August 27-31, 2023
FLORENCE - ITALY
16th International Conference on Wind Engineering
ICWE 16

Deep data mining and prediction of vortex-induced vibration of circular cylinders

Zhen Wang [1], Zhitian Zhang [2]

[1]School of Civil Engineering, Tianjin University, Tianjin, China, Email address: wangz999@tju.edu.cn
[2]College of Civil Engineering and Architecture, Hainan University, Haikou, China, Email address: zhangzhitian@hainanu.edu.cn

SUMMARY:
An unprecedented amount of data has been accumulated in recent decades by means of numerical, experimental, and field-measurement of vortex-induced vibration (VIV) of circular cylinders, and then benefited from the development of machine learning (ML) algorithms and computers, which make it available to study VIV using ML. In this study, ML models are developed for predicting the maximum amplitude Y^* and amplitude response-reduced wind speed curves of circular cylinders undergoing VIV. The published literature data are aggregated as a dataset. Three ML models, support vector regression with particle swarm optimization (PSO+SVR), extreme learning machine (ELM) and ELM combined with preprocessed least squares QR decomposition (PLSQR+ELM), are trained. Three important parameters, mass damping ratio, Reynolds number and mass ratio, are extracted by partial least square (PLS) method to characterize VIV of circular cylinder. The results show that the prediction results of the three algorithms are acceptable when there is no noise interference. However, when noise is taken into account, PLSQR+ELM has the most economical and efficient performance.

Keywords: vortex-induced vibration, circular cylinders, machine learning

1. INTRODUCTION

Vortex-induced vibration (VIV) of circular cylinders is of practical interest to many fields of engineering, such as civil engineering, marine engineering, and mechanical engineering. Therefore, VIV has been extensively studied by researchers since the 19th century from theoretical, experimental and numerical simulation perspectives. This is discussed in the review papers by Sarpkaya (2004), Williamson and Govardhan (2008) and Bearman (2011). Although considerable efforts have been made to study the VIV properties of cylinders, expensive and time-consuming wind tunnel experiments or computational fluid dynamics are essential to determine the VIV phenomena in circular cylinders in specific flow fields.

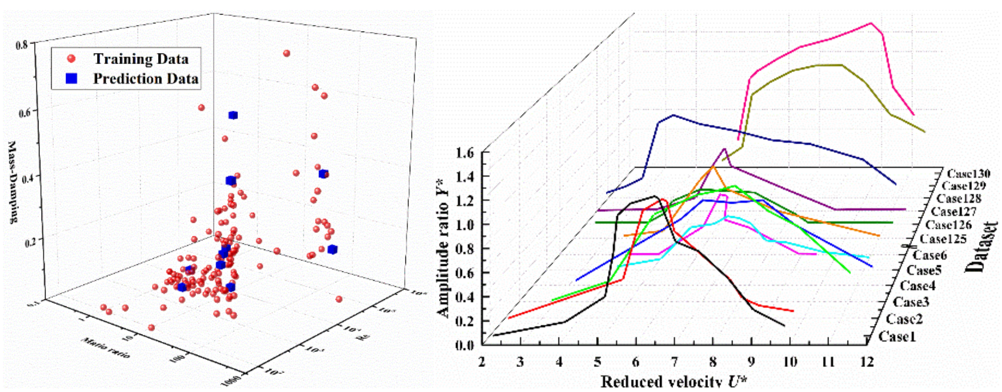
Fortunately, an unprecedented amount of data on VIV of cylinders has been accumulated in past studies, which provides the basis for model building using machine learning (ML) to predict VIV performance. Currently, ML is being explored in various fields of wind engineering (Wu, et al. 2022). Jin et al. (2021) conducted an initial investigation using a physically informed neural network (PINN) to encode the Navier-Stokes control equations directly into ML for their solution by automatic differentiation. Hu et al. (2020a, b) adopted ML algorithm and generative adversarial neural network to predict the mean and pulsating wind pressures for circular cylinders and high-rise building surfaces, respectively.

The purpose of this study is to develop ML prediction models for maximum amplitude and amplitude response-reduced wind speed of circular cylinders based on a large amount of previous reliable data. An efficient and accurate evaluation technique is provided for the VIV study of circular cylinders.

2. DATA COLLECTION AND DATABASE ESTABLISHMENT

The data from the published high-quality literature are summarized for predicting maximum amplitude and amplitude response-reduced wind speed curves. In this paper, 152 sets of data are used to predict the maximum amplitude Y^* and 132 data are available for predicting the amplitude curve.

In this study, the Partial Least Square (PLS) method is employed to decouple the input features and outputs, and the importance of each parameter on the VIV performance is datamined. The PLS method is adopted to extract the mass-damping ratio $m^*\zeta$, Reynolds number Re and mass ratio m^* as the main factors affecting the maximum amplitude, and the contributions are 46.01%, 40.31% and 12.71%, respectively. The data set collected in this study has a wide distribution, as shown in Fig. 1.



(a) (b)

Figure 1. Data set: (a) maximum amplitude Y^*; (b) amplitude response-reduced wind speed curves

3. PLSQR+ELM ALGORITHM

The extreme learning machine (ELM) is generalized single-layer feed-forward network (SLFN) whose hidden layer does not require tuning and only needs to find the appropriate hidden nodes to guarantee accuracy. To improve the robustness of ELM, a preprocessed least squares QR decomposition (PLSQR) regularization algorithm is introduced to optimize the ELM and the following equation is obtained:

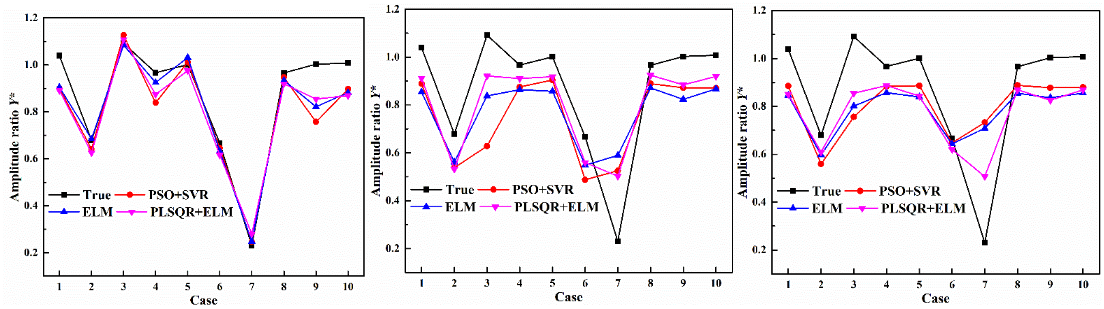
$$\boldsymbol{\beta}_k = \sum_{i=0}^{k-1} \zeta_i \left(\mathbf{L}_{\mathbf{H}}^{+}(\mathbf{L}_{\mathbf{H}}^{+})^T \mathbf{H}^{\mathrm{T}}\mathbf{H}\right)^i \mathbf{L}_{\mathbf{H}}^{+}(\mathbf{L}_{\mathbf{H}}^{+})^T \mathbf{H}^{\mathrm{T}}\mathbf{Y} + \boldsymbol{\beta}_{\mathbf{0}} \quad (1)$$

where k is the kth iteration, ζ_i is a constant, and $\mathbf{L}_{\mathbf{H}}^{+}$ is the regularization matrix. $\boldsymbol{\beta}_{\mathbf{0}}$ is the truncated singular value matrix. $\mathbf{Y}$ is the output target.

4. RESULTS AND DISCUSSIONS

4.1. Maximum amplitude Y^* prediction

In this sub-section, three machine learning algorithms, PSO+SVR, ELM and PLSQR+ELM, are employed to predict the amplitude Y^* of the VIV of the circular cylinder. The prediction results are shown in Fig. 2(a). The errors of case 1, 9 and 10 are slightly larger, however, PLSQR+ELM performs relatively better. The prediction results for the rest of the cases are in complete agreement with the experimental data, and the ELM algorithm has the smallest error in each case. Further, PLSQR+ELM has the highest R^2=0.942, indicating the best model training performance.



(a) (b) (c)

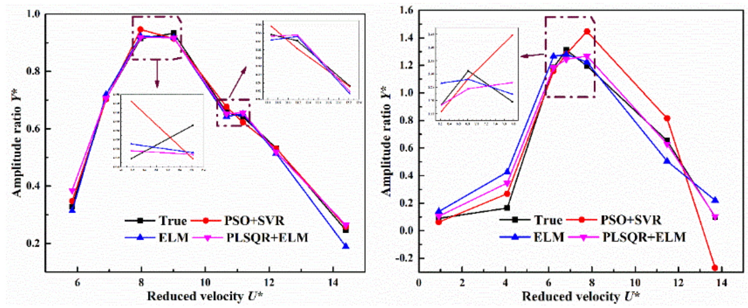
Figure 2. Maximum amplitude prediction: (a) Noiseless; (b) SNR=25dB; (c) SNR=20dB.

4.2. Generalization capability

To verify the generalization ability of the three models, two types of Gaussian white noise with signal-to-noise ratios (SNR) of 25dB and 20dB are introduced in the training set. Fig. 2(b) presents the results for SNR=25dB. Compared with the noiseless case, the accuracy of the three models has decreased. However, the accuracy of PLSQR+SVR is still the highest among the three. The Fig. 2(c) demonstrates the prediction results for SNR=20dB. The errors of the first two algorithms are further increased, whereas, PLSQR+ELM has the best performance. As the noise increases, the PSO+SVR algorithm is the most sensitive and has the weakest generalization ability. ELM is the next most robust. PLSQR+ELM has the most superior robustness.

4.3. Amplitude response-reduced wind speed curves prediction

For further validation, the three algorithms are developed as ML models for amplitude response-reduced wind speed curve prediction. The patterns of the predicted curves are generally consistent with the actual curves as shown in Fig. 3. However, the predicted values of PSO+SVR show negative values, which is contrary to the physical information, as shown in Fig. 3(b). The error at the peak of PSO+SVR is the largest among the three algorithms as seen from the local magnification, which is unacceptable. Therefore, the two cases together indicate that the PSO+SVR performance is unstable. The error of ELM is similar to PLSQR+ELM, but it is slightly better in terms of peak and overall trend. In addition, the efficiency of the ELM-type algorithm is much higher than that of PSO+SVR. The computation time of ELM is basically around 1s, while PSO+SVR is basically between 100-150s.



(a) (b)

Figure 3. Amplitude response-reduced wind speed curve prediction: (a) case 1; (b) case 2

5. CONCLUSIONS

In this study, three machine learning algorithms are employed to predict the maximum amplitude and amplitude response-reduced wind speed curves for VIV of a circular cylinder. The specific conclusions are as follows:

(1) Three parameters, mass-to-damping ratio, Reynolds number and mass ratio, are extracted by the PLS method as the most important indicators affecting the VIV of a circular cylinder.

(2) The accuracy of all three algorithms is acceptable in the maximum amplitude Y^* prediction case. However, when there is noise added to the training set, the prediction performance of the more constrained PSO+SVR drops sharply. In contrast, the robustness of PLSQR+ELM is better. In the amplitude response-reduced wind speed curve case, ELM has the best results and PSO+SVR performance is unstable. In addition, the prediction efficiency of PSO+SVR is much lower than that of ELM type due to the more hyperparameters of SVR.

ACKNOWLEDGEMENTS

Authors would like to express their gratitude to the financial support from the Hainan Provincial Natural Science Foundation of China (Grant Number 520CXTD433); They are also indebted to the National Natural Science Foundation of China (Grant Number 51938012 and 52268073).

REFERENCES

Bearman, P., W., 2011. Circular cylinder wakes and vortex-induced vibrations. Journal of Fluids and Structures 27, 648-658.

Hu, G., Kwok, K., 2020a. Predicting wind pressures around circular cylinders using machine learning techniques. Journal of Wind Engineering and Industrial Aerodynamics 198, 104099.

Hu, G., Liu, L., Tao, D., Song, J., Tse, K.T., Kwok, K., C., S., 2020b. Deep learning-based investigation of wind pressures on tall building under interference effects. Journal of Wind Engineering and Industrial Aerodynamics 201, 104138.

Jin., X., W., Cai, S., Z., Li, H., Karniadakis, G., E., 2021. NSFnets (Navier-Stokes Flow nets): Physics-informed neural networks for the incompressible Navier-Stokes equations. Journal of Computational Physics.

Sarpkaya, T., 2004. A critical review of the intrinsic nature of vortex-induced vibrations. Journal of Fluids and Structures 19, 389-447.

Williamson, C., H., K., Govardhan, R., 2008. A brief review of recent results in vortex-induced vibrations. Journal of Wind Engineering and Industrial Aerodynamics 96, 713-735.

Wu, T., Snaiki, R., 2022. Applications of machine learning to wind engineering. Frontiers in Built Environment, 8, 811460.