# Research on Intelligent Identification of Vortex-Induced Vibration of Stay Cables Based on Multi-Dimensional Feature Extraction and Deep Learning

JIAN GUO and GUO-LIANG ZHANG


## ABSTRACT

The multimodal vortex-induced vibration (VIV) of stay cables in long-span cable-stayed bridges poses a severe challenge to the real-time identification capabilities of bridge health monitoring systems due to its complex dynamic characteristics and multifactor coupling effects. Existing methods mostly rely on single-dimensional features (such as time-domain or frequency-domain indices) and fail to systematically integrate environmental and structural parameters, thereby limiting identification accuracy. To address this issue, this study proposes an intelligent identification framework based on multidimensional feature extraction and deep learning to enhance the accuracy and real-time performance of VIV identification. Based on the analysis of health monitoring data from a cable-stayed bridge with a main span of 620 meters, a statistical analysis of environmental parameters sensitive to VIV was conducted to determine the wind speed and direction ranges most likely to trigger VIV. On this basis, the time-domain and frequency-domain characteristics of VIV were analyzed, and a multidimensional feature vector was constructed. Subsequently, a BiLSTM-MHA model combining bidirectional long short-term memory networks (BiLSTM) and multi-head attention (MHA) mechanisms was developed to dynamically capture the time-frequency features of vibration signals. Finally, leveraging this model, accurate identification of various stages of VIV was successfully achieved, significantly enhancing the intelligence level of bridge health monitoring and providing an effective technical approach for real-time detection and control of VIV.


## INTRODUCTION

Long-span cable-stayed bridges are widely used in modern transportation networks due to their excellent mechanical performance, but the slender and flexible nature of stay cables makes them highly susceptible to VIV, posing significant threats to structural safety and service life. Long-term VIV not only accelerates fatigue damage and material degradation of stay cables but can also trigger cascading failures such as

---

Jian Guo[1,2], Guo-liang Zhang[1,2], [1]State Key Laboratory of Bridge Intelligent and Green Construction, Chengdu 610031, Sichuan, China; [2]School of Civil Engineering, Southwest Jiaotong University, Chengdu 610031, Sichuan, China
*Corresponding author e-mail: liang_zgl@my.swjtu.edu.cn (Guo-liang Zhang)

damper malfunctions [1–2]. Therefore, accurate identification and control of VIV are crucial in bridge structural health monitoring.

Although scholars have revealed the vibration mechanisms of VIV through wind tunnel experiments and numerical simulations, such as the axial flow–Kármán vortex street coupling effect proposed by Matsumoto et al. [3], and have developed various aerodynamic and mechanical vibration control measures. Chen et al. [4] further demonstrated that stay cables exhibit different VIV behaviors under varying wind speed conditions. However, current health monitoring systems still face two major bottlenecks: first, the VIV identification relies on single features (such as power spectral density or vibration amplitude), making it difficult to accommodate the complexities of multimodal vibrations and nonstationary wind fields; second, the traditional models are sensitive to data labeling quality and bridge-specific variations, resulting in insufficient generalization capabilities.

In recent years, deep learning-based intelligent identification technologies have offered new solutions to these problems. For example, He et al. [5] extracted feature indices from the frequency and complex domains to achieve automatic identification of single-mode VIV in stay cables, but their method is not applicable to multimodal vibrations. Guo et al. [6] employed convolutional neural networks for VIV classification, but their feature extraction was limited to time-domain root mean square (RMS) values. Su et al. [7] proposed a deep learning framework based on time-history images and power spectral density (PSD) sequences, which improved the identification accuracy for suspenders in suspension bridges but did not account for environmental parameters. Moreover, existing methods generally neglect the dynamic evolution characteristics of VIV stages (e.g., development, stabilization, and decay), leading to inadequate early warning timeliness.

In response to these challenges, this study proposes an intelligent identification framework based on multidimensional feature extraction and BiLSTM-MHA. By integrating time-frequency features and environmental parameters, a multidimensional feature vector is constructed, and the model's focus on key features is optimized using an attention mechanism. Based on long-term monitoring data from a coastal long-span cable-stayed bridge, the effectiveness and engineering applicability of the proposed method are systematically validated.

## OVERVIEW OF THE STUDIED BRIDGE AND STRUCTURAL HEALTH MONITORING SYSTEM

This study focuses on a cable-stayed bridge with a main span of 620 m, where the main girder adopts a steel box girder structure and is located in the eastern coastal region of China, experiencing significant wind environmental effects. A total of 168 stay cables are symmetrically arranged on two inclined planes on both sides of the main girder. To enhance the structural safety and operational performance of the bridge during its service life, a comprehensive structural health monitoring (SHM) system has been deployed since its opening to traffic in 2009. A schematic diagram of the sensor spatial layout is shown in Figure 1, and the detailed technical parameters are listed in TABLE I.

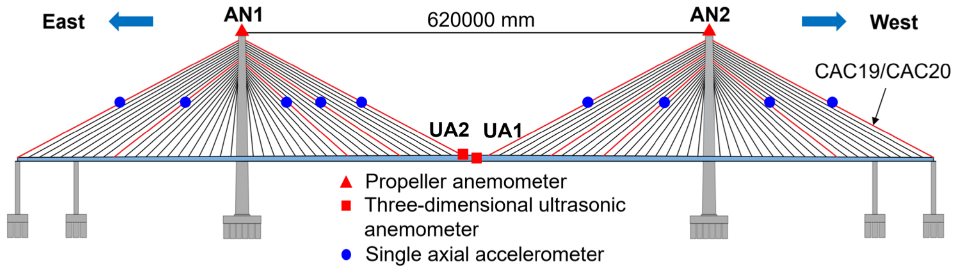


Figure 1. Cable-stayed bridge and sensor layout

TABLE I. SENSOR PARAMETER

| Three-dimensional ultrasonic anemometer | | Propeller anemometer | Single axial accelerometer | |
|---|---|---|---|---|
| Wind speed range | 0.1-60 m/s | 0-80 m/s | Measurement range | ±5 g |
| Resolution | 0.01 m/s | 0.3 m/s | Sensitivity | 1000 mV/g |
| Wind direction range | 0-360° | 0-360° | High accuracy | 1% |
| Resolution | 0.1° | 0.1° | Frequency range | 0-400 Hz |
| Sampling frequency | 32 Hz | 1 Hz | Sampling frequency | 100 Hz |

## MULTIDIMENSIONAL FEATURE EXTRACTION AND ANALYSIS OF VIV

### Influence of Incoming Wind Parameters on Vibration Response

Based on the structural health monitoring system, this study collected three months of continuous wind environmental data and stay cable vibration response data at the bridge site, providing fundamental data support for the investigation of VIVs in stay cables. Wind field data from November 20, 2018, was selected for analysis, as shown in Figure 2. The wind speeds were mainly distributed between 3–8 m/s, with a predominant wind direction of 135° (southeast wind). To more clearly illustrate the distribution characteristics of the wind environment, a wind rose diagram was plotted, as shown in Figure 3.

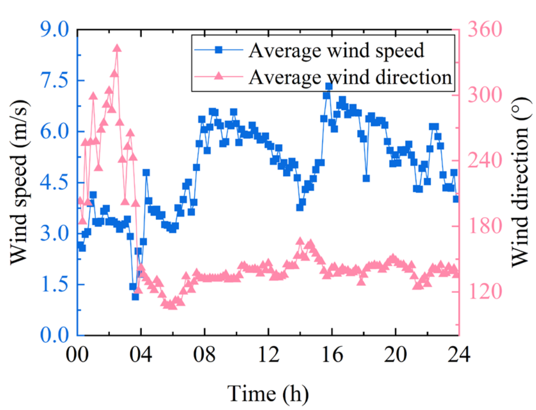


Figure 2. Incoming wind speed and direction

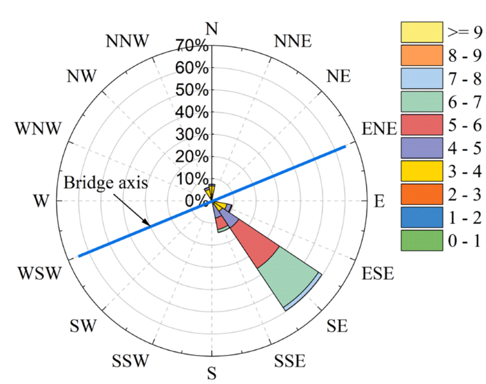


Figure 3. Wind rose diagram

Although wind speed data corresponding to the accelerometer installation height was obtained, the incoming wind is typically not orthogonal to the cable plane, but rather intersects the bridge axis at a certain skew angle, thereby generating excitation, as illustrated in Figure 4. Specifically, the incoming wind can be decomposed into two components, $U(z)\cos\beta$ and $U(z)\sin\beta\sin\theta$, both of which are perpendicular to the cable plane. Here, $\beta$ represents the skew angle of the wind, and $\theta$ denotes the inclination angle. The longest stay cable of the bridge (labeled CAC20) was selected as the representative object, and based on its geometric and dynamic characteristics (listed in TABLE II), a systematic analysis was conducted on the relationship between its vibration characteristics and wind parameters, further extracting wind feature indices that influence VIV.

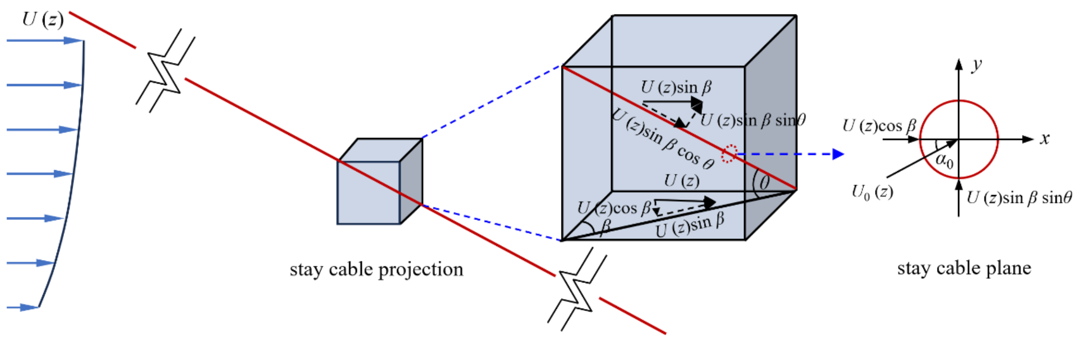



Figure 4. Schematic diagram of incoming air acting on the No. CAC20 cable

TABLE II. CAC20 STAY CABLE PARAMETERS

| Specifications | Length | Diameter | Tension | Inclination angle | Fundamental frequency |
|---|---|---|---|---|---|
| Parameters | 323.5 m | 120 mm | 3329 kN | 26.3° | 0.3711 Hz |

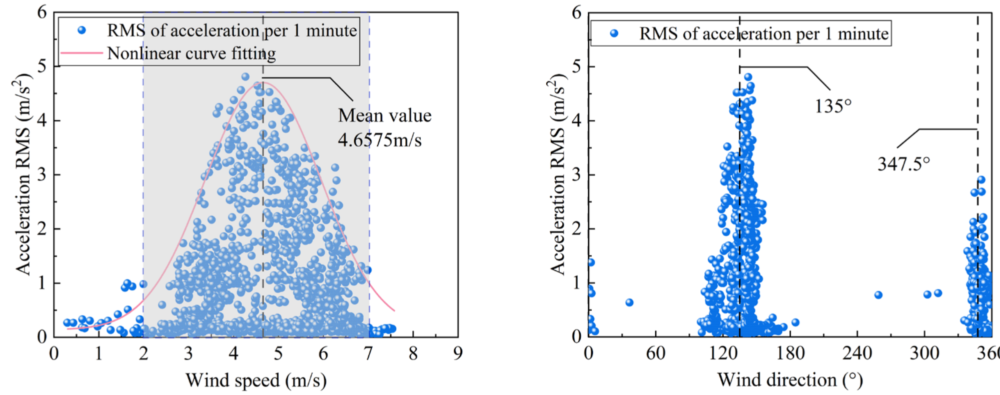
The relationship between the RMS of stay cable vibration acceleration and wind speed, wind direction was analyzed. Figure 5 (a) shows that the RMS value increases with wind speed, peaks around wind speeds of 4–6 m/s, and then rapidly decreases, with vibrations primarily concentrated in the wind speed range of 2–7 m/s. A nonlinear function was used to fit the relationship between the maximum vibration amplitude and wind speed, resulting in the following expression:

$$f(U) = f_0(U) + \frac{A}{\sigma\sqrt{\pi/2}}\exp\left(-2\frac{(U-\mu)^2}{\sigma^2}\right) \tag{1}$$

This expression is in the form of a Gaussian distribution correction function, where $f(U)$ represents the response at the mean wind speed $U$; $f_0(U) = 0.14$ is the baseline response when no VIV occurs; $A = 14.79$ is the additional response peak caused by VIV; $\mu$ and $\sigma$ are the mean and standard deviation of the mean wind speed, respectively.

Figure 5 (b) further demonstrates the relationship between RMS response and wind direction, with the results showing that the vibration amplitude is mainly concentrated in two directions: 135° and 347.5°.

Based on the above analysis, the key wind parameter ranges corresponding to significant vibration in stay cable CAC20 are preliminarily identified: the wind speed range is 2–8 m/s, and the wind direction range is primarily concentrated within two directional bands, i.e., (105°–165°) and (337.5°–357.5°).




(a) (b)

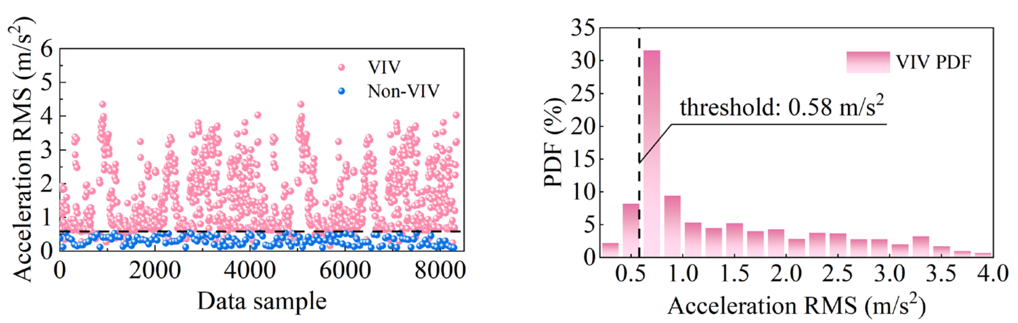
Figure 5. The RMS of acceleration varies with wind speed and direction

## Time-Frequency Domain Feature Index Analysis

However, to achieve accurate identification of VIV events, it is necessary to further analyze the vibration response characteristics of the stay cables. Based on statistical distribution patterns, the mean and standard deviation of RMS values for non-VIV and VIV samples were calculated separately, and the minimum crossing point in the overlapping region of their probability distributions was selected as the identification threshold. The RMS identification threshold was ultimately determined to be 0.58 m/s² using Equation (2).

$$\text{Threshold} = \text{mean}(\text{RMS}_{\text{non-VIV}}) + 2 \times \text{std} \tag{2}$$

As shown in Figure 6, the proportion of VIV samples with acceleration RMS within the range of 0.58–5 m/s² is as high as 89.4%, indicating that this threshold has good identification accuracy. When RMS continuously exceeds 0.58 m/s² during a certain time period, it can be preliminarily determined that a VIV event has occurred.




(a) Scatter plot of acceleration RMS (b) Acceleration RMS distribution

Figure 6. Statistical analysis of cable vibration acceleration RMS

In addition to time-domain indices, frequency-domain features can also provide important evidence for VIV identification. This study uses the Wavelet Packet Transform (WPT) method for multi-scale analysis of acceleration signals and calculates their frequency band energy distribution. Figure 7 shows single-mode VIV, where the dominant frequency is below 5 Hz, and the energy in the dominant frequency band accounts for more than 80%. Figure 8 shows multimodal VIV, where the dominant frequency is greater than 6 Hz, and the energy distribution is not only concentrated in the dominant frequency band but also extends to the adjacent frequency bands, indicating a complex multimodal participation process.

Based on this, this study proposes "energy ratio" as a frequency-domain identification index, defined as follows:

$$\mathrm{ER} = \frac{E_{M-1} + E_M + E_{M+1}}{E_T} \tag{3}$$

where ER is the energy ratio; $E_M$ is the maximum frequency band energy ratio; $E_{M\text{-}1}$ and $E_{M+1}$ are the energies of the previous and next frequency bands of the maximum frequency band, respectively; $E_T$ is the total energy. When ER $\geqslant$ 0.8, it is determined that VIV behavior exists in that segment of the signal.

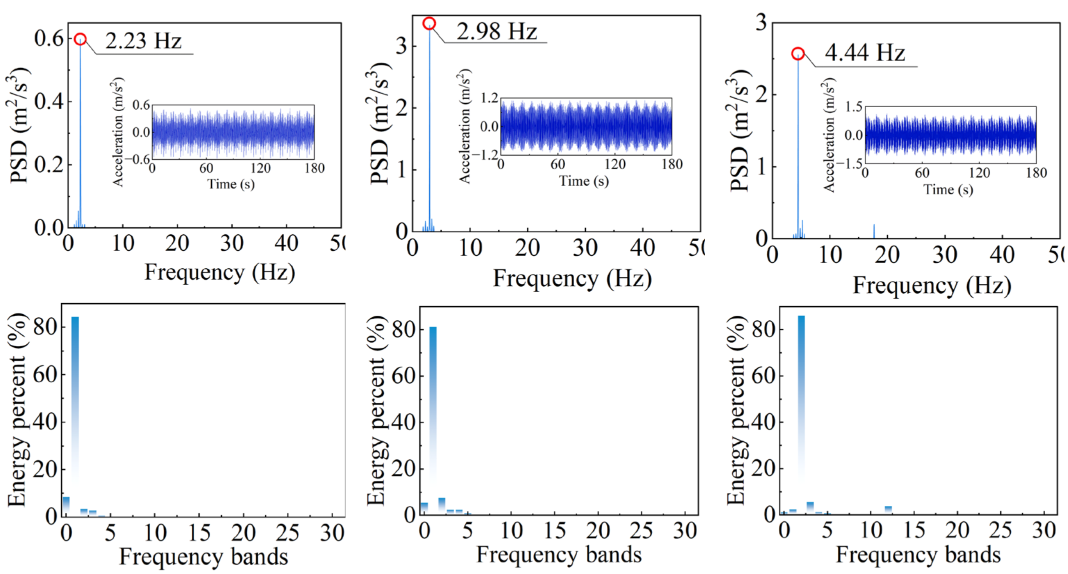



Figure 7. The PSD and frequency band distribution (FBD) of single-mode VIV samples

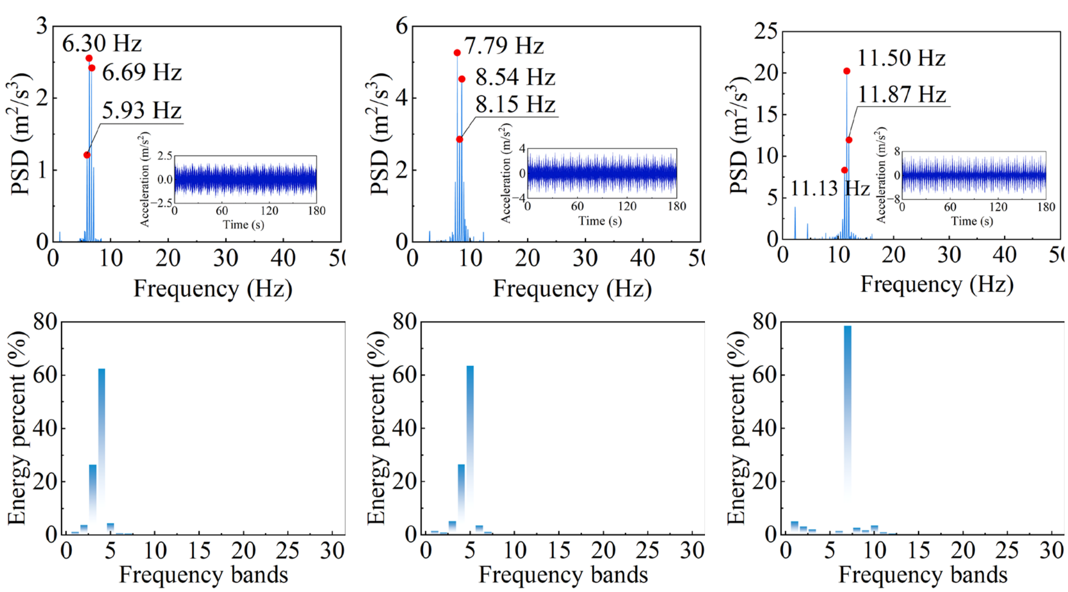



Figure 8. The PSD and frequency band distribution (FBD) of multi-mode VIV samples

## INTELLIGENT IDENTIFICATION OF VIV BASED ON BiLSTM-MHA MODEL

This study integrates the output information of MHA and BiLSTM to efficiently capture the contributions of the RMS of acceleration and frequency band energy ratio. These features extracted from the time domain and frequency domain can be emphasized and enhanced to improve the accuracy of stay cable VIV identification. The overall BiLSTM-MHA model is shown in Figure 9.

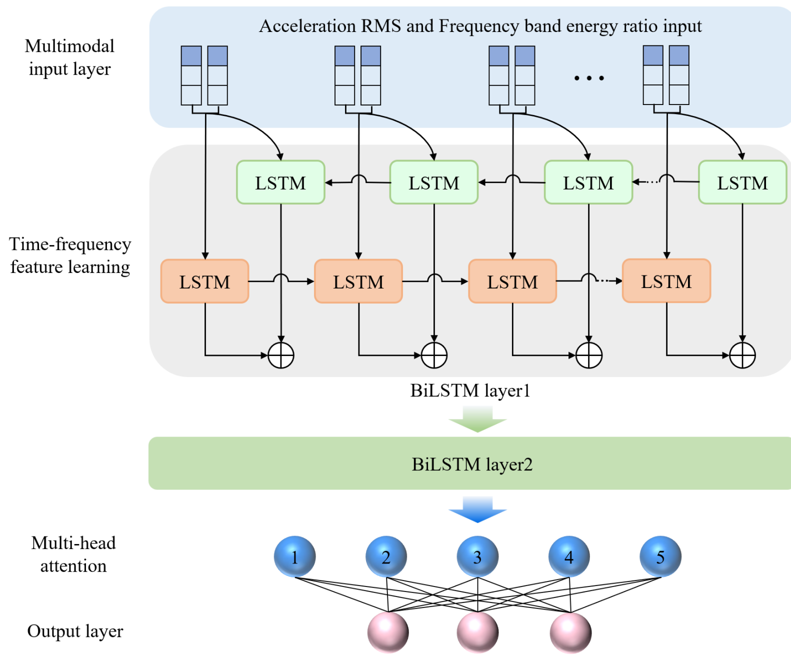



Figure 9. VIV identification framework based on BiLSTM-MHA

Based on the BiLSTM-MHA model, 21,060 samples are input for training, with a time step of 10, corresponding to 30 minutes, and 2 features. A weighted cross-entropy loss function is used to address the sparsity of VIV samples. The Adam optimizer dynamically adjusts the learning rate, and gradient clipping is limited to [-1, 1] to prevent gradient explosion.

Through the above process, the confusion matrix obtained from the test data is shown in Figure 10. The complete cycle of VIV is divided into: development stage (DV), stabilization stage (SV), and recessionary stage (RV), with NV representing non-VIV. Overall, the model demonstrates satisfactory results in identifying stay cable VIVs, with recognition accuracy for each stage exceeding 93%. Additionally, based on the identification results, the relationship between the RMS of acceleration and frequency band energy ratio is plotted, as shown in Figure 11. The amplitude of non-VIV is generally less than 0.58 m/s², while the amplitude of VIV is greater than 0.58 m/s², and the frequency band energy ratio is concentrated around 0.8.

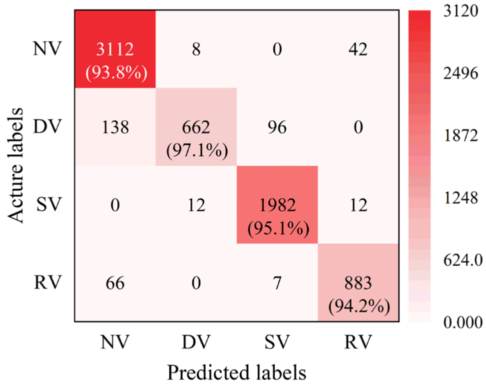


Figure 10. The confusion matrix obtained from the test data

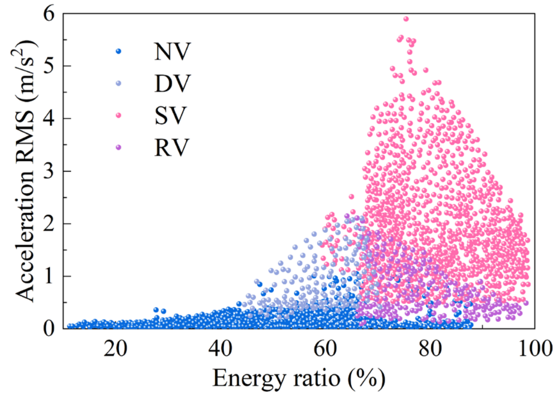


Figure 11. Recognition result classification

## CONCLUSION

This study proposes an intelligent identification framework combining multidimensional feature extraction and the BiLSTM-MHA deep learning model, addressing reliance on single features in traditional methods. By analyzing wind speed, wind direction, and vibration features, key environmental factors for VIV are identified, and effective thresholds are established. The BiLSTM-MHA model improves dynamic adaptability in VIV identification, achieving over 93% recognition accuracy, demonstrating strong practical application potential.


## ACKNOWLEDGEMENTS

The authors would like to acknowledge a grant from the National Natural Science Foundation of China (Grant No. U22A20231).


## REFERENCES


1. Berthellemy, J., Siegert, D., Berton, É., and Quentin, P. 2022. "Stockbridge Dampers for Extending the Fatigue Life of a Cable at St Nazaire Cable Stayed Bridge," *Eng Fail Anal*, 141: 106581.
2. Wang, Y. F., Chen, Z. Q., Yang, C., Liu, Z. W., He, J., and Feng, Z. Q. 2022. "A novel eddy current damper system for multi-mode high-order vibration control of ultra-long stay cables," *Eng Struct*, 262: 114319.
3. Matsumoto, M., Shirato, H., Yagi, T., Goto, M., Sakai, S., and Ohya, J. 2003. "Field observation of the full-scale wind-induced cable vibration," *J Wind Eng Ind Aerod*, 91(1-2): 13-26.
4. Chen, W. L., Li, H., Ou, J. P., and Li, F. C. 2013. "Numerical simulation of vortex-induced vibrations of inclined cables under different wind profiles," *J Bridge Eng*, 18(1): 42-53.
5. He, M., Liang, P., Wang, Y., Xia, Z. L., and Wu, X. Y. 2022. "Online automatic monitoring of abnormal vibration of stay cables based on acceleration data from structural health monitoring," *Measurement*, 195: 111102.
6. Guo, J., Mao, R. J., Ma, K. J., and Chen, D. J. 2024. "Deep learning-based approach for identifying vortex-induced vibrations in stay cables," *Adv Struct Eng*, 28(4): 690-715.
7. Su, X., Mao, J. X., Wang, H., Gao, H., and Li, D. 2025. "Deep learning-based automated identification on vortex-induced vibration of long suspenders for the suspension bridge," *Mech Syst Signal Pr*, 224: 112070.