1956) systematically discussed galloping based on quasi-steady assumption and created a criterion, i.e. Den Hartog criterion, to evaluate the possibility of galloping. However, its weakness is still well documented. It is still impossible to completely explain and estimate galloping through the quasi-steady theory (Mannini et al., 2015a, 2018; Massai, 2016).

Wind tunnel aeroelastic tests and fluid-structure interaction (FSI) numerical simulations have been widely applied to assess crosswind vibrations of rectangular cylinders. However, both aeroelastic tests and FSI numerical simulations are very time-consuming (Gao and Zhu, 2017). Furthermore, the accuracy of numerical simulation is still controversial (Fang and Gu, 2008; Tang et al., 2015). Therefore, an economical and effective supplement to these traditional research tools is essential for investigating crosswind vibrations of rectangular cylinders.

Due to the large amount of accurate and reliable experimental data accumulation in the literature and the growing demand for mathematical methods to process big data, machine learning (ML) technique has made great breakthroughs in engineering applications in recent years (Hu and Kwok, 2020; Hu et al., 2020; Li et al., 2020). Therefore, due to the complexity of wind tunnel aeroelastic tests and the unreliability of numerical simulation of fluid-structure interaction, this study aims to build a ML model to predict crosswind responses of rectangular cylinders based on a large number of reliable wind tunnel test datasets collected from previous studies.

2. Data collection and processing

The main factors include side ratio (*B/D, B* is the streamwise dimension of rectangular cylinders and *D* is the cross-flow dimension of rectangular cylinders which is perpendicular to the incident flow), turbulence intensity (*Ti*) and Scruton number (*Sc*, $Sc = 4\pi M\xi/\rho BDL$, where M is the effective mass of the system, ξ is the mechanical damping ratio, ρ is the air density and *L* is the length of rectangular cylinders). These factors are all displayed important roles in the crosswind vibrations of rectangular cylinders (Mannini et al., 2016a, 2014, 2015b, 2016b, 2017).

In this study, only zero wind attack angle is considered in the study due to the limitation of datasets. Meanwhile, the influence of Reynolds number on the crosswind vibrations of bluff bodies with sharp edges can be negligible (Holmes, 2018). Therefore, the inputs of ML models in this study include side ratio, turbulence intensity, Scruton number and reduced wind speed ($U/f\,D$, where *U* is the wind speed of the oncoming flow and *f* is the natural frequency of the structure), while the output of ML models is the dimensionless crosswind response (*A/D*, where *A* is the crosswind vibration displacement of rectangular cylinders) as shown in Figure 1.

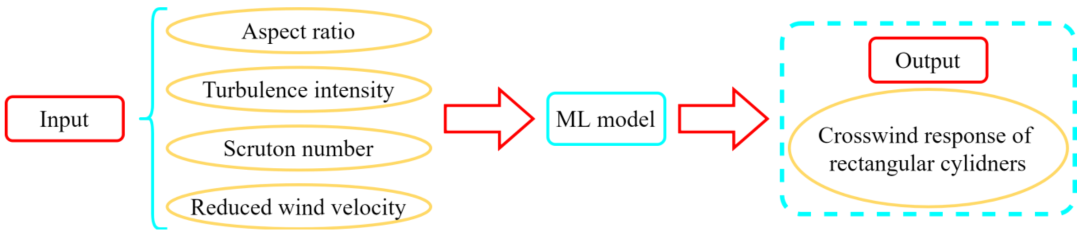

Figure 1: Architecture of machine learning prediction model

Due to the significance of crosswind vibrations of rectangular cylinders, a series of studies have been made to advance the research of crosswind vibrations, during which a large number of wind tunnel test datasets have been accumulated. Such datasets (227 sets with 5574 sample points), as listed in Table 1, are the foundation of building ML models, which are used to train, test, and validate ML models. Meanwhile, in order to verify the generalization of the model, four types of crosswind vibration (over-coupled, coupled, semi-coupled and decoupled) that may occur on rectangular cylinders were randomly selected. In terms of these four types of oscillations, 6 sets of data which is not participated in model training and testing were set aside solely for validating the ML models.

3. Machine learning model training

Five ML algorithms including 2 single learner algorithms, i.e. decision tree regression (DTR) and K-nearest neighbor regression (KNN), and 3 ensemble methods, i.e. random forest (RF), gradient boosting regression tree (GBRT), and histogram gradient boosting regression tree (HISGBRT) were selected to predict the crosswind responses of rectangular cylinders. *K*-fold cross-validation (*k*-CV) was used to evaluate performance of models. The details of this method is given in Hu and Kwok (2020). In this study, *k* was set to 10 to evaluate the model. These machine learning algorithms used in this study were implemented based on the scikit-learn package.

Table 1. Datasets of crosswind vibrations of rectangular cylinders in the literature

No	Experimental resource	Ti (%)	B/D	Sc	Samples
1	(Mannini et al., 2014)	1.00	1.50	4.50-149.84	425
2	(Mannini et al., 2015a)	1.00	1.50	9.11-147.49	204
3	(Mannini et al., 2015b)	0.70-16.00	1.50	2.90-154.48	944
4	(Itoh and Tamura, 2002)	0.40	2.00	4.36-112.13	135
5	(Zhu et al., 2017)	0.40	1.50	5.35-30.12	364
6	(Wawzonek, 1979)	0.10	1.00	2.20-97.98	441
7	(Mannini et al., 2016a)	0.60-3.00	1.50	4.16-118.52	594
8	(Mannini et al., 2016b)	0.90	1.50	51.60-53.65	81
9	(Mannini et al., 2018)	0.70-15.10	1.50	4.80-65.50	597
10	(Amandolèse and Hémon, 2010)	0.90	1.00	9.26	33
11	(Washizu et al., 1978)	0.30	2.00	3.00-60.00	125
12	(Massai, 2016)	0.70	1.50	7.18-8.27	46
13	(Santosham, 1966)	0.05	2.00	10.74-426.93	153
14	(Bearman et al., 1987)	0.04	1.00	10.97-68.56	130
15	(Borri et al., 2012)	0.50	0.71-1.40	9.22-20.88	144
16	(Gao and Zhu, 2017)	0.90	2.00	6.89-52.60	109
17	(Hémon and Santi, 2002)	4.00-7.50	2.00	71.00	207
18	(Hémon, 2012)	0.90	1.00	116.88-146.93	63
19	(Laneville, 1973)	0.07-12.70	1.00-2.00	17.90-35.80	183
20	(Miyata et al., 1983)	0.05-11.00	1.00-3.00	2.00-80.00	260
21	(Parkinson and Brooks, 1961)	0.25	1.00	10.05-41.01	53
22	(Smith, 1962)	0.40	1.00-3.00	5.55-63.96	283
23	Total	0.04-16.00	0.71-3.00	2.00-426.93	5574

During the training process, hyper-parameters optimization is indispensable in order to achieve the best performance for the ML models. The gridsearch (GS) method, as a straightforward optimization method, aims to find out the best combination of multiple parameters at their given ranges. After roughly determining the potential range that the optimal hyper-parameters fall into based on GS, the Particle Swarm Optimization (PSO) algorithm was used to further determine the exact optimal hyper-parameters of the ML model, for which PSO extension toolkit pyswarms was used.

4. Results and analyses

4.1 Performance of different ML models

R-squared scores of these models based on testing datasets are given in Figure 2 (a)-(e). Evidently, the DTR model has the worst performance among the five models. The GBRT model exhibits the largest score compared to the other models. The superiority of the GBRT model is further proven by the lowest MSE values among these five models calculated by the predictions of crosswind response and all testing data as shown in Figure 2 (f). Therefore, the GBRT model with its optimal hyper-parameters was considered as the best ML model in predicting the crosswind responses of rectangular cylinders.

4.2 Generalization ability of the optimal ML models

As shown in Figures 2, although the GBRT model presents the best performance in the testing datasets, it is necessary to verify its generalization ability. Meanwhile, the R- squared score and MSE of the four models, i.e. KNN, RF, GBRT and HISGBRT, only exhibit slight differences. Hence, the four models with their optimal hyper-parameters were all used to predict the crosswind responses of rectangular cylinders from the validation datasets. As shown in Figure 3, four different types of crosswind vibrations together with two high turbulence intensity cases were covered in this validation process, in order to comprehensively validate the generalization capability of the four models for predicting various types of crosswind vibrations of rectangular cylinders.

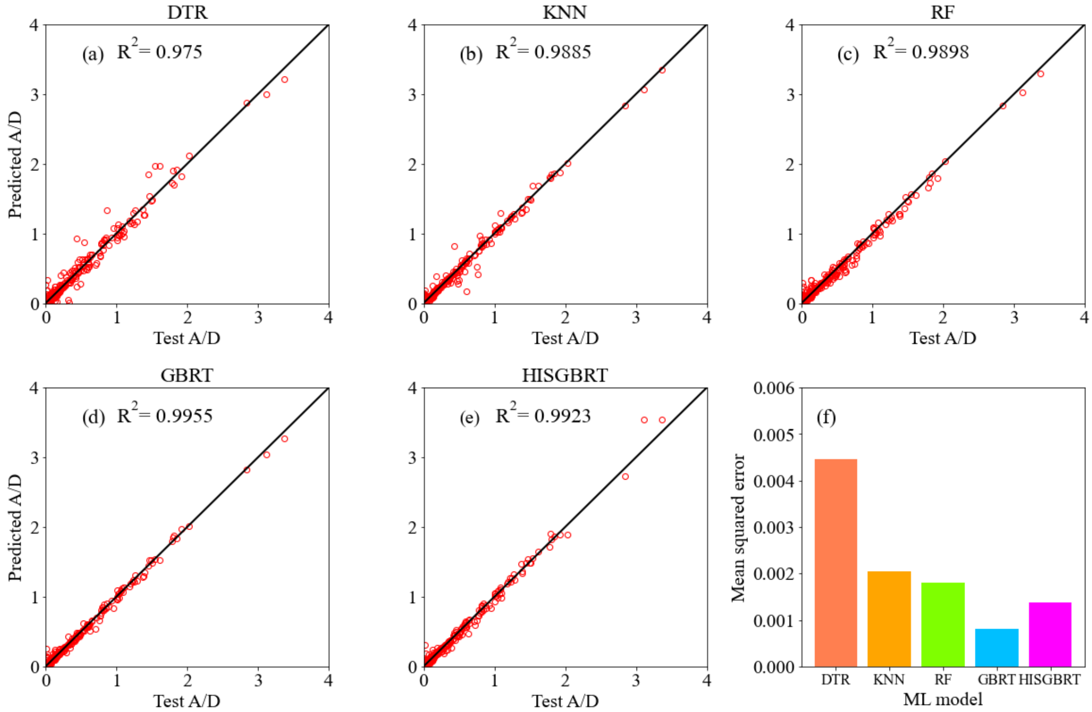

Figure 2: Comparisons of R-squared score and mean squared error of ML models

As shown in Figure 3 (a), the four models accurately predict the over-coupled vibrations of rectangular cylinders. For the coupled type of crosswind vibrations shown in Figure 3 (b), the crosswind responses predicted by the KNN model are highly consistent with the experimental data. The predictions of the other three models exhibit a similar trend as the experimental data despite discrepancies between predictions and experimental data. In Figure 3 (c), all models accurately predict the responses at low reduced velocities, but the predictions are not ideal at high reduced velocities, possibly induced by the limited amount of training datasets. What's more, the KNN model shows the worst performance. Meanwhile, three models, including KNN, GBRT and HISGBRT, provide accurate predictions for the decoupled type of vibrations except at high reduced velocities in Figure 3 (d). The RF model obviously overestimates crosswind responses. Besides, two additional high turbulence cases were tested and shown in Figure 3 (e) and (f). The excellent performance of the RF and GBRT models in these two cases demonstrates that these two models are more appropriate than the KNN and HISGBRT models to make predictions on the crosswind vibrations of rectangular cylinders under high-turbulence wind.

In summary, both KNN and GBRT models have the ability to predict the crosswind response of rectangular cylinders according to the 6 testing cases. However, based on the results of R-squared score and mean square errors of 5 ML models on the whole dataset, the GBRT model is finally selected in this study to predict the crosswind response of rectangular cylinders.

5. Conclusions

This paper uses machine learning techniques to establish prediction models of the crosswind responses of rectangular cylinders based on a large amount of high-quality and reliable datasets collected from the literature. Five ML algorithms, including DTR, KNN, RF, GBRT and HISGBRT, were

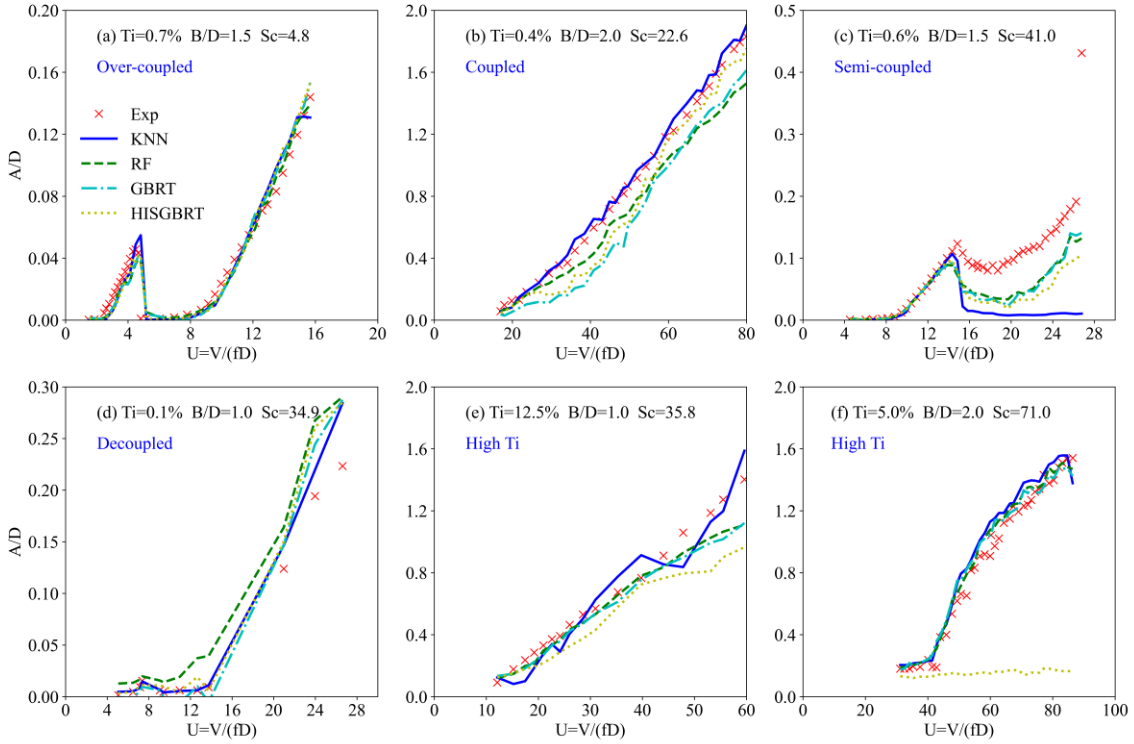

Figure 3: Predictions of crosswind responses of the validation cases by using GBRT

used to build prediction models. After comparing the performance of these models, it has been found that the GBRT model exhibits a satisfactory performance in predicting the crosswind responses of rectangular cylinders in wind flow with a turbulence intensity from 0 to 16%, side ratio from 0.75 to 3 and Scruton number from 0 to 150. Meanwhile, some non-ideal predictions may be improved by feeding the ML models with more datasets. Therefore, it is believed that the machine learning model could be a supplement to traditional wind tunnel tests and numerical simulations in future.

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