Advanced Learning Techniques for Predicting Torsional Responses: Application to a Long-Span Bridge

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**Abstract.** Torsional vibration responses of cable-supported bridges subjected to strong wind loads can induce severe twisting motions that significantly compromise structural integrity, potentially leading to catastrophic failures, reduced driving comfort, and accelerated fatigue in structural components, ultimately threatening both safety and longevity of such bridges. Accordingly, understanding and predicting wind-induced torsional vibration responses of cable-supported bridges bring substantial benefits to ensuring structural safety, enhancing service life, improving driving comfort. This study proposes a machine learning-aided prediction framework based on a Bayesian Neural Network (BNN) to forecast the root-mean-square (RMS) values of torsional acceleration responses in a long-span suspension bridge. Wind data, including speed and direction, are collected from a tri-axial anemometer installed at the mid-span of the bridge deck. To address potential multicollinearity issues arising from diverse wind features, a variance inflation factor (VIF)-based feature selection and predictor normalization are applied to enhance model stability. The proposed BNN model is trained as a regressor, incorporating rigorous hyperparameter optimization and k-fold cross-validation to improve generalization while capturing both aleatoric and epistemic uncertainties effectively. Results confirm the effectiveness of the proposed method in achieving the prediction accuracy rates of 97% during the training phase and 77% during the testing phase.

**Keywords:** Bayesian Neural Network, Structural Health Monitoring, Wind-Induced Vibration, Long-Span Suspension Bridge, Uncertainty Quantification

1. Introduction

Cable-supported bridges are critical components of modern infrastructure, enabling the spanning of vast geographical features such as rivers, seas, and valleys with remarkable efficiency. Their lightweight and flexible design allows for long spans that are both economically and structurally advantageous. However, these very characteristics also render them particularly susceptible to wind-induced vibrations and dynamic loading effects. Strong winds can trigger excessive oscillations, leading to fatigue damage in critical components such as girders, cables, and towers, which compromises the structural integrity and service life of the bridge [1-3]. Uncontrolled vibrations not only disrupt the static equilibrium and functional performance of cable-supported bridges but also pose significant risks to public safety, especially during extreme weather events. Consequently, measures such as bridge closures, emergency interventions, and precautionary actions are often required to mitigate these risks and ensure the safety and reliability of the structure.

The implementation of structural health monitoring (SHM) programs through advanced sensing systems plays a crucial role in ensuring the safety, functionality, and longevity of cable-supported bridges. These monitoring technologies provide continuous, real-time assessment of structural performance, which enable early detection of anomalies and changes in bridges before any catastrophic event. In SHM programs, one attempt to capture key structural responses (e.g., acceleration, displacement, strain, etc.) and environmental/operational parameters (e.g., temperature, humidity, wind, traffic, etc.), which bring valuable insights into current conditions of the bridges and their operational modes [4]. These monitoring programs not only enhance traditional inspection strategies but also aid in optimizing bridge management by minimizing unnecessary inspections and reducing costs.

Torsional vibration responses in cable-supported bridges are critical indicators of structural stability and integrity under dynamic loading conditions [5,6]. Unlike vertical and lateral vibrations, which primarily affect the bridge deck and towers, torsional vibrations introduce complex twisting motions that can lead to severe stress concentrations and fatigue in both the main cables and supporting towers [5]. These oscillatory movements, often triggered by wind-induced aerodynamic effects such as flutter [7] and vortex shedding [8], can amplify structural displacements, disrupt load distribution, and compromise the bridge overall performance. Notably, historical events such as the collapse of the Tacoma Narrows Bridge in 1940 underscore the devastating consequences of uncontrolled torsional vibrations [9]. In modern engineering practice, understanding and controlling these responses are vital for preventing resonance conditions that can magnify vibrations exponentially.

While the installation of SHM systems in cable-supported bridges to record structural responses and environmental/operational factors is highly beneficial for understanding bridge dynamic behavior and analyzing torsional vibration responses, several limitations hinder their effectiveness in comprehensive monitoring. In this regard, the deployment of a dense network of sensors across vast bridge spans, while applicable and existing, is often cost-prohibitive and logistically challenging, particularly in hard-to-reach areas such as main cables and towers. Furthermore, the durability and maintenance of these sensors are major concerns, as exposure to extreme weather conditions and mechanical strain can lead to signal loss or sensor failure over time. Even with optimal sensor placement, SHM systems are inherently limited by spatial resolution, in which case those may provide discrete point-based measurements that may miss localized deformations or critical vibration modes. Machine learning-aided data prediction frameworks can address these limitations by leveraging historical SHM data and environmental inputs to model the dynamic responses of cable-supported bridges with high accuracy and temporal resolution. Supervised regressors make predictive models for predicting structural responses across civil structures under different scenarios or even future anticipation. Depending on the type and size of structural responses, the type and configuration of civil structures, and the type of excitation loads, various supervised regressors have been developed to predict structural responses of different civil structures. These responses included bridge deformations [10,11], building modal frequencies [12,13], dam displacements [14,15], and seismic-induced displacements [16,17].

In relation to predicting wind-induced vibration responses, various machine learning predictive methods have been developed. Entezami and Sarmadi [18] introduced an innovative machine learning-assisted predictive framework based on regularized neighborhood components analysis for wind feature selection and a regularized support vector machine for predicting vertical, lateral, and torsional vibration responses of a long-span suspension bridge. Zhang et al. [19] proposed a data-driven methodology for real-time prediction of typhoon-induced responses (TIR) in long-span bridges by leveraging quantile random forest combined with Bayesian optimization to achieve probabilistic predictions of TIR. H. Wang et al. [20] developed a probabilistic machine learning-based framework for forecasting wind gusts by using an ensemble learning model that integrated three distinct machine learning techniques; that is, random forest, long short-term memory neural network, and Gaussian process regression. Q-A Wang et al. [21] proposed an advanced modeling and forecasting framework for strain measurements in large suspension bridges during typhoon events by introducing a variational heteroscedastic Gaussian process regression. Ye et al. [22] presented a data-driven approach for predicting vibration amplitudes of girders and towers in long-span cable-stayed bridges during strong wind events, s, aiming to enhance early warning mechanisms and improve structural safety, by using random forests. Therefore, the predictive capability of machine learning-aided predictive models not only reduce dependence on dense sensor networks but also enhance real-time decision-making by forecasting critical structural states and responses.

Due to the critical importance of torsional vibration responses, this study proposes a machine learning-aided predictive method via a Bayesian neural network (BNN). The proposed method also intend to address the problem of multicollinearity in wind-induced vibration prediction [18], by a feature selection mechanism based on variance inflation factor (VIF). Moreover, the BNN model is rigorously trained through hyperparameter optimization and validated using k-fold cross-validation to achieve robust generalization and capture both aleatoric and epistemic uncertainties in the predictions. The primary contributions of this study are threefold: (1) the development of a BNN-based framework specifically tailored for predicting torsional vibration responses under varying wind conditions, addressing a significant gap in existing SHM practices for long-span suspension bridges; and (2) the implementation of VIF-based feature selection to mitigate multicollinearity, which is often overlooked in traditional wind-induced vibration modeling. Field data collected from the Hardanger Bridge in Norway, i.e., one of the longest suspension bridges in the world, are used to validate the proposed method.

1. Proposed Predictive Method

The proposed predictive method establishes an integrated two-stage framework, beginning with VIF-based predictor selection to tackle multicollinearity and continuing with the BNN for robust, nonlinear regression modeling. Fig. 1 presents the flowchart of this method, which illustrates how it begins with data preparation and feature filtering, hyperparameter tuning and BNN-aided regression modeling, and validation and result interpretation.



**Fig. 1**. The flowchart of the proposed predictive method

From Fig. 1, the first stage of the proposed method is to prepare sufficient data including wind and vibration data and preprocess them for providing the wind features (predictors) and torsional vibration response [18]. In the following, the VIF-based feature selection and normalization are employed to select the most appropriate wind features for torsional vibration prediction. For the second stage, the selected predictors (wind features after selection) and torsional response serve as the inputs. In this case, the k-fold cross-validation algorithm is used to tune the main hyperparameters of the BNN. Using the optimized hyperparameter, the BNN-oriented regressor is trained by using the training data, which include a fraction of the selected wind predictors and torsional response samples. The test data are the newly selected wind predictors that are incorporated into the trained BNN model for predicting unseen torsional vibration response samples. In the third stage, the residual analysis between the original and predicted response points is carried out to ensure the correctness of the prediction process. To further ensure the validation stage, some well-known performance evaluation metrics for the regression problem including the R-squared (R²), root-mean-squared-error (RMSE), and mean absolute error (MAE) are used to numerically assess the prediction accuracy. Finally, the results of the prediction process are presented and interpreted.

* 1. Variance Inflation Factor (VIF)

In the regression-oriented prediction problem, the multicollinearity occurs when two or more predictors in a regression model exhibit strong mutual correlation, leading to unstable coefficient estimates and reduced model interpretability [23]. VIF is a well-established metric used to detect and quantify this problem by measuring the extent to which the variance of a regression coefficient is inflated due to collinearity with other predictors [24]. For each predictor **x***i*in a set of *p* variables, where *i*=1,…,*n*, an auxiliary regression is performed, where **x***i*​ is treated as the dependent variable and all other predictors **x***j*, where **x***j*≠**x***i*, serve as independent variables. Let be the coefficient of determination (i.e., the R-squared metric) of this auxiliary regression. The VIF value of the predictor **x***i*​ is then calculated as follows:

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| --- | --- | --- |
|  |  | (1) |

Accordingly, a higher indicates that **x***i*​ is closely explained by the remaining predictors, resulting in a larger VIF and signaling strong multicollinearity. Furthermore, In the **feature selection mode**, predictors with VIF values exceeding a specific threshold (i.e., commonly set to 5 or 10) are considered highly multicollinear and are recommended for removal or further investigation [23]. This step enhances the stability of the regression modeling and reduces the sensitivity to irrelevant predictors, thereby improving the overall reliability of the regression model.

* 1. Normalization

Normalization is a crucial preprocessing step for enhancing the performance and stability of predictive models, particularly when predictors differ significantly in scale or measurement units [25]. The primary objective of normalization, specifically standardization, is to transform each predictor to have a mean of zero and a standard deviation of one. This adjustment prevents predictors with larger numerical ranges from disproportionately influencing the model. Accordingly, the standardization of each predictor is performed as follows:

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|  |  | (2) |

where *xij* represents the original value of the *j*th predictor for the *i*th observation, where *i*=1,…,*n* and *j*=1,…,*p*; *μj* the mean of the *j*th predictor, and *σj* is its standard deviation. This process ensures that each predictor is centered around zero with a unit variance, enhancing numerical stability and optimizing convergence during model training. In addition, the same normalization technique is applied to the response variables (e.g., the torsional root-mean-square (RMS) values) to maintain consistency across all input and output data processed by the predictive model.

* 1. Hyperparameter Optimization

Hyperparameter optimization is a crucial step in enhancing the predictive performance and generalizability of machine learning models. It systematically evaluates various combinations of algorithm parameters before the final model training stage, ensuring optimal configuration for robust predictions. In this study, hyperparameter optimization is conducted using a structured grid search strategy coupled with the k-fold cross-validation algorithm [26]. The main objective of hyperparameter search is to identify the best parameter combination for elements such as neural network architecture, learning rates, dropout probabilities, and regularization strengths. A systematic grid search explores different configurations within the defined hyperparameter space, assessing each combination performance using cross-validation. Specifically, various network structures, learning rates, dropout probabilities, and *L*2 regularization terms are tested iteratively.

The evaluation process employs **k-fold cross-validation**, where the training dataset (**X**,**y**) is divided into *k* subsets (folds). For each iteration, one subset serves as the validation set (,), where *r*=1,…,*k*, and the remaining *k* −1 subsets form the training set. This rotation ensures that every subset is used for validation exactly once, providing a robust estimate of model performance. The objective function for hyperparameter optimization is formulated as the maximization of the average coefficient of determination or the R-squared (R²) across all validation folds, which is expressed as follows:

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|  |  | (3) |

where *θ* represents a specific hyperparameter combination from the hyperparameter space **Θ**, and *fθ* denotes the predictive function trained using the parameters *θ* [25]. Ultimately, this rigorous hyperparameter search strategy allows the selection of optimal parameters that significantly enhance the model predictive accuracy, stability, and reliability.

* 1. Bayesian Neural Network

Long-span cable-supported bridges operate in complex and uncertain wind environments, making accurate prediction and uncertainty estimation of structural responses, such as torsional accelerations, crucial for SHM aspects. BNNs address these challenges by incorporating a probabilistic framework that inherently quantifies uncertainty while maintaining high predictive accuracy. Unlike conventional neural networks, which treat weights as fixed parameters, BNNs model the network weights **W** as random variables with assigned prior distributions [27,28]. This probabilistic treatment allows BNNs to represent both model predictions and their associated uncertainties, offering a robust mechanism for decision-making in SHM applications.

After the **VIF-based feature selection**, the refined predictor matrix is represented as ,where*n* is the number of samples and *q* denotes the number of selected predictors after multicollinearity reduction. The target variable, representing the torsional RMS response, is denoted as the vector . Accordingly, in a BNN, a prior distribution is assumed over the network weights **W**, typically modeled as a Gaussian distribution:

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|  | ) | (4) |

where **μ** is the mean vector of the prior distribution and is the variance, representing prior uncertainty. Given the refined predictor matrix and network weights **W**, the likelihood of observing the torsional response **y** is expressed as:

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|  |  | (5) |

where *f*(;**W**) represents the model predicted response for the input data , and *σ*2 denotes the noise variance, capturing **aleatoric uncertainty** arising from inherent measurement noise [29]. In the following, the posterior distribution of the weights **W**, given the data 𝒟=(,**y**) is computed via Bayes' theorem:

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|  |  | (6) |

Since the exact computation of this posterior is analytically intractable due to the high dimensionality and nonlinearity, approximation techniques such as **variational inference** or **Monte Carlo sampling** (e.g., Hamiltonian Monte Carlo, dropout-as-approximation) are employed to estimate [27,25].

To make predictions for a new input , the **predictive distribution** integrates over all possible weight configurations, weighted by their posterior probabilities:

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|  |  | (7) |

This formulation yields both the **expected prediction (mean)** and the **predictive uncertainty (variance)**, which are essential for SHM applications where risk assessment and confidence intervals are critical [28]. This is particularly valuable for long-span cable-supported bridges, where safety-critical decisions must account for prediction reliability under varying wind conditions.

BNN inherently provides a robust framework for quantifying two primary types of uncertainty: **aleatoric** and **epistemic**. Aleatoric uncertainty, represented as , accounts for inherent noise and variability in the torsional response data, capturing measurement errors and unpredictable environmental influences. This form of uncertainty is irreducible, as it is tied directly to the randomness in the observed data itself. In contrast, **epistemic uncertainty**, denoted as , reflects the model uncertainty arising from limited training data or incomplete understanding of the system underlying dynamics. This uncertainty is represented by the spread of the posterior distribution over the network weights **W** and can be reduced with additional training data or more refined model learning. The total predictive uncertainty is the sum of these two components, expressed as follows:

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|  |  | (8) |

1. Case Study

This section briefly introduces the long-span suspension bridge, which is employed to use the recorded wind and vibration data [4] for validating the proposed method. This case study refers to the Hardanger Bridge, where is located at the west coast of Norway. Fig. 2 shows real views of this bridge. The Hardanger Bridge features a large length-to-width ratio, making it slender and highly susceptible to wind-induced vibrations. To address this vulnerability, a comprehensive SHM system was deployed, consisting of twenty triaxial accelerometers, nine triaxial ultrasonic anemometers, data loggers, Wi-Fi antennas, and GPS sensors to monitor both normal and storm conditions. Fig. 3illustrates the sensor arrangement and labels.



**Fig. 2**. The long-span suspension bridge called the Hardanger Bridge located in Norway

A diagram of a diagram

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**Fig. 3**. Sensor systems and locations in the Hardanger Bridge [5]

Four accelerometers (T1W, T1E, T2W, and T2E) were installed on the bridge towers, while the remaining sixteen were positioned inside the girder to capture torsional motions, with the exception of H2W and H8E. Each accelerometer is capable of measuring up to ±4g at a 200 Hz sampling rate. Among the nine anemometers, eight were mounted along the deck at a height of 8 meters to minimize flow disturbances, while the remaining anemometer (A9) was positioned on the second tower. All anemometers are designed to measure wind speeds of up to 65 m/s at a sampling rate of 32 Hz [4]. During 2015–2016, the Hardanger Bridge experienced some strong windstorms. In this study, wind data and acceleration responses of four storms are used to validate the proposed method. The wind data are related to the anemometer A6 and the vertical acceleration responses of the accelerometers H5W and H5E are used to compute the torsional vibration response given the width bridge equal to 18.3 m.

1. Results and Discussions

The prediction of torsional dynamic responses under wind-induced loads is performed using a supervised regression approach through the BNN-aided predictive model. The first step involves defining the training and testing datasets. In this study, each dataset consists of wind-related predictors, including mean wind , wind direction , yaw Angle , turbulence intensities , standard deviations , gust factor , and turbulence length scale , together with the torsional acceleration RMS response.

* 1. Analysis of Torsional Response and Key Wind Parameters

To analysis the torsional vibration response and wind parameter, the raw acceleration and wind data are averaged under the averaging time interval of 10 min. For the torsional response, the main vibration feature is the RMS value (i.e., in the unit of rad/s²) of each averaging interval, yielding 180 samples for four storms. Fig. 4(a) shows the variations in 180 RMS values of the torsional response under the four storms. Moreover, the use of the 10 min averaging interval leads to the same number of mean wind speed and mean wind direction, as shown in Fig. 4(b)-(c), respectively.

For more details, Fig. 5 indicate the variability relationship between the torsional response of the mean wind speed and mean wind direction. In Fig. 5(a), one can observe that there is a **positive correlation** between mean wind speed and torsional RMS acceleration for all storm events. As the wind speed increases, the torsional vibration response also increases, indicating that stronger winds contribute to more significant torsional effects. Notably, the distribution is more scattered for Storm 3, suggesting greater variability in torsional response for a given wind speed compared to other storms, while Storm 1 appears more linearly correlated, with a clear upward trend. In contrast, as Fig. 5(b) appears, there is no clear linear relationship between wind direction and torsional RMS. The torsional response seems more **dispersed** across different wind directions, indicating that directionality alone is not a strong predictor of torsional vibration.

Given the bridge-axis angle identical to −25∘ relative to north, Fig. 6 illustrates a rose diagram of mean wind speed against mean wind direction. This plot provides a comprehensive visualization of the wind patterns impacting the bridge during the four storm events. This graphical representation enables us to easily identify prevailing wind directions, intensity distributions, and the frequency of high-speed gusts associated with varying storm scenarios.



**Fig. 4**. Mean wind and vibration data of four storms: (a) the RMS values of the torsional response, (b) the mean wind speed (m/s), and (c) the mean wind direction (°)



**Fig. 5**. Variability of the torsional vibration response versus the mean wind speed (a) and the mean wind direction (b)



**Fig. 6**. Rose plot of the mean wind speed versus mean wind direction of the four storms

* 1. Prediction of Torsional Response

Before developing the BNN model for predicting the torsional response of the Hardanger Bridge, an initial evaluation of wind-related predictors is essential. Multicollinearity can significantly impair the ability of regression-based models, i.e., including BNNs, to accurately isolate the individual impact of each predictor. In such cases, minor fluctuations in one predictor can disproportionately influence the model response, resulting in unstable and unreliable parameter estimates. To diagnose and mitigate this issue, the **VIF value of each predictor** is calculated. Therefore, wind features (i.e., *p*=13) exceeding the VIF threshold equal to 10 are excluded the original predictor dataset **X**.

After selecting the optimal predictors , both the wind feature and RMS values of the torsional response are normalized tozero mean and unit variance. On this basis, the prediction of the torsional response of the Hardanger Bridge via the BNN begins with the creation of training and test datasets from the available 180 RMS measurements. The training data contains the wind features and RMS values of the torsional response of the first three storms leading to 126 samples (*n*=126). Hence, the remaining 54 samples of the selected wind predictors are used as the test data to evaluate the performance of the proposed method for predicting the unseen 54 RMS values of the torsional response.

The 10-fold cross validation algorithm is applied to optimize the hyperparameters of the BNN including the architecture layers, dropout rate, learning rate, *L*2 regularization factor. The search domains include the hidden layers varying 1-3, dropout rate 0.3-0.5, the learning rate 10–4-10–2, and *L*2 regularization 10–3-10–1. The best set of hyperparameters maximizes the mean R² over multiple folds. Using the trained BNN model, Fig. 7 shows the results of the prediction of the torsional response of the Hardanger bridge. In this figure, the original torsional response samples are compared with their corresponding predicted ones during the training and testing phases. As can be observed, the predicted RMS values in the training phase are in good agreement with the original training point. For the testing phase, one can discern the same reliable behavior, while the prediction performance during the training phase is better than the testing stage.



**Fig. 7**. Prediction of the torsional vibration response by the proposed method and BNN-aided regression modeling

**Table 1**. Performance evaluation of the proposed method via the regression metrics

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| --- | --- | --- |
| Metrics | Training Phase | Testing Phase |
| R² | 0.97 | 0.77 |
| RMSE | 5.76×10–5 | 8.49×10–5 |
| MAE | 4.72×10–5 | 6.90×10–5 |

To further analyze the prediction result, Table 1 lists the regression-based performance evaluation metrics, that is, R², RMSE, and MAE. As the data reveal, the proposed method achieves the reliable prediction in the training and testing phases with the accuracy rate of 97% and 77%, respectively. On the other hand, the RMSE and MAE quantities are inconsiderable indicating good match between the original and predicted response samples. Therefore, one can conclude that the proposed method can accurately predict the torsional response of the Hardanger Bridge subjected to some strong windstorms.

1. Conclusions

This study presented a machine learning-aided prediction framework utilizing the **BNN** to forecast the torsional vibration responses of the Hardanger Bridge under strong windstorms. To enhance model reliability and interpretability, the proposed method incorporated a VIF-based feature selection to mitigate multicollinearity among wind-related predictors. The BNN model was then trained and validated through a structured cross-validation approach to optimize its hyperparameters, ensuring robust predictions during both the training and testing phases.

The performance evaluation of the proposed BNN-based predictive model clearly demonstrates its effectiveness in forecasting the torsional vibration responses of the Hardanger Bridge under wind-induced loads. The model exhibited strong predictive accuracy during both the training and testing phases, reflecting its ability to capture the complex nonlinear dynamics associated with wind-induced torsional vibrations. Moreover, the model predictions showed a high degree of consistency with the actual measured responses, validating its reliability and robustness. These findings indicate that the proposed BNN framework is a valuable tool for structural health monitoring of long-span cable-supported bridges, offering accurate and reliable predictions of torsional dynamics during severe wind events. This capability not only enhances real-time monitoring but also supports proactive decision-making for bridge safety and maintenance.

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