**A Novel Data-Augmented Deep Learning Framework for Predicting Wind-Induced Vibrations in Long-Span Bridges under Small Sample Conditions**

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**Abstract.** Wind-induced vibrations pose significant risks to the safety and serviceability of long-span bridges. However, the rarity of extreme wind events and sensor failures during such events often result in sparse monitoring datasets, impeding the reliability of predictive models. This study introduces SMOGN-GRU, a novel predictive framework that integrates statistical data augmentation and deep regression learning to address small-sample challenges in structural health monitoring (SHM) of bridges. The framework combines the Synthetic Minority Over-sampling technique with Gaussian Noise (SMOGN) to augment sparse wind and vibration datasets, and a Gated Recurrent Unit (GRU) network to learn complex nonlinear relationships and forecast bridge responses. Applied to the Hardanger Bridge in Norway, the framework demonstrates strong performance in predicting both vertical and torsional accelerations under critical windstorms. Comparative ablation studies against alternative data augmentation and regression methods confirm the superiority of the proposed framework in enhancing prediction accuracy and data sparsity mitigation. The results underscore the framework’s potential to improve safety assessments and operational decisions in SHM, particularly for scenarios where real-time data is limited or incomplete. SMOGN-GRU thus offers a robust and practical tool for advancing predictive analytics in bridge structures under challenging data conditions.

**Keywords:** Structural Health Monitoring, Windstorm Prediction, Data Augmentation, SMOGN, GRU, Deep Regression, Long-Span Bridges, Small Sample Learning

1. Introduction

Long-span bridges are essential for spanning rivers, canyons, and enabling large-scale transportation infrastructure [1, 2]. Common forms such as suspension and cable-stayed bridges involve complex design and construction, and require rigorous maintenance and monitoring due to various safety risks. Non-natural threats include fatigue from vehicle loads, material degradation, and collisions, while natural factors such as temperature changes, earthquakes, and especially strong winds and wind-induced vibrations pose serious challenges. Among these, wind-induced vertical and torsional responses can cause significant structural stress, underscoring the importance of structural health monitoring (SHM) [3, 4].

SHM systems, particularly in-situ monitoring using sensors, are widely used to track real-time structural behavior [5, 6]. Despite their benefits, they face issues such as high cost, complex installation, and susceptibility to environmental interference [7-9]. These limitations have led to growing interest in data-driven approaches [10, 11]. With advances in artificial intelligence (AI), machine learning (ML) has emerged as an effective alternative for predicting structural response [12]. Supervised regression models, using environmental and operational inputs to predict bridge responses, fall into two main categories: statistical and artificial neural network (ANN) methods [13]. ANN-based models, including feed-forward networks, RNNs, LSTMs, and GRUs, offer both shallow and deep learning configurations for accurate prediction [14].

Despite advancements in supervised regression methods using statistical or ANN-based models, significant challenges remain when predicting structural responses with limited data [15]. Machine learning models, particularly regressors, often struggle with small datasets. Insufficient data can undermine parameter significance and hinder model convergence, leading to unstable or biased predictions—posing serious issues for SHM of large-scale structures.

To overcome these limitations, data augmentation has emerged as a practical approach for enriching training data without collecting new samples. By introducing controlled randomness or transformations, statistical augmentation techniques generate synthetic data consistent with the original distribution. Common methods include polynomial feature expansion, noise injection, Synthetic Minority Oversampling Technique (SMOTE), borderline-SMOTE and adaptive synthetic sampling, all of which enhance model robustness and performance across various tasks [16, 17].

In SHM, combining data augmentation with deep regression offers an effective solution for small-sample prediction. Deep models like GRU outperform traditional regressors by capturing nonlinear patterns and latent dependencies through their memory cells. Although wind-induced vibration prediction isn’t explicitly time-dependent, GRU can still uncover hidden temporal features within predictors, which is essential given the complex nature of wind-related variables.

This study proposes a novel framework integrating SMOGN-based data augmentation with a deep GRU regression model for predicting wind-induced responses in long-span bridges under limited data. Synthetic Minority Over-sampling Technique for Regression with Gaussian Noise (SMOGN) generates synthetic samples by distinguishing between rare and regular cases, enriching the input with realistic wind characteristics and vibration responses. The main contributions are: (1) Development of a hybrid regression approach combining statistical augmentation and deep learning for rare wind event prediction; (2) Application of SMOGN to expand training data for improved representation of strong wind scenarios; (3) Deployment of a deep GRU model to improve predictive performance; (4) Validation on real-world monitoring data from the Hardanger Bridge, demonstrating strong results in predicting vertical and torsional vibrations, supported by ablation studies.

1. Proposed Framework

Input features of the framework include wind characteristics such as mean speed, direction, angle of attack, and turbulence intensity, while the output targets are the root-mean-square (RMS) values of vertical and torsional bridge vibrations. To reduce time-series effects, RMS acceleration is used as the main response indicator. The dataset is split into training and testing subsets, with the training data enhanced using the SMOGN technique to improve sample diversity. A GRU model is then trained on the combined original and augmented data to predict bridge vibration responses under upcoming strong wind conditions.

2.1 SMOGN technique

To address the limited sample size caused by infrequent strong wind events, statistical data augmentation methods prove particularly effective for dataset expansion. This approach concurrently generates both predictor characteristics (strong wind features) and target variables (vibration response RMS values), forming completed new data samples. Following standard practice, augmentation is exclusively applied to training data while maintaining the original test set configuration due to their distinct functional roles in model development.

SMOGN represents a specialized regression-focused augmentation technique designed for small-sample scenarios, integrating Gaussian noise injection with modified Smote-R methodology [18, 19]. The algorithm implements a dual strategy: random under-sampling for majority class reduction combined with synthetic sample generation for minority class enhancement. The synthesis process involves two-phase interpolation between carefully selected minority instances - a base sample and its randomly chosen k-nearest neighbor. Attribute values for new samples derive from linear interpolation between these pairs, with corresponding target values calculated as distance-weighted averages of the original targets. To optimize sample quality and diversity, SMOGN employs a conditional noise introduction mechanism. The technique prioritizes Smote-R-based interpolation when the seed instance and its neighbor exhibit sufficient feature-space proximity [20]. For distantly separated pairs where interpolation might produce less reliable samples, the method strategically substitutes Gaussian noise addition, thereby maintaining data integrity while enhancing variation. This adaptive approach ensures synthetic samples preserve original data distributions while effectively expanding the training dataset.

The core idea of SMOGN technology is as follows:

1. The methodology begins by constructing two sequential data partitions: containing rare/critical samples and comprising standard samples. This categorization leverages inter-sample correlation analysis, where instances exhibiting significant feature interdependencies are systematically grouped into the subset.
2. The second phase implements differentiated sampling strategies: partitions undergo synthetic over-sampling where multiple artificial instances are created per seed sample, while subsets are subjected to data reduction through under-sampling techniques.
3. The over-sampling process dynamically determines the generation strategy by analyzing each seed sample and its selected k-nearest neighbors. A critical safety criterion is established as 50% of the median pairwise distance between and other samples within . When this threshold is satisfied, synthetic samples are created through proximity-based interpolation with a randomly chosen k-nearest neighbor, mathematically formalized in Eq. (1):

(1)

where is one of the k-nearest neighbors, and acts as a stochastic parameter governing the interpolated position of synthetic instances along the vector connecting the seed sample and its k-nearest neighbor.

Conversely, failure to satisfy the safety threshold signifies excessive distance between the seed sample and its k-nearest neighbor, rendering direct interpolation unsuitable. In such scenarios, synthetic samples are instead produced through Gaussian noise injection, mathematically formulated in Eq. (2):

(2)

where denotes a multivariate Gaussian distribution characterized by a zero mean vector and covariance matrix , with representing the identity matrix in multidimensional space.

2.2 GRU model

For predicting wind-induced bridge vibration responses using wind characteristic data, Gated Recurrent Unit (GRU) networks represent an optimal deep learning framework. The Gated Recurrent Unit (GRU) is a variant of the Recurrent Neural Network (RNN) designed to address the vanishing gradient problem and improve learning of long-term dependencies. It introduces gating mechanisms to control the flow of information, enabling more effective sequence modeling with fewer parameters compared to Long Short-Term Memory (LSTM).

A GRU cell is defined by the following operations:

1. Update gate.

(3)

This gate determines how much of the previous hidden state should be retained.

1. Reset gate.

(4)

The reset gate controls how much of the past information to forget.

1. Candidate hidden state.

(5)

This represents the new memory content based on the current input and reset-modified previous state.

1. Final hidden state.

(6)

The hidden state is a linear interpolation between the previous hidden state and the candidate hidden state.

where is the sigmoid function, represents element-wise multiplication, and are weights and biases.

1. Application: Hardanger Bridge
   1. Overview of Hardanger Bridge

As a 1,380-meter suspension bridge spanning Norway’s Hardanger fjord, the Hardanger Bridge (**Fig. 1**) pioneered as the world’s longest narrow-span suspension structure upon completion. Its slender design renders it wind-vibration sensitive, necessitating an advanced SHM system.



**Fig. 1.** Hardanger Bridge in Norway

The SHM integrates triaxial accelerometers, ultrasonic anemometers, and GPS sensors. Sixteen accelerometers along the main girder track torsional vibrations. Post-construction, the system recorded multiple extreme wind events, capturing synchronized wind parameters and structural responses. The wind characteristics and bridge responses of four typical storms Ole, Urd, Tor, and Nina from February 2015 to December 2016 are used as the dataset for this paper [21].

* 1. Predictors

Effective prediction of wind-induced vibrations in long-span bridges requires identifying critical influencing parameters. The mean wind speed and direction, angle of attack, turbulence intensities, standard deviations, length scales of the along-wind, cross-wind, vertical turbulence components and wind gust factor are considered as key predictors [22]. These predictors are represented by the RMS value over a certain time interval which is defined as 10 minutes.

Bridge structures under strong wind loads are predominantly influenced by two critical parameters: the time-averaged wind velocity and the directional angle . The measurement results of these two key parameters are shown in **Fig. 2**.



**Fig. 2.** Mean wind speed and mean wind direction of the storms acting on Hardanger Bridge

Moreover, some important factors are defined according to the following formula:

1. The wind speed in the horizontal direction , the vertical direction are measured by anemometers. Hence, the along-wind turbulence components , cross-wind turbulence components , and vertical turbulence components are calculated as

(8)

1. The angle of attack is defined as:

(9)

1. The turbulence intensities in the three directions , , and are defined as:

(10)

where , and are the standard deviations of the turbulence components.

1. The length scales in the three directions are the factors describe the turbulent structure in a wind field, and they are defined as:

(10)

where is the cross-correlation function of the turbulence component and is the time lag.

1. The gust factor is describes the relationship between instantaneous fluctuations in wind speed and average wind speed, and it is defined as:

(11)

where is the gust wind speed averaged over the gust interval.

* 1. Targets

Acceleration serves as a primary metric for quantifying vibration responses in long-span bridges, with RMS values of time-series data adopted in this study as the evaluation criterion. To capture torsional vibrations, paired accelerometers are strategically distributed across both sides of the bridge girders. Vertical vibration acceleration and torsional vibration acceleration are defined as follows:

(11)

(11)

where and are the bilateral acceleration from symmetrically deployed sensors on opposite girder surfaces, and is the width of the girder.

1. Prediction of Vertical Vibration Responses
   1. Prediction Results

The predictors employed in this study are defined in Sections 3.2, with response targets specified in Section 3.3. Sensor-acquired data from the Hardanger Bridge during four strong wind events (Ole, Urd, Tor, Nina) form the original dataset. Initial data partitioning allocates 126 samples from Ole, Nina, and Tor to the training set, reserving 54 Urd-derived samples for testing. To address limited sample size, the SMOGN augmentation technique expands the training set from 126 to 239 samples. **Table 1** quantitatively compares the distributions of vertical vibration responses in original versus SMOGN-enhanced training sets.

**Table 1.** Vertical vibration responses distributions of training sets (before and after SMOGN)

|  |  |  |
| --- | --- | --- |
| Interval | Quantity (before SMOGN) | Quantity (after SMOGN) |
| (0.005, 0.01] | 11 | 29 |
| (0.01, 0.015] | 27 | 48 |
| (0.015, 0.02] | 67 | 102 |
| (0.02, 0.025] | 17 | 52 |
| (0.025, 0.03] | 4 | 8 |
| Total | 126 | 239 |

The enhanced training set is used as the input for the GRU model, and the testing set (the response of Trd wind) is used as the evaluation. **Fig. 3** shows the predicted results of vertical vibration response. In **Fig. 3(a)**, the actual values of the training set are marked with blue circles, the actual values of the testing set are marked with red circles, and the predicted values of both the training and testing sets are marked with orange stars. **Fig. 3(b)** shows the residual plot of the prediction result.





**Fig. 3.** Prediction results for vertical vibration responses using proposed framework. (a) Comparison between actual and predicted values, (b) residual plot

* 1. Comparative study

To validate the superiority of the proposed framework, four comparative prediction frameworks are implemented:

1. Baseline without data augmentation, exclusively using the GRU model for prediction;
2. Data augmentation technique with noise injection, where the enhanced dataset is processed by the GRU model;
3. SMOGN-augmented training set combined with a comparative prediction model (Support Vector Machine, SVM);
4. SMOGN-augmented training set combined with a comparative prediction model (Multilayer Perceptron, MLP).

The prediction results of these four comparative prediction frameworks are shown in **Table 2**.

**Table 2.** value of the proposed framework and four comparative frameworks (vertical)

|  |  |  |  |
| --- | --- | --- | --- |
| Framework | Training set | Testing set | Whole set |
| Proposed framework | 0.919 | 0.883 | 0.907 |
| 1. GRU | 0.783 | 0.757 | 0.777 |
| 1. noise injection+GRU | 0.817 | 0.768 | 0.805 |
| 1. SMOGN+SVM | 0.785 | 0.757 | 0.775 |
| 1. SMOGN+MLP | 0.561 | 0.526 | 0.554 |

The experimental results demonstrate the superior predictive capability of the proposed framework (SMOGN-enhanced GRU) across all evaluation metrics. As shown in the table, the proposed method achieves the highest scores in training set (0.919), testing set (0.883), and overall performance (0.907), indicating robust generalization capability with minimal overfitting.

1. The standalone GRU framework (a) exhibits significantly lower testing accuracy (0.757 vs. 0.883), confirming the critical role of SMOGN augmentation in enhancing model robustness.
2. The testing performance degradation (0.768) of the noise-injection (b) suggests inferior generalization compared to SMOGN.
3. The SMOGN+SVM (c) and SMOGN+MLP (d) configurations yield substantially reduced accuracy (testing scores 0.757 and 0.526, respectively), highlighting the GRU’s inherent advantage in modeling temporal dependencies within wind-vibration sequences.

These findings collectively validate the synergistic effectiveness of integrating SMOGN augmentation with GRU architecture for bridge vibration prediction tasks.

1. Prediction of Torsional Vibration Responses
   1. Prediction Results

Using the same training/testing set segmentation method and SMOGN data augmentation technique as vertical vibration, the data distribution of the enhanced training set for torsional vibration is shown in **Table 3**.

**Table 3.** Torsional vibration responses distributions of training sets (before and after SMOGN)

|  |  |  |
| --- | --- | --- |
| Interval () | Quantity (before SMOGN) | Quantity (after SMOGN) |
| (2, 6] | 44 | 36 |
| (6, 10] | 64 | 51 |
| (10, 14] | 15 | 89 |
| (14, 18] | 3 | 28 |
| Total | 126 | 239 |

According to the same method as vertical vibration, the enhanced training set is input to the GRU model, and the testing set is used as the evaluation. **Fig. 4** shows the predicted results of vertical vibration response. In **Fig. 4(a)**, the actual values of the training set are marked with blue circles, the actual values of the testing set are marked with red circles, and the predicted values of both the training and testing sets are marked with orange stars. **Fig. 4(b)** shows the residual plot of the prediction result.





**Fig. 4.** Prediction results for torsional vibration responses using proposed framework. (a) Comparison between actual and predicted values, (b) residual plot.

* 1. Comparative study

The four comparative frameworks described in Section 4.2 are also used to validate the effectiveness of the proposed framework when predicting the torsional vibration responses. The quantitative description of the prediction results of the framework proposed in this paper and four comparative frameworks is shown in **Table 4**.

**Table 4.** value of the proposed framework and four comparative frameworks (torsional)

|  |  |  |  |
| --- | --- | --- | --- |
| Framework | Training set | Testing set | Whole set |
| Proposed framework | 0.983 | 0.959 | 0.973 |
| 1. GRU | 0.964 | 0.931 | 0.955 |
| 1. noise injection+GRU | 0.911 | 0.869 | 0.893 |
| 1. SMOGN+SVM | 0.885 | 0.808 | 0.868 |
| 1. SMOGN+MLP | 0.713 | 0.657 | 0.702 |

The proposed framework achieves superior performance in torsional vibration prediction, attaining near-perfect scores across all datasets (training: 0.983, testing: 0.959, whole: 0.973). Key observations are as follows:

1. The standalone GRU ranks second but shows a notable testing set gap (0.931 vs. 0.959), confirming SMOGN’s critical enhancement effect.
2. Noise injection degrades GRU’s performance (testing : 0.869 vs. baseline 0.931), indicating improper augmentation harms temporal pattern learning.
3. Traditional models (SVM/MLP) with SMOGN yield significantly lower scores (testing: 0.808/0.657), underscoring GRUs superiority in data modeling.

This demonstrates the framework’s exceptional capability in capturing complex wind-torsion relationships while maintaining generalization robustness.

1. Conclusion

Vibrations in long-span bridges, addressing the critical challenge of limited monitoring data in SHM. By incorporating key wind parameters (mean speed/direction, turbulence characteristics, gust factors) as predictors and vibration accelerations as targets, the framework effectively resolves small-sample limitations through SMOGN-enhanced training while leveraging GRU’s modeling capabilities. Validated against 2015–2016 SHM data from Norway’s Hardanger Bridge, the method demonstrates superior accuracy in both visualization and quantitative metrics, with ablation experiments confirming the synergistic benefits of combining SMOGN and GRU. The framework establishes a robust solution for vibration prediction under data scarcity conditions, offering significant practical value for high-cost bridge monitoring systems through its generalizable architecture and enhanced performance in extreme wind scenarios.

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