Chapter 6
Modal Property Identification of the Bear Mountain Bridge

CDT Gautam Namjoshi, CDT Philip Williams, CDT Ethan Espinosa, and Dr. Thomas Matarazzo

Abstract The Bear Mountain Bridge is a historic suspension bridge located in the lower Hudson Valley of New York. A sensor network consisting of eight accelerometers installed on the bridge's main suspended span is used to collect operational vibrations for modal property identification. This paper analyzes the data recorded by the fixed sensor network to estimate the bridge's vertical and torsional modal frequencies and mode shapes. Three different system identification methods were implemented to estimate modal properties. Through direct comparisons of the estimated frequencies and stabilization diagrams, modal frequencies and mode shapes were evaluated. Overall, thirteen possible modal frequencies were identified below 2.5 Hz, of which six modes were cross validated by all three methods. This paper reports the first known estimates of the modal properties of this bridge.

Keywords System Identification · Bridge · Modal Properties · Sensor Network · Structural Health Monitoring

Introduction

Bridge inspections can be a costly and time-intensive process that generally does not evaluate structural dynamics behavior. Structural dynamic properties are important as they are linked to the mass and stiffness of the system. Over the past few decades, numerous vibration-based structural health monitoring methods have been developed with the goal of determining dynamics properties and inferring structural condition. Ambient modal analysis is the practice of recording structural vibrations in operational conditions and using these measurements to estimate structural modal properties [1]. Such dynamic properties are useful for calibrating finite-element models, computing damage-sensitive features, supporting condition assessments, and other applications [2].

The Bear Mountain Bridge was opened in 1924 and possesses cultural and economic significance for Hudson Valley region of New York State [3]. As a suspension bridge, its modal properties are generally comparable to other cable-supported, long-span bridges, such as the Golden Gate Bridge, on which similar characterizations have been conducted [3, 4]. In this study, vertical and torsional modal frequencies and mode shapes of the Bear Mountain Bridge are estimated from the accelerometer data. The determination of modal properties of the bridge supports a baseline, from which, changes may be more easily identified. Such a baseline should be calibrated with respect to environmental variables to better infer a change in structural state.

Data Collection

Modal identification in this study is based on the measurements of a network of accelerometers installed on the bridge. The accelerometer sensor network is comprised of eight accelerometers with two on the North side of the bridge, and six on the South side of the bridge (see Fig. 1). Sensors are distributed across the 1632 feet long main span of the bridge, to capture spatial dynamics of the suspended main span [3]. The New York State Bridge Authority personnel greatly assisted with the planning and installation of the sensor network. All accelerometers were hard-wired to a base station (data acquisition system) on the West side of the bridge. Sensors were affixed to the bridge using a combination of mounting adhesive and clamps and positioned in such a way to resist detrimental environmental conditions.

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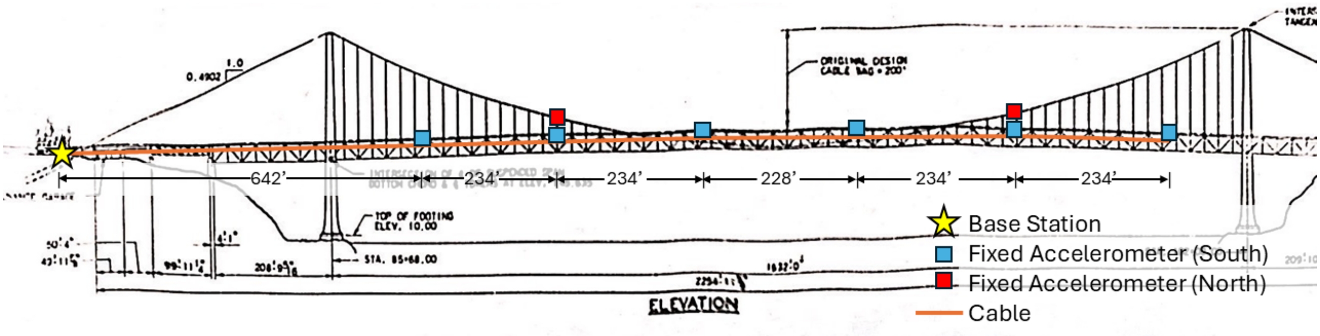


Fig. 1 Overview of Sensor Network Layout

Data collected from the "fixed" set of sensors requires on-site personnel to collect data, and so the data set is restricted to the bridge's working hours of 0800-1600. Data was collected in 2022 between the months of May and August. The sensors are effective at all ranges, including the expected range of 0-2.5 Hz for the relevant modal frequencies of the bridge.

Modal Property Identification Methods

The principal challenge with determining the modal properties of the Bear Mountain Bridge stems from the quality of the bridge response data. Since this study considers operational modal analysis data, output-only system identification methods are most appropriate. Three different output-only system identification methods were used to analyze the operational acceleration data: Automated Frequency Domain Decomposition (AFDD) [5], Eigensystem Realization Algorithm-Natural Excitation Techniques (ERA-NExT) [6], Covariance-driven Stochastic Subspace Identification(SSI-COV) [7]. These three output-only methods formed the primary methods for analysis; results from these methods were then compared within datasets via stabilization diagrams to identify stable modes and between datasets using histograms to identify the occurrences of modal frequencies. In addition to the lack of input data, due to technical difficulties with the performance of the sensor network, some erroneous datasets were discarded.

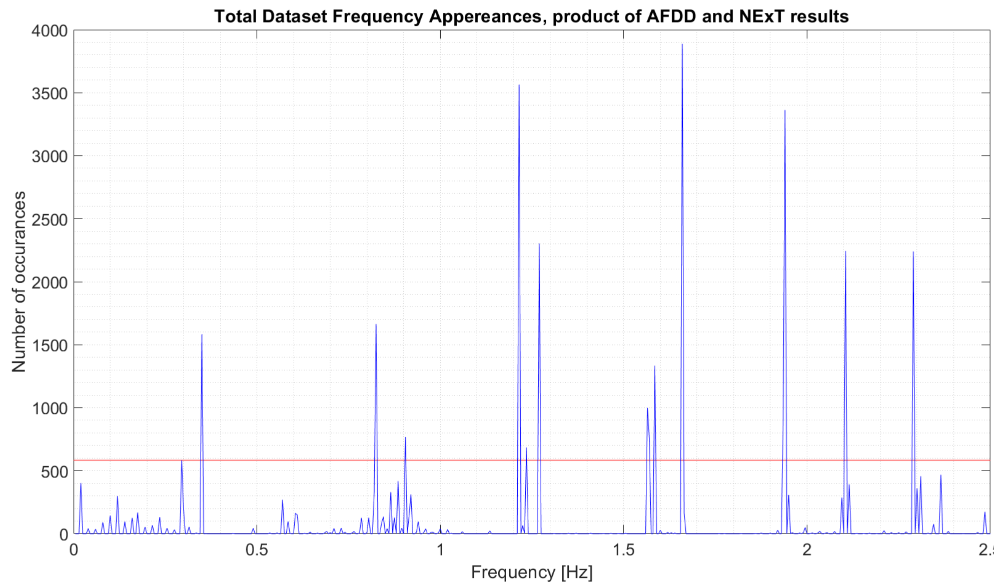
Determination of Reference Modal Frequencies

To determine reference frequencies based on their prevalence in the results, AFDD methods and ERA-NExT methods—across a range of model orders from ten to sixty—were used as they are quick at identifying modal properties. AFDD has proven to be an effective and computational efficient method to approach capable of finding closely spaced modes [5]. ERA-NExT is a modification of the Eigensystem Realization Algorithm that embeds an assumption for random, uncorrelated input excitation, which is best suited for ambient vibration [6, 8]. While ERA-NExT has the capability to generate stabilization diagrams, for the purposes of this paper only the generated frequencies were used as results were more accessible.

These methods were primarily used to generate reference modal frequency estimates. The computational efficiency of these two methods allowed for execution of the methods across a large number of datasets, allowing for a histogram of results to be generated as seen in Fig. 2. Should the frequency generated be a likely real modal frequency, it should be time-invariant and therefore be present in multiple datasets. The peaks of the histogram should then represent accurate estimates of the modal frequencies of the bridge. In order to determine peak selection, a statistical analysis of the results through a cumulative distribution function was conducted. Occurrence counts over n = 583 contained the top 20% of data, therefore this value was selected as a minimum value for selecting peaks as reference frequencies. While not a detailed stabilization diagram analysis, this method of data analysis is scalable and efficient, allowing for accurate reference estimates to then be compared against other methods' stabilization diagrams.

Stabilization Diagrams through SSI-COV

To further validate the found frequencies, stabilization diagrams were developed through one additional method, SSI-COV. Results from the diagram were then cross validated with the reference frequencies generated by the histogram. SSI-COV was initially developed to simplify the computation of SSI, utilizing weighted data correlations instead of orthogonal projections



CDF Cutoff Value n=583 indicated by red line

Fig. 2 Histogram of AFDD/ERA-NExT (considering all 393 data sets)

to determine stable modal properties [7]. The tangible benefit of using this model, however, is the ease of developing stabilization diagrams. Stabilization diagrams help verify modal properties within the same dataset by finding patterns of stability. Vertical lines that appear on the graph indicate a trend of stability as modal order increases, as the continued presence of stable poles as the complexity of the model increases is indicative of real, stable modal frequencies. Selecting stable modes through this action helps distinguish likely modal frequencies against computational artifacts. As seen in Fig. 3, vertical lines are visible on the stabilization diagrams, identifying those stable modal frequencies. Limitations caused by the data

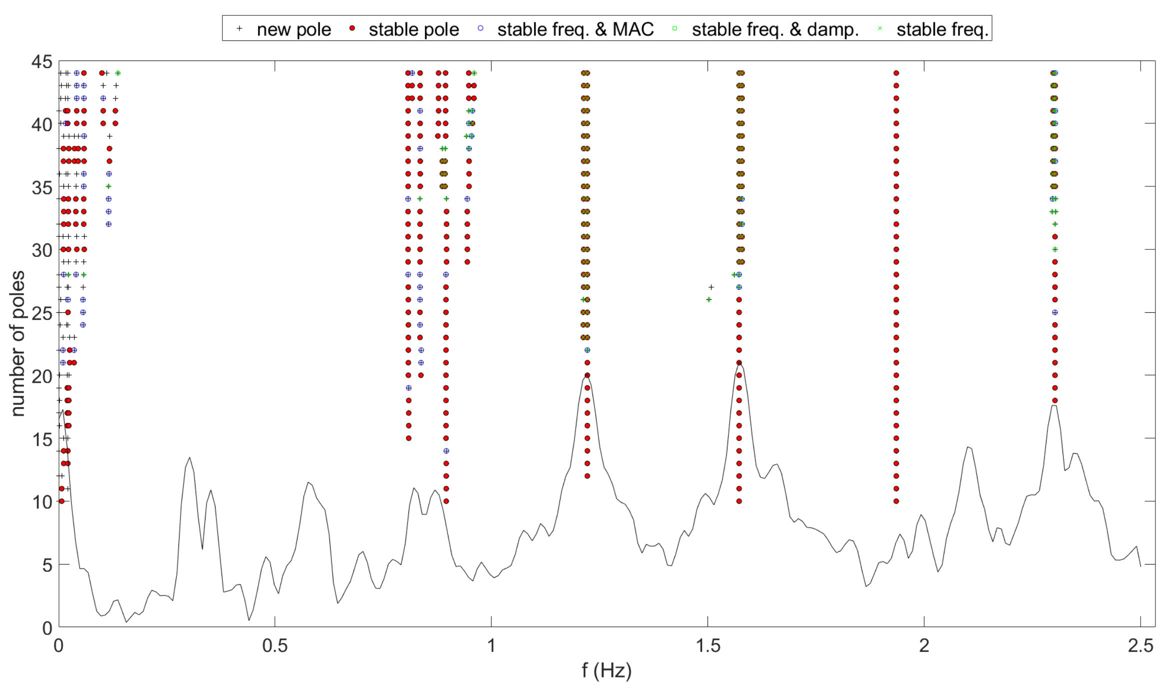


Fig. 3 Sample Stabilization Diagram for SSI-COV (one dataset)

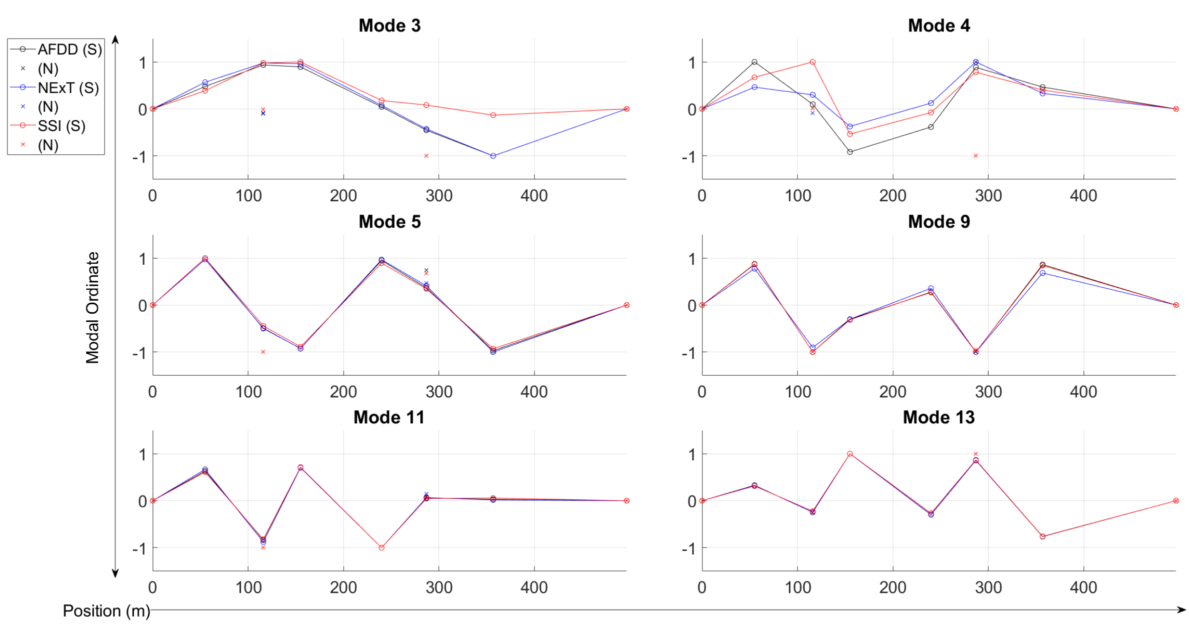
collection method are also visible here. Due to the lack of precision of the fixed sensors at low frequencies, the stability for frequencies below 1 Hz is not as apparent as those above 1 Hz.

The diagram of stable modal frequencies as generated in Fig. 3 helps identify those specific frequencies for further analysis. Stable modes are considerably more useful for analysis, as the process of selecting stable frequencies removes computational artifacts present in other output-only models, refining the list of results and reducing the workload of analyzing mode shapes since instead of investigating all frequencies, thorough investigation can be limited to stable frequencies.

Results

The histogram in Fig. 2, gives us a foundational understanding of the spread of frequencies found by the AFDD and ERA-NExT methods across various datasets. The frequencies that make up the peaks provide us with a set of reference frequencies that are more likely to be modal frequencies due to their prevalence within the full set of data. In addition, these frequencies are validated by comparing them to the results of the stabilization diagrams from the SSI-COV model. While SSI-COV utilizes results from comparing different model orders within the *same* dataset the AFDD/NExT scaled results use data from *multiple* datasets from the same day. By validating results from both within datasets and between datasets, frequencies that appear across these different methods gain reasonable certainty in representing real modal frequencies.

Analyses of the mode shapes is simplified once the modal frequencies are known. By comparing the mode-shapes of different models at similar frequencies, as seen in Fig. 4, it is clear that method type, while impacting the exact values of the mode shape, does not matter when analyzing the general shape of the mode as the three methods produce visually similar mode shapes for similar modal frequencies. The visual correlation between these mode shapes serves as evidence towards the likelihood of these modal frequencies being real modal frequences, as similar mode shapes would not be found if the results were computational artifacts. Another critical component of the mode shape analysis is the type of mode found. Having sensors placed on both sides of the bridge allows for a determination of one of two modes. Torsional modes are indicated by opposing sensor movements for either side while vertical modes are indicated by unison sensor movements. Torsional Modes can be found in Mode 4 in Fig. 4, where sensors on the north side of the bridge are clearly moving opposite the motion of the south side. Vertical modes make up the rest of the stable modes identified in Table 1 and depicted in Fig. 4. Analysis of the type of mode, seen in Table 1, provides valuable information on the properties of the bridge under those specific frequencies, allowing for a better baseline understanding of the modal properties of the structure.



S = South, N = North

Fig. 4 Mode Shapes for Specific Frequencies

Table 1 Frequency Results from Histogram and Stabilization Diagrams

Mode Number	Mode Type (V, T)	Frequency Estimates [Hz]	
		AFDD and ERA-NExT Histogram	SSI-COV
1*	V	0.295	–
2*	?	0.350	–
3	V	0.825	0.809
4	T	0.905	0.895
5	V	1.215	1.221
6*	?	1.235	–
7*	T	1.270	–
8*	V	1.565	–
9	V	1.585	1.572
10*	?	1.660	–
11	V	1.940	1.935
12*	T	2.105	–
13	V	2.290	2.302

V = vertical mode, T = torsional mode. * = unconfirmed by SSI-COV stabilization diagram

Conclusion

This paper presents a preliminary analysis of the modal properties of the Bear Mountain Bridge. Through the application of three output-only system identification methods, AFDD, ERA-NExT, and SSI-COV, thirteen possible modal frequencies were identified, with six cross-validated by all three methods.

Analysis of the mode shapes also validates that these are real modal frequencies. For each modal frequency found in both histogram and stabilization method, corresponding mode shape results display shapes similar to what is expected at these low frequencies from previous research on bridge system identification, for example in studies done on the Golden Gate Bridge [4]. All six mode shapes are also consistent across the three output-only models used. Limitations with the number of sensors impacts the clarity of the mode shape results, but still provides enough of a picture to make determinations about the type of mode present at each analyzed modal frequency.

Estimation of modal frequencies and determination of mode types through mode shape analysis establishes baseline modal properties for the Bear Mountain Bridge. Since changes in modal properties are now easily identified through comparison with the baseline, basic structural health monitoring can now be conducted on the bridge.

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