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Experimental Damping Identification of a Bridge Case Study in Norway under Still Air Conditions

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ABSTRACT

Aeroelastic effects are a fascinating yet problematic phenomenon that lies in between the fields of aeronautical and bridge engineering, as many long-span bridge decks show dynamic behaviors similar to the ones of wing airfoils when met with strong winds. In particular, modal damping is a critical factor in understanding the dynamic behavior of bridges when exposed to these kinds of interactions between aerodynamic forces and their structural elastic properties. This short contribution presents an in-depth investigation of modal damping identification through output-only operational modal analysis (OMA) in a bridge deck case study in Norway subjected to still-air conditions, where aeroelastic damping can be neglected. However, in this long-span suspension bridge, its slenderness implies having several closely-spaced modes of interest below 1.00 Hz. Therefore, the herein-considered still air wind condition represented a critical situation for proper activation of some first modes of interest, highlighting that experimental OMA can not properly identify the right value of the expected structural damping ratio associated with those modes from comparisons with other literature results.

Keywords: Automatic Operational Modal Analysis, Wind Operational Conditions, Damping Ratio, Stochastic Subspace Identification, Long-span Suspension Bridges Dynamic Identification, Machine Learning.

1. INTRODUCTION

The analysis of output-only vibration response of structures represents a widespread indirect nondestructive testing (NDT) within the scope of dynamic identification and structural health monitoring (SHM) fields. The operational modal analysis (OMA) technique allows for estimating modal properties describing the intrinsic dynamical behavior of structures under in-service operational conditions [1]. The increase in the number of continuous monitoring system implementations for infrastructures and the built environment worldwide is nowadays challenging researchers to develop novel and reliable Automatic operational modal analysis (AOMA) methods. Nowadays, the rise of modern machine learning (ML) tools devises new possibilities in OMA and dynamic identification of structures, e.g. [2, 3]. Nevertheless, deeper investigations are still needed for newly developed techniques, especially for evaluating their functionality and resilience during exceptional operation conditions, such as extreme wind loads (e.g. storms). The automatic estimation of modal parameters in operational conditions permits a continuous overview of the evolution of health status over time. This has been extensively applied in the output-only identification of civil structures and infrastructures [2, 3], but is also gaining traction in different aerospace applications [4, 5]. In aerospace engineering, the motion equation typically explicitly includes the effects of wind speed, encompassing aeroelastic parameters describing the drag and lift contributions, vortex shedding, etc. This is also typically in the civil engineering sector, i.e. when dealing with long-span suspension bridges. Indeed, its slender and flexible structure may increase wind effects sensitivity, delivering in the worst scenarios toward aeroelastic instability collapses [6]. In those cases, the equivalent viscous damping should be theoretically split into two components, one associated with the classic structural damping, and one component instead related to the adsorbed energy by the wind blowing which activates the wind-related instability phenomena (flutter, galloping, buffeting).

In the current contribution, the authors focused on an iconic suspension bridge, the Hardanger Bridge [7], located in Norway. In [8], the authors explored and compared two different AOMA methods and their reliability under various wind loading conditions, i.e. still air, normal wind conditions (low intensity), and storm conditions. This previous study evidenced that for these kinds of slender structures, the damping ratio should be the modal property of primary interest. Indeed, at high wind speeds, it has been demonstrated the activation of aeroelastic interaction effects, leading OMA methods to often overestimate the actual damping ratio. Moreover, since in [8], the damping ratios were the more uncertain quantity even in still air wind scenario, in the current contributions the authors focused on in-depth analysis of damping ratio results for the sole still air condition with the intelligent-AOMA (i-AOMA) method [2]. Indeed, before proceeding with a reliable modal parameter tracking procedure, it is necessary to identify also the reliability and uncertainty associated with modal properties estimates, especially in pure data-driven methods [9]. In the current analyzed case, the aerodynamic effects can be neglected, showing that the experimental damping ratio estimates should be related only to the structural system itself. However, for providing a more global and general study, the herein preliminary obtained results under the still air wind condition only should be compared in the future with the other sustained and storm wind conditions analyzed in [8].

2. THE CASE STUDY

The herein-considered case study is the 1.3 km long Hardanger Bridge [7, 10], a suspension bridge illustrated in Fig. 1. It is located in Norway, precisely in the Hardangerfjord area. This is a high latitude complex orographical territory where strong winds are the normality. The deck is a hollow core prismatic section 18.3 m wide and 3.2 m high. The deck is supported with 130 hangers, two lateral main cables, and extremal towers approximately 200.0 m high. The authors in [7] implemented a continuous monitoring system in 2013, and published an open-source database for the collected data, becoming a benchmark for this type of structure. The monitoring system is composed of 9 sonic anemometers for collecting wind data, a meteorological station, and 20 triaxial accelerometers deployed on the two sides of the deck for capturing also the torsional behavior.

Figure 1: Geographical localization of the case study, and photo of the Hardanger Bridge courtesy of Nico West from Pixabay.

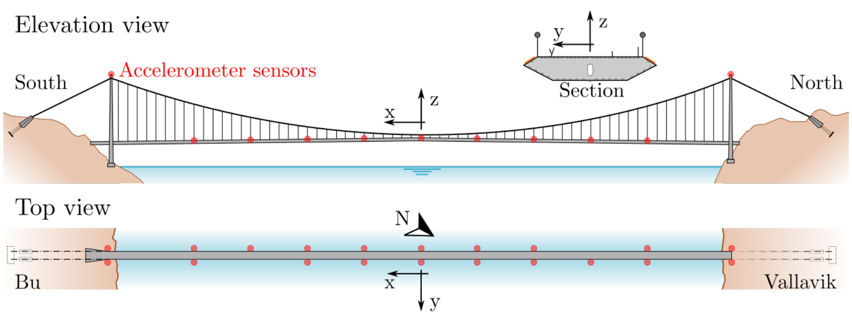


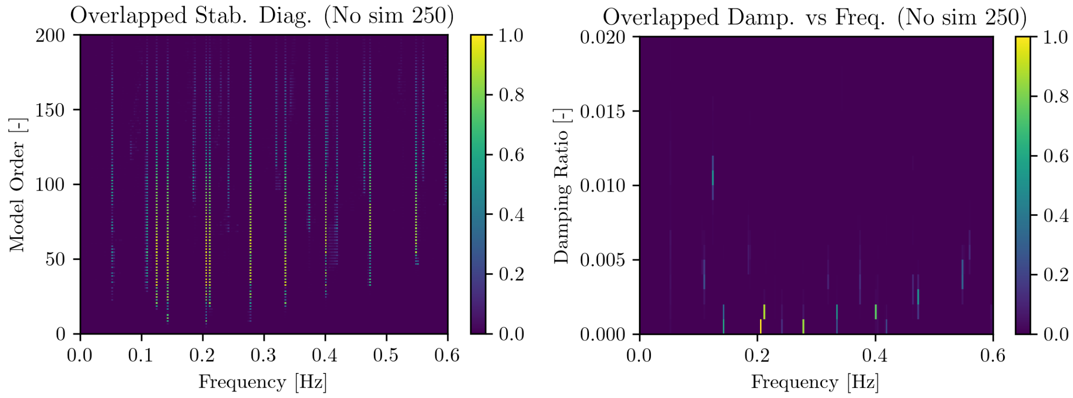
Figure 2: Accelerometer sensors layout on the Hardanger Bridge.

3. INTELLIGENT AND AUTOMATIC OMA TECHNIQUE

The time-domain parametric stochastic-subspace identification algorithm in its covariance-driven (SSI-cov) version is often adopted for AOMA solutions [3]. Nonetheless, the SSI-cov algorithm can sometimes detect spurious modes completely unrelated to the structural modes of actual interest. This is mainly related to the fact that when dealing with real-world structural elements, the exact number of degree of freedom is undetermined since it is theoretically infinite. However, the vibration response is collected by a finite number of measurement points. Therefore, the stabilization diagram allows for locating the most probable modal parameters with a conservative approach of increasing the model order, and identifying modal properties as those stable poles which remain aligned at a certain natural frequency [1]. Despite this approach, this can lead to the inclusion of non-physical poles alongside genuine ones also when alignments are very clear to identify. Additionally, improper selection of SSI governing parameters can further degrade the quality of the results.

Due to those uncertainty sources when dealing with SSI-cov, two recent studies by [11, 12] have attempted to improve the accuracy of SSI in identifying true structural modal parameters. They proposed a Monte Carlo-based method that constructs the stabilization diagram by varying two key input parameters: the length of signals within a shorter time window and the maximum model order. Their approach involved running multiple Monte Carlo simulations with these parameters and performing subsequent SSI-cov analyses. This method showed that while spurious modal alignments were occasionally detected, the actual structural modes were consistently identified across repeated analyses. However, this approach has its drawbacks. First, it arbitrarily sets the number of Monte Carlo simulations to 100 without establishing a clear convergence criterion. Second, it still requires users to manually define the time shift, which affects the reliability of the proposed AOMA framework and hinders its automation. Furthermore, despite employing a Monte Carlo-based methodology, no uncertainty evaluation was conducted, leaving room for further refinement.

Therefore, the i-AOMA proposed in [2] attempted to overcome these issues in [11, 12] by developing a two-phase intelligent data-driven solution. In Phase 1, a quasi-Monte Carlo sampling approach [13] is



(a) **(b)**

Figure 3: Overlapped stabilization diagram (a) and overlapped damping clusters (b).

employed to explore four critical SSI-cov control parameters: time shift (i.e. number of block rows in the Hankel matrix), maximum model order, time window length, and its centered time target [1]. During this initial exploratory stage, the user is required to define only a broad permissible range for these input parameters for the Monte Carlo sampling. The number of Monte Carlo simulation analyses has been set to 100 based on prior recommendations [12]. It influences the subsequent ML-driven Phase 2. To ensure computational efficiency, any unfeasible set of governing parameters is labeled as non-informative in order to train the intelligent core of the i-AOMA method. In Phase 2, a random forest (RF) is trained to provide the intelligent core of the quasi-Monte Carlo sampling process, avoiding sampling around those sets which has been labeled non-informative ones. The algorithm searches for new solutions until reaching a convergence criterion, based on the acceptable shifting band-rule of the trace of the sampling covariance matrix of mode shapes (see [2] for a detailed discussion). When convergence has been achieved, stability criteria are finally applied to retain only stable poles from the generated stabilization diagrams. Post-processing involves overlapping these diagrams to identify recurring stable pole alignments. Instead of relying on traditional clustering algorithms, this is achieved through kernel density estimation (KDE) [14]. KDE helps detect poles clustered around sharp peaks, which correspond to physically stable alignments within a specified frequency band. This process enables the selection of relevant poles using an automated, statistics-based criterion, further streamlining the identification of true structural modes.

4. EXPERIMENTAL DATA ANALYSIS

In this study, the still-air data conditions of the open-source database curated by [7] were collected on 14th November 2015 at 03:52:21 am. The recorded wind speed from the 9 sonic anemometers registered an average speed of 1.86 m/s with a standard deviation of 0.38 m/s. Since the speed is lower than 5 km/s, it is possible to exclude any aerodynamic effect of the wind blowing over the OMA damping estimation. Afterward limiting the governing parameters, i.e. maximum order to 200 and maximum block-row at 100, a number of 100 of quasi-Monte Carlo sampling simulations have been performed in the training phase 1. Then, phase 2 started the sampling with the RF acting as the intelligent core of the sampling parameters, reaching a convergence within 5% of the relative difference in the trace of the sampling covariance matrix between simulations 197-247. The overlapped stabilization diagram and the damping versus frequency clusters are illustrated in Fig. 3. 18 natural frequencies have been identified with the KDE along the frequency axis, using a beta distribution fitting and a prominence threshold computed at its 95th percentile. The damping ratio of the clusters of stable poles extracted around these 18 natural frequencies have been further analyzed with boxplot diagrams and another dedicated KDE graph, as reported in Fig. 4. The boxplot evidenced the possibility of further reducing the poles of actual interest

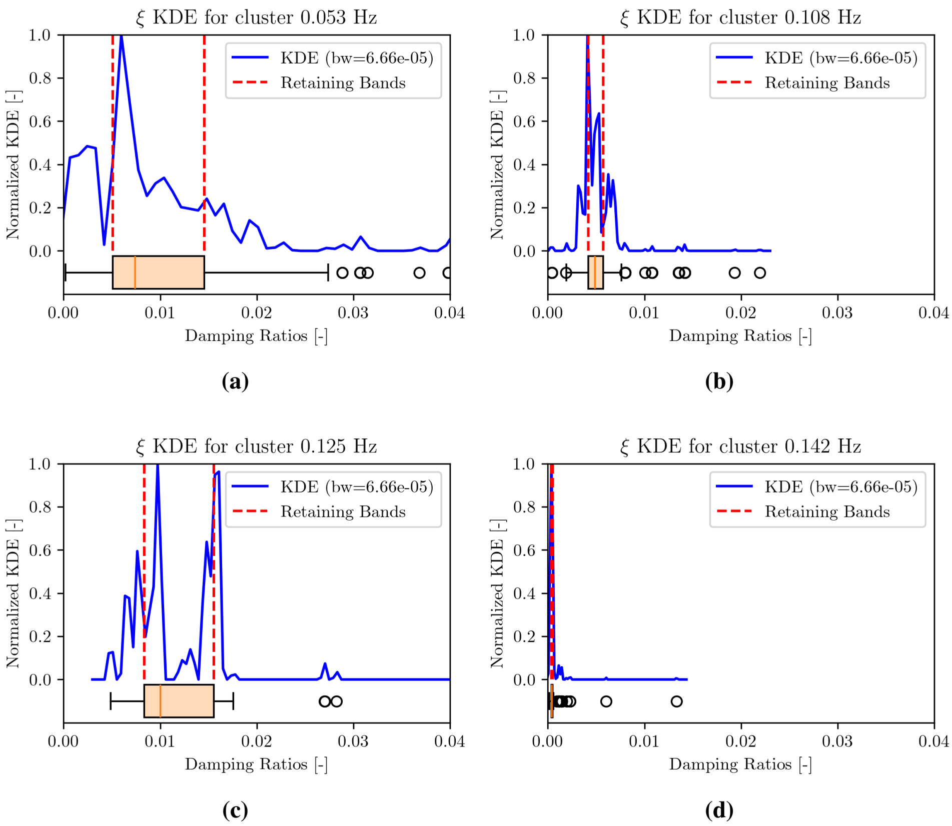


Figure 4: Damping ratio KDE distribution within every cluster of stable poles alignments.

by considering only those within the interquartile range (IQR) distance. The modal parameter results in terms of mean and standard deviation of natural frequencies and in terms of median, first, and third quartiles of damping ratios results are reported in Tab. 1.

5. CONCLUSIONS

In this study, the intelligent automatic operational modal analysis (OMA) by [2] has been employed for studying the damping ratio modal estimates for the Hardanger suspension bridge in Norway under still air wind conditions. The results in Tab. 1 are promising, and in quite good agreement with the literature reference results, except for mode at 0.241 Hz (not present in the literature reference) and mode at 0.272 and mode at 0.516 Hz and 0.529 Hz. Still-air conditions better align with the fundamental OMA assumptions, as they do not necessitate aeroelastic interpretations, unlike stronger wind conditions. However, weak ambient excitation is probably the main cause for the poor agreement with the literature references for the damping ratio estimates at modes 0.142, 0.333 Hz, and 0.464 Hz. For providing a more global and general study in the future, the current preliminary obtained results under the still air wind condition should be compared with other sustained and storm wind conditions, such as in [8].

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Table 1: Hardanger bridge experimental modal properties. μ_f indicates the average natural frequency, σ_f is its standard deviation, $\xi_{0.50}$ is the median damping ratio, whilst $\xi_{0.25}$ and $\xi_{0.75}$ are the first quartile and third quartile of damping ratio boxplot graph respectively.

[15] Petersen, Øiseth, & Lourens 2020				i-AOMA - Still Air Case					Relative Differences	
Mode Naming	f [Hz] OMA	f [Hz] FEM	ξ [%] FEM	μ_f [Hz]	σ_f [Hz]	$\xi_{0.50}$ [%]	$\xi_{0.25}$ [%]	$\xi_{0.75}$ [%]	Δf [%]	$\Delta \xi$ [%]
H1	0.052	0.051	0.65	0.053	3.82E-05	0.74	0.51	1.46	-1.91	-12.39
H2	0.105	0.105	0.77	0.108	3.91E-05	0.49	0.42	0.57	-2.77	57.59
V1	0.119	0.112	1.77	0.125	3.54E-05	1.00	0.83	1.55	-4.79	76.48
V2	0.142	0.142	0.65	0.142	2.16E-05	0.04	0.04	0.05	-0.01	N/A
H3	0.183	0.185	0.77	0.186	3.68E-05	0.56	0.50	0.61	-1.61	37.01
V3	0.206	0.203	0.27	0.206	2.43E-05	0.31	0.31	0.31	-0.01	-11.70
V4	0.212	0.212	0.35	0.213	2.92E-05	0.19	0.17	0.20	-0.46	84.81
-	-	-	-	0.241	3.34E-05	0.10	0.07	0.11	-	-
V5	0.276	0.276	0.26	0.277	2.53E-05	0.17	0.16	0.27	-0.37	55.03
H4	0.318	0.318	0.63	0.321	3.27E-05	0.58	0.44	0.64	-0.94	8.39
V6	0.333	0.332	0.25	0.334	3.17E-05	0.10	0.09	0.11	-0.29	150.86
T1	0.374	0.371	0.41	0.374	3.91E-05	0.48	0.40	0.59	0.00	-14.26
V7	0.401	0.401	0.24	0.401	3.32E-05	0.15	0.14	0.16	0.01	57.44
*	0.418	-	-	0.417	4.18E-05	0.09	0.08	0.11	0.24	-
H5	0.464	0.463	1.56	0.464	3.25E-05	0.26	0.22	0.30	0.00	N/A
V8	0.471	0.468	0.26	0.472	3.89E-05	0.21	0.21	0.23	-0.21	21.40
P1	0.516	0.511	0.16	-	-	-	-	-	-	-
P2	0.529	0.518	0.22	-	-	-	-	-	-	-
V9	0.547	0.545	0.31	0.549	3.08E-05	0.36	0.31	0.38	-0.36	-12.78
T2	0.560	0.550	0.65	0.559	3.49E-05	0.57	0.53	0.60	0.18	13.22

* [16] Dederichs, A. C., & Øiseth, O. 2023

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REFERENCES

[1] Carlo Rainieri and Giovanni Fabbrocino. Operational modal analysis of civil engineering structures. *Springer, New York*, 142:143, 2014.

[2] Marco Martino Rosso, Angelo Aloisio, Jafarali Parol, Giuseppe Carlo Marano, and Giuseppe Quaranta. Intelligent automatic operational modal analysis. *Mechanical Systems and Signal Processing*, 201:110669, 2023.

[3] Marco Civera, Luigi Sibille, Luca Zanotti Fragonara, and Rosario Ceravolo. A dbscan-based automated operational modal analysis algorithm for bridge monitoring. *Measurement*, page 112451, 2023.

[4] Gabriele Dessena and Marco Civera. Improved tangential interpolation-based multi-input multi-output modal analysis of a full aircraft. *European Journal of Mechanics-A/Solids*, 110:105495, 2025.

[5] Gabriele Dessena, Marco Civera, Alessandro Pontillo, Dmitry I Ignatyev, James F Whidborne, and Luca Zanotti Fragonara. Noise-robust modal parameter identification and damage assessment for aero-structures. *Aircraft Engineering and Aerospace Technology*, 96(11):27–36, 2024.

[6] Alberto Carpinteri. *Advanced structural mechanics*. CRC Press, 2017.

[7] Aksel Fenerci, Knut Andreas Kvåle, Øyvind Wiig Petersen, Anders Rønnquist, and Ole Øiseth. Data set from long-term wind and acceleration monitoring of the hardanger bridge. *Journal of Structural Engineering*, 147(5):04721003, 2021.

[8] Marco Civera, Marco Martino Rosso, Giuseppe Carlo Marano, and Bernardino Chiaia. Validation and comparison of two aoma approaches for the ambient vibration testing of long suspension bridges under strong wind loads. In *International Operational Modal Analysis Conference*, pages 475–484. Springer, 2024.

[9] Sérgio Pereira, Edwin Reynders, Filipe Magalhaes, Alvaro Cunha, and Jorge P Gomes. The role of modal parameters uncertainty estimation in automated modal identification, modal tracking and data normalization. *Engineering Structures*, 224:111208, 2020.

[10] Øyvind Wiig Petersen, Ole Øiseth, and Eliz-Mari Lourens. The use of inverse methods for response estimation of long-span suspension bridges with uncertain wind loading conditions: Practical implementation and results for the hardanger bridge. *Journal of civil structural health monitoring*, 9: 21–36, 2019.

[11] Kang Zhou, Qiu-Sheng Li, and Xu-Liang Han. Modal identification of civil structures via stochastic subspace algorithm with monte carlo–based stabilization diagram. *Journal of Structural Engineering*, 148(6):04022066, 2022.

[12] Kang Zhou and Qiu-Sheng Li. Modal identification of high-rise buildings under earthquake excitations via an improved subspace methodology. *Journal of Building Engineering*, 52:104373, 2022.

[13] Art B Owen. A randomized halton algorithm in r. *arXiv preprint arXiv:1706.02808*, 2017.

[14] Artur Gramacki. *Nonparametric kernel density estimation and its computational aspects*, volume 37. Springer, 2018.

[15] Øyvind Wiig Petersen, O Øiseth, and E Lourens. Investigation of dynamic wind loads on a long-span suspension bridge identified from measured acceleration data. *Journal of Wind Engineering and Industrial Aerodynamics*, 196:104045, 2020.

[16] Anno Christian Dederichs and Ole Øiseth. Experimental comparison of automatic operational modal analysis algorithms for application to long-span road bridges. *Mechanical Systems and Signal Processing*, 199:110485, 2023.