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REAL TIME ESTIMATION OF DAMPING IN WIND TURBINES

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Abstract. *In this paper we propose a combination of strategies which allow a real-time calculation of the modal parameters of Wind Turbines (WT), focusing on damping estimation. The procedure builds firstly on the idea we presented in a previous publication to identify, and later remove, the interfering harmonics from the raw acceleration signal. The same idea is now alternatively implemented by a linear Kalman Filter (KF) to extract not only the harmonics but also the very modes. Each isolated mode represents a degree of freedom whose signature (a damped sinusoid) is extracted by a Random Decrement Technique (RDT), avoiding the calculation of correlation functions. Then damping is straightforwardly obtained. All these procedures are amenable to be implemented in real time and with low computational cost.*

1. INTRODUCTION

Structural health monitoring (SHM) is a field of engineering that involves the continuous or periodic assessment of the integrity and performance of structures to detect and evaluate any potential damage or deterioration. It relies on sensor networks and data analysis techniques to provide real-time or long-term insights into the structural condition, aiding in maintenance and safety measures [1].

One of the most common ways to apply SHM to structures is by monitoring the modal parameters of the different modes inherent to these structures. In the case of WT, Operational Modal Analysis (OMA) techniques are typically used to estimate these parameters. OMA is a structural engineering technique that identifies the dynamic properties of a system based on its response to ambient or operational loads [2]. However, the acceleration signals measured in WT have the drawback of containing harmonics originating from hub rotation (1P, 3P, 6P, etc.), making it challenging for OMA techniques to distinguish them from the actual structural modes and complicating the estimation of modal parameters.

The traditional techniques used for OMA in WT, while often accurate in estimating modes frequencies, tend to struggle when identifying mode damping and lack precision. This is not the only drawback of these OMA techniques. Most of them involve complex and time-consuming calculations, hindering real-time monitoring, requiring substantial computational resources, and necessitating post-processing with more sophisticated equipment.

In this paper, an algorithm is presented that allows for real-time estimation of wind turbine mode damping using simple-to-implement algorithms. Combined with the optimal results obtained in various application scenarios, this algorithm represents a superior alternative to traditional OMA techniques for estimating wind turbine mode damping.

The algorithm is a combined use of linear Kalman filtering and the application of the Random Decrement Technique (RDT). The latter was developed in the 1970s by a team of NASA engineers and scientists led by H.A. Cole [3]. Since then, it has been tested for SHM and the estimation of modal parameters of structural modes. However, a common limitation has always been that the function obtained from this technique is only proven to be proportional to the free vibration decay of the system (from a specified initial displacement) for a Single-Degree-of-Freedom (SDOF) system [4].

The RDT may not have received the attention it deserves, perhaps due to the limitation mentioned above. However, it is true that in some circumstances, it has been used "bypassing" the theoretical conditions with nonetheless positive results [4]. Another limitation in the case of WT is the fact that under operating conditions acceleration signals are contaminated by harmonics generated from the hub rotation. This is the reason why RDT is not used in this context although it has continued to be used, for instance, in buildings [5], recognizing that it may have advantages for real-time operation. In the algorithm proposed in this paper, the two limitations are overcome by decomposing a complex Multi-Degree-of-Freedom (MDOF) system into a set of SDOF systems, eliminating at the same time, or at least minimizing, the influence of harmonics.

In Section 2, we outline the various steps comprising this algorithm, necessary for its implementation. In Section 3, we describe the different validations environments settled to assess the algorithm's performance, while in Section 4, the obtained results are explained. Finally, in Section 5, we provide detailed conclusions drawn from this study.

2. METHODOLOGY

The algorithm proposed in this article to estimate the damping of a specific mode of a wind turbine in a real-time manner consists of several steps, which will be described below.

2.1 Mode modeling

The first step to perform, and one of the key points of this algorithm, is mode modeling. Essentially, it involves selecting the mode for which modal parameters, specifically damping, are to be estimated. To achieve this, the mode will be modeled in the time domain, allowing us to access the corresponding signal in isolation. In other words, we will be able to isolate the signal component that corresponds solely to the contribution of the selected mode.

The response of a SDOF system to a gaussian white noise excitation, as it is routinely assumed in OMA for WT, can be modelled as a sinusoid which is modulated in both phase and amplitude. In this way, each mode can be isolated, and the conditions to further apply the RDT are met. Therefore, the methods proposed so far to isolate non-stationary harmonics such as the one proposed in [6] can be also used to estimate the modes.

As mentioned, this step is of utmost importance because it allows to transition from having a signal composed of multiple modes and harmonics, that is, a MDOF system, to a SDOF system. The significance of having a SDOF will become apparent in the next step.

The procedure for separating the mode from the rest of the signal is based on the concept presented in [6]. This article develops an algorithm to identify and remove harmonics from raw wind turbine signals. In this case, it will not be used to eliminate harmonics but to identify and extract specific modes of the wind turbine. Moreover, instead of using a least-squares solution we will employ Kalman filtering, enabling real-time implementation of the algorithm.

Structural analysis of WT commonly relies on the study of vibrations, typically collected by accelerometers placed in locations such as the tower or the nacelle under natural excitation conditions. These acceleration signals, denoted as $a(t)$, comprise various natural modes of the wind turbine and their components, represented as $u(t)$, along with undesired harmonics generated by rotor rotation (1P, 3P, 6P, etc.), $h(t)$, and a primarily noise-based residue, $r(t)$.

$$a(t) = \sum_{k=1}^{K} u_k(t) + \sum_{p=1}^{P} h_p(t) + r(t) \tag{1}$$

with K the number of natural modes and P the number of harmonics.

Continuing with the concept introduced in [6], both modes and harmonics are modeled as sinusoidal signals with variable amplitude $A(t)$ and phase $2\pi f_0 t + \varphi(t)$. Therefore, the mode to be estimated is represented as follows:

$$u_k(t) = A_k(t) cos\big(2\pi f_0 t + \varphi_k(t)\big) \tag{2}$$

where f_0 is the mean frequency of the mode to be isolated and should be approximately known. On the other hand, $\varphi(t)$ represents the non-linear instantaneous phase deviation, which can also accommodate errors in the initial estimation of f_0. This model poses challenges due to its non-linearity, necessitating the use of a KF adapted to this characteristic, which results in increased complexity and computational cost. In order to avoid that issue and work with a linear KF, a series of modifications are made to the model.

By applying trigonometric relationships to equation (2) (the subscript "k" is removed to simplify the equation, but we continue to refer to a single natural mode) $u(t)$ can be written as:

$$u(t) = A(t)cos(2\pi f_0 t)cos\varphi(t) - A(t)sin(2\pi f_0 t)sin\varphi(t) \\ = \alpha(t)sin(2\pi f_0 t) + \beta(t)cos(2\pi f_0 t) \tag{3}$$

where,

$$\alpha(t) = -A(t)sin\,\varphi(t) \\ \beta(t) = A(t)cos\,\varphi(t) \tag{4}$$

For this model the parameters $\alpha(t)$ and $\beta(t)$ (the state variables) can be estimated using a linear KF. These parameters will be modeled with a first-order autoregressive model, further simplifying the implementation of the step explained here.

This KF enables to estimate the parameters $\alpha(t)$ and $\beta(t)$ sample by sample, allowing to reconstruct the signal, that is, the mode to be estimated, in real-time. The equations, in their discrete-time formulation, can be expressed as follows. First, the dynamic model equation is:

$$x_n = ax_{n-1} + e_{n-1} \tag{5}$$

and the state equation is:

$$\hat{x}_{n,n} = \hat{x}_{n,n-1} + K_n(z_n - H\hat{x}_{n,n-1}) \tag{6}$$

where

$$H_n = [\sin(2\pi f_0 t_n) \quad \cos(2\pi f_0 t_n)\,] \qquad x_n = \begin{bmatrix}\alpha_n \\ \beta_n\end{bmatrix}$$

2.2 Random Decrement Technique (RDT)

Once there is an isolated time-domain signal corresponding solely to the contribution of a specific mode, there is a transition from a MDOF system to a SDOF system. As elucidated in several articles discussing the theory of the RDT [4], it is only when dealing with SDOF systems that the function obtained from applying the aforementioned technique is proportional to the exponential decay of the system. In this case, thanks to having an algorithm that allows the extraction of specific modes from the raw acceleration signal, RDT can be employed for OMA. We must note that the potential to calculate, in an efficient way, modal parameters from the RD signature was recognized and described very early. First, the conditions to use the RD as an unbiased estimator for the autocorrelation (i.e. power spectrum) of the signal were investigated in [7]. Then, the estimation of modal parameters from such RD signatures were analyzed but only for a simulated SDOF implemented by an ARMA (2:1) model in [8] and in an unpublished paper [9]. No further attempts have been made for MDOF systems.

The RDT is based on identifying at each time instant whether a sample of the analyzed signal meets a specific condition (triggering condition). This sample is referred to as a triggering point. Whenever this condition is met, a segment of the signal with a fixed and predetermined size at both sides of the triggering point is captured. These segments are averaged each time the triggering condition is met. The obtained result from RDT is a damped sinusoidal signature, known as the Random Decrement signature (RD), which describes the dynamic behavior of the selected mode. All of this can be achieved without the need for the complex calculations associated with correlation functions. Consequently, the second step after isolating the desired mode will be the application of the RDT.

There are several parameters to be selected when applying RDT. The first of these is choosing the condition that determines which points in the signal are selected as trigger points. There are various options available, as mentioned in [10]. The chosen condition is the Positive Triggering Condition (PTC), as recommended in[10]. Although in [11] it is advised to use the Local Extremum Triggering Condition (LEC) under nonlinear conditions, PTC is not considered a poor choice. It has a significant advantage over LEC, which has led to its adoption – it allows for obtaining a much higher number of trigger points. This enables the extraction of more stable RD signatures that better capture the system's dynamics. Additionally, as will be shown in the results, using this condition in this context has been found to be appropriate and yields good results.

The condition used, PTC, involves selecting as triggering points all those samples whose values fall within an interval defined by two user-configured levels [a1, a2].

Another parameter to configure is the size of the segments that are being averaged and captured with each trigger point. This choice has been made based on two considerations. The first is to ensure that the resulting RD captures at least 3 periods of the mode, allowing for an accurate representation of the mode's dynamics. The second consideration is to have a segment length that is sufficiently long to ensure stable damping estimation. This is because the estimation procedures used require enough samples to converge to the correct value.

From the obtained RD, two sets of damped sinusoidal free decays are available, from whose dynamics the modal parameters of the mode isolated in step 1 can be extracted or estimated.

2.3 Damping estimation

The procedure that has been developed to estimate the damping of the mode from its RD signature involves calculating its upper envelope. There are several methods for calculating the envelope of a damped sinusoidal signal, and from it, the corresponding damping [8]. In our case, the fundamental concept for extracting damping from the envelope relies on approximating it by an exponential signal. This is achieved using again a linear KF that uses an autoregressive dynamic model of order one and a polynomial equation also of first order as the state equation. Once again, this step aligns with the preceding ones and incurs low computational cost and real-time estimation.

The estimation of damping is updated for each sample point of the envelope, resulting in damping values computed for as many samples as the length of the RD signatures. Consequently, the final damping value is determined by averaging the estimations of each sample, while accounting for the standard deviation among them. Because the KF requires a convergence time to track the model signal, the damping estimation also needs time to converge to its final value. Consequently, the initial estimated samples are discarded.

As a result, two mean values and two standard deviations are obtained for damping, with each pair of results corresponding to a RD signature. The idea is that the values obtained in one

RD signature must closely match those in the other, serving as an indicator that the procedure has been correctly executed and the obtained result is meaningful.

3. CASE STUDIES

To validate that the proposed methodology works correctly, aligns with the estimation of modal parameters of WT and yields precise results, two different kinds of signals have been analyzed.

- Output of an ideal Second-order system with known excitation.
- Synthetic signals from an OpenFAST model.

As it can be seen, the testing progresses from a fully controlled setting to a simulated wind turbine. This comprehensive approach aims to validate the methodology's accuracy and applicability across various scenarios.

Furthermore, when possible, comparison will be conducted between the results obtained using our methodology and those obtained by applying state-of-the-art OMA techniques. This comparative analysis aims to assess the methodology's performance relative to established OMA approaches.

4. RESULTS

4.1 Second-order system

A band-pass type second-order system is implemented to simulate the mode that needs to be isolated. Both the frequency and damping of this system can be freely chosen. This setup enables to assess the precision of the proposed methodology under various conditions of damping and frequency. In this controlled environment, various types of input signals can be tested, ranging from basic ones like noise and pulses, to more complex inputs. For the specific case addressed in this paper, the study aims to closely mimic real-world conditions to assess the performance of the proposed technique as reliably as possible. Hence, the input signals used are excitation signals measured on the blades of an actual wind turbine.

This type of input introduces harmonics from rotor rotation along with a noise base consistent with real-world measurements. Therefore, this test environment offers significant flexibility to evaluate the methodology under diverse conditions while remaining closely aligned with the actual operation of a WT.

The proposed method has been tested under three different sets of parameters of the second-order system:

- Case 1. Natural frequency: 1 Hz, Damping: 3%
- Case 2. Natural frequency: 0.3 Hz, Damping: 1%
- Case 3. Natural frequency: 0.3 Hz, Damping: 5%

Furthermore, in each of the analyzed cases, an attempt will be made to estimate the damping using several techniques traditionally employed in OMA. This allows for a performance comparison between the proposed technique and the currently utilized ones. The techniques chosen for comparison are:

- Covariance-driven Stochastic Subspace Identification (SSI-COV) [2] [12]
- Data-driven Stochastic Subspace Identification (SSI-DATA) [2] [12]
- Eigensystem Realization Algorithm (ERA) [2]
- Auto Regression model-based identification technique (AR) [2]

From the three proposed cases, we will show in more detail the Case 1.

The first step involves the isolation of the mode for which the frequency is known. In Fig 1, the periodogram of the signal generated by the system and the outcome of modeling the desired mode are presented.

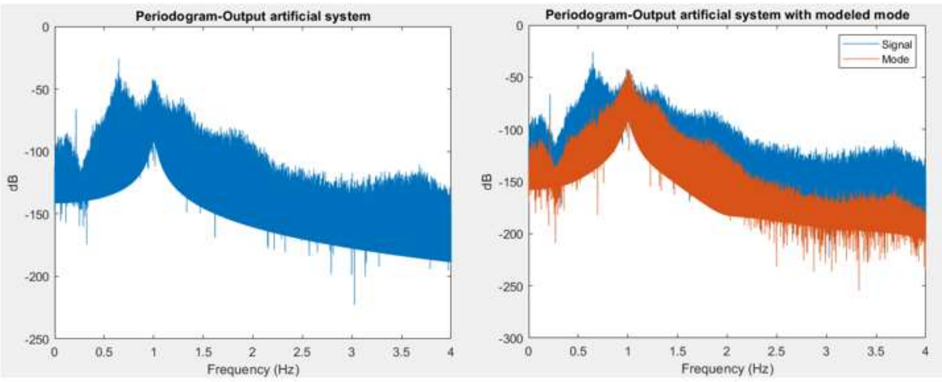

Fig 1. Periodogram of the signal (left). Periodogram of the signal and the mode modelled (right). System 1, second order system.

Subsequently, the Random Decrement Technique (RDT) is applied as outlined in section 2.2. The result is depicted in Fig 2a. Next, the obtained signature is divided into two parts: the section with positive time values, RD (+), and the portion corresponding to negative times, RD (-). The envelope of each of these parts is calculated, as illustrated in Fig 2b and 2c.

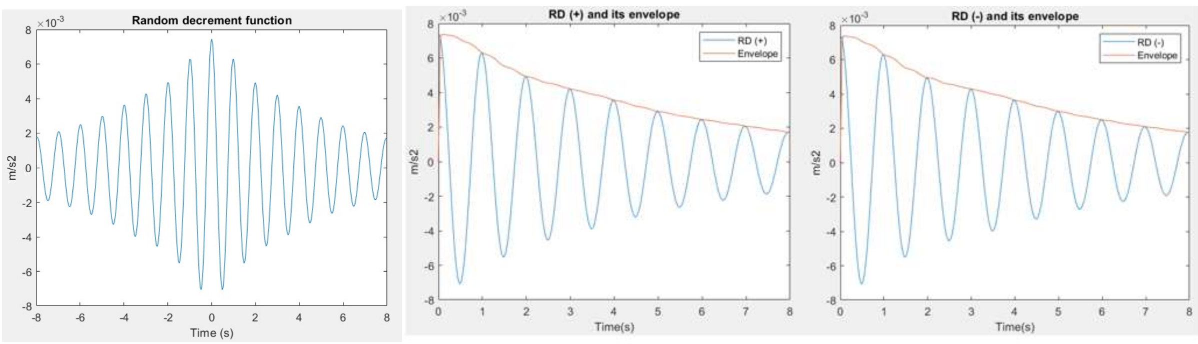

Fig 2. RD function, RD (+) and RD (-) with their envelopes calculated for Case 1.

After estimating the envelope, the final step is the damping estimation, as it can be seen in Table 1. Mean values and standard deviations are calculated for times longer than 4 seconds due to convergence considerations.

The obtained damping closely matches the theoretical value of the second-order system, that is, the mode that has been isolated, with a remarkably small standard deviation. Furthermore, the results from RD (+) and RD (-) exhibit strong similarities. All of these observations indicate that the proposed algorithm provides an accurate estimation of damping in the generated environment.

In the Case 2, both frequency and damping are lower, 0.3 Hz and 1% respectively. The same methodology is applied, and the results are also satisfactory: the similarity between RD (+) and RD (-) persists, and the estimated value of damping is very close to the theoretical one. Something similar happens for Case 3, where frequency and damping are 0.3 Hz and 5% respectively. The summary of the results is shown in Table 1.

Finally, for all the cases discussed, a comparison is conducted between the results obtained by using the proposed methodology and the techniques traditionally employed in OMA. The result of this comparison is also shown in Table 1. The following observations can be made:

In Case 2, the algorithm presented yields results very similar to those obtained with the SSI-COV and SSI-DATA techniques. However, in Cases 1 and 3, where the damping value is higher, the proposed algorithm clearly outperforms all other techniques by a significant margin. Only SSI-COV provides values that are not too far in both cases. When the damping is not very high (Case 1), SSI-DATA approach the theoretical value somewhat but still falls short of the methodology presented in this paper.

Table 1. Comparison of damping results between different OMA techniques.

Comparison of damping results between different OMA techniques						
Technique	Case 1		Case 2		Case 3	
	Average value (%)	Error	Average value (%)	Error	Average value (%)	Error
Theoretical value	3	-	1	-	5	-
Proposed method - RD (+)	3.0085	0.283%	1.0334	3.34%	4.8598	2.804%
Proposed method - RD (-)	2.9219	2.603%	1.0118	1.18%	5.0637	1.274%
SSI-COV	2.6657	11.143%	1.0444	4.44%	5.29	5.8%
SSI-DATA	3.532	17.73%	1.0688	6.88%	6.485	29.7%
ERA	0.54	82%	0.81	19%	3.36	32.8%
AR	5.90	96.67%	3.47	247%	15.54	210.8%

4.2 Synthetic signals from OpenFAST

The next step in validating the algorithm presented in this paper involves testing it in an environment that resembles closely the conditions of a wind turbine, while still having an *a priori* knowledge of the theoretical values of the modes for performance evaluation.

To accomplish this, the OpenFAST software is employed, which provides synthetic signals simulating acceleration measurements at specific points on the wind turbine. This is an opensource software for performing coupled nonlinear aero-hydro-servo-elastic simulations of WT in the time domain. It has been developed by NREL (National Renewable Energy Laboratory) and it is certified for the design of onshore and offshore WT. It can perform highly realistic simulations under different wind turbine operating and loading conditions. The 5 MW NREL onshore reference wind turbine, used in this research as a benchmark, consists of a 3-bladed, 126 m diameter wind rotor on a tower 87.6 m high and it has been widely used in several research studies [13]. To validate the proposed algorithm, we will focus on estimating the following modes:

- Mode 1FA: Frequency of 0.33Hz and damping of 8.1%.
- Mode 2SS: Frequency of 2.94Hz and damping of 1.2%.

4.2.1 Mode 1FA

The first case under analysis using synthetic signals generated in OpenFAST corresponds to the first mode of the WT, where the nacelle moves fore-aft (FA) in the axial direction of the rotor. According to [13] this mode is at 0.3Hz with an 8.1% damping ratio. We have proceeded to apply the proposed algorithm modeling the desired mode, as shown in Fig 3. Note that isolation of the mode removes the influence of both harmonics (e.g., 3P around 0.6 Hz) and modes (2nd FA around 2.89 Hz).

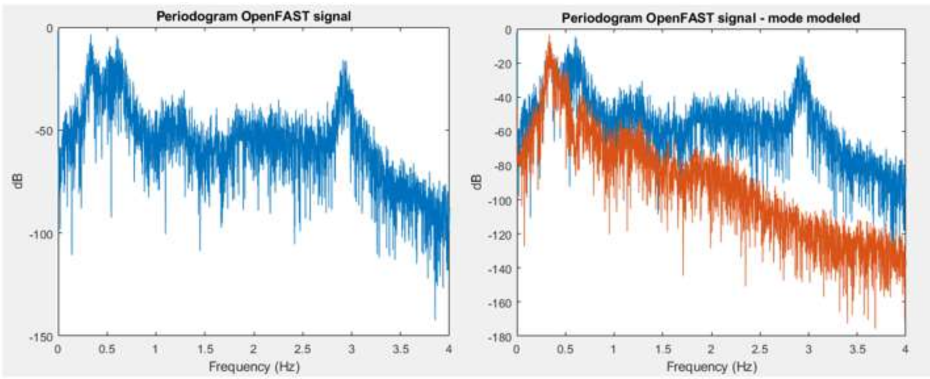

Fig 3. Periodogram of the signal (left). Periodogram of the signal and the mode modelled (right). Mode 1FA, synthetic signals.

Once the mode is isolated, it can be treated as a SDOF system and then the conditions for the applicability of RDT are met. Therefore, it can be assumed that the obtained signature is an exponential decay function that encapsulates the dynamic characteristics of the mode.

As outlined in the methodology, the next stage involves the computation of the envelopes for RD (+) and RD (-), followed by the estimation of their corresponding damping coefficients (with 3s for convergence). The obtained results are summarized in Table 2.

Table 2. Damping estimation values. Mode 1FA, synthetic signals.

	Damping	
Signature	Mean (%)	STD (%)
RD (+)	8.19	0.6479
RD (-)	7.9591	0.5058

The mean values obtained from both RD (+) and RD (-) closely align with the theoretical damping coefficient. While the standard deviation is slightly larger compared to the first case studied, it's worth considering that the damping ratio is higher in these scenarios, and the signals reflect a more real-world nature, making the obtained values entirely acceptable.

4.2.2 Mode 2SS

To conclude the performance analysis of the proposed algorithm when tested with synthetic signals from OpenFAST, it is now attempted to estimate the damping of the wind turbine tower's second lateral/transverse mode, known as Side-to-Side mode. The theoretical characteristics of this mode include a frequency of 2.94Hz and a damping of 1.2%.

The same steps as in the previous case are followed. The algorithm is initiated by isolating the desired mode. Following this, in accordance with the proposed methodology, RDT is applied, the envelopes for RD (+) and RD (-) are calculated and the damping is estimated from each of the envelopes. The Table 3 presents the mean value and standard deviation of these calculations after allowing sufficient time for convergence (3 seconds).

Table 3. Damping estimation values. Mode 2 SS, synthetic signals.

	Damping	
Signature	Mean (%)	STD (%)
RD (+)	1.1633	0.0424
RD (-)	1.1604	0.0368

The acquired values consistently align with the theoretical mode's expected damping, exhibiting minimal deviation for both RD (+) and RD (-). This reinforces the conclusion that the damping estimation is highly accurate.

5. CONCLUSIONS

In this paper, a methodology has been introduced for estimating the damping of the natural modes of the wind turbine. The techniques employed in this methodology facilitate real-time implementation of the algorithms involved with low computational costs. It is based on the Random Decrement Technique, which has been recovered for the wind energy industry. This algorithm overcomes its limitations as we work on SDOF systems, making it a valuable tool for wind turbine structural health monitoring.

The algorithm presented in this paper has been validated in two different environments, starting from a simpler context, and progressing to synthetic signals that simulate real-world signals.

The first environment involved a second-order system with a real input excitation from wind turbine blades. While this environment is the farthest from reality, it allowed for a controlled setting where conditions could be flexibly modified. This helped assess the performance of the procedure for various values of the modal parameters. This initial validation was successfully conducted, yielding fairly accurate values compared to the theoretical values set in the second-order system.

An important but logical observation is that as the damping ratio value increases, precision decreases. The mean value deviates from the theoretical value, and the standard deviation increases. This makes sense since higher damping ratios widens the mode's frequency bandwidth, leading to more mixing with other components and making isolation more challenging.

Additionally, for each case in this initial validation, a comparative analysis was performed with the results obtained from the main traditional OMA techniques. It was found that the algorithm presented here offers the best results, especially when the damping value increases.

The second validation, involving synthetic signals from OpenFAST, brought us closer to a real-world environment while still allowing us to know the theoretical values to be obtained. The results, although not as precise as in the previous case, are considered good estimates, particularly given the very high theoretical damping value in one of the cases.

These analyses allow us to conclude that the presented algorithm, at least in the conducted experiments, is capable of accurately estimating damping ratios in WT acceleration signals. Moreover, comparisons with traditional OMA techniques indicate that it not only serves as a viable alternative but also outperforms these techniques.

Importantly, it accomplishes this with straightforward implementation, quick execution, and low computational cost, offering advantages over other OMA techniques. Additionally, its real-time implementation potential makes it suitable for autonomous devices that can provide information directly to the SCADA system, eliminating the need for multiple devices and personnel for post-processing.

6 ACKNOWLEDGEMENTS

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