Minimum Detectable Damage on Magerholm Linkspan Via Finite Element Model Updating and Damage Simulation

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ABSTRACT

Norway's extensive coastline and island communities rely heavily on linkspans, critical infrastructure vital for economic development. Subjected to harsh environmental conditions and demanding operational schedules, they are susceptible to accelerated degradation, highlighting the need for robust Structural Health Monitoring (SHM). This study applies and expands upon a recently proposed Minimum Detectable Damage (MDD) framework to establish curves showing variation of probability of damage detection with respect to different damage levels. The investigation focuses on the lifting towers that vertically support the linkspan at the Magerholm ferry quay, using an updated Finite Element (FE) model of the structure. Temperature variability and measurement noise are considered to reflect real-world monitoring conditions. This research employs and compares four different outlier detection methodologies to derive Damage Indices (DIs) from simulated natural frequencies.

INTRODUCTION

The geography of Norway, characterized by its extensive coastline and numerous islands, necessitates a well-developed and dependable transportation network. Within this network, linkspans also called ferry docking bridges, serve as indispensable connectors, facilitating the movement of people, goods, and services between coastal communities and islands. However, these critical infrastructure components are subjected to harsh environmental conditions prevalent in Norway, including severe weather patterns, corrosive marine environments, and significant temperature variations. Coupled with demanding operational schedules and heavy usage, these factors contribute to the accelerated degradation of linkspan structures [1], underscoring the critical need for effective and continuous SHM to ensure their safety and operational reliability .

The concept of MDD holds significant promise for advancing vibration-based SHM by defining the smallest reliably detectable damage level with controlled detection and false alarm probabilities [2, 3]. Despite its crucial implications, recent literature reveals a relative scarcity of in-depth research specifically focused on MDD methodologies and their practical implementation. A notable contribution in this area is the work by Kamali et al. [4], which presented a framework for establishing alarm thresholds based on Possibility of False Alarm (PFA) and Possibility of Dectection (POD) to define MDD, using simulated natural frequencies and the Mahalanobis distance. While the original framework provided a methodological foundation, its demonstration was limited to a relatively simpler 2D truss structure, this study aims to build upon it and expand its to application to real-case scenario - Magerholm linkspan. Furthermore, recognizing the potential limitations of relying solely on a single DI calculation method, this work employs and critically compares the performance of four distinct outlier detection methodologies for deriving damage indices from simulated natural frequencies obtained from an updated FE model of the linkspan [5].

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THE UPDATED FINITE ELEMENT MODEL

Magerholm Updated FE Model

The Magerholm linkspan (Figure 1), connecting Magerholm and Sykkylven, is a vital component of the transportation infrastructure in Møre og Romsdal County, Norway, experiencing significant daily use [1]. A key structural feature is its hydraulic lifting towers, which adjust the linkspan to accommodate tidal variations for seamless ferry docking [5]. Notably, these lifting towers were believed to have failure during the severe Ingunn storm [6], a major weather event that led to the deck's detachment and subsequent recovery efforts. Consequently, the structural integrity of these towers is the primary focus of the damage simulation in this study.

Figure 1. Magerholm linkspan and its finite element model (ABAQUS [7]).

An initial FE model, based on structural drawings, was subject to uncertainties arising from the age of the materials, modeling assumptions and simplifications made during its creation, and the long-term degradation of the structure. To accurately simulate damage and establish a baseline for detecting even minor structural changes, it was crucial to update this initial model to better reflect the actual dynamic behavior of the platform. To achieve this, the authors employed the Finite Element Model Updating (FEMU) framework developed by Svendsen et al. [8,9], utilizing Mottershead's sensitivity method [10]. This iterative process aims to minimize the discrepancies between the FE model's predictions and real-world measurements. Field measurements, obtained using strategically placed accelerometers across the linkspan, provided the necessary data for system identification and the derivation of the structure's true modal characteristics.

Following the FEMU procedure, the stiffness of the lifting towers was determined to be 20736 kN/m. This calibrated stiffness value will be systematically reduced to simulate varying degrees of damage in the towers. Five natural frequencies from the updated FE model f_1 = 3.18 Hz, f_2 = 4.26 Hz, f_3 = 8.63 Hz, f_4 = 10.84 Hz, and f_5 = 15.2 Hz, corresponding to the measured frequencies, were selected as the primary modal characteristics for damage index calculation. More information on the mentioned five frequencies can be found in [5].

Damage Scenarios Simulation

To realistically capture environmental variability, a representative temperature profile for Norway was generated using three components: a yearly sinusoidal pattern for seasonal changes, a daily sinusoid for diurnal fluctuations, and Gaussian noise ($\sigma = 3\,^{\circ}\mathrm{C}$) for short-term variability. The annual trend included a reduced amplitude and a cold-biased offset to reflect Norway's climate. This produced an hourly temperature dataset

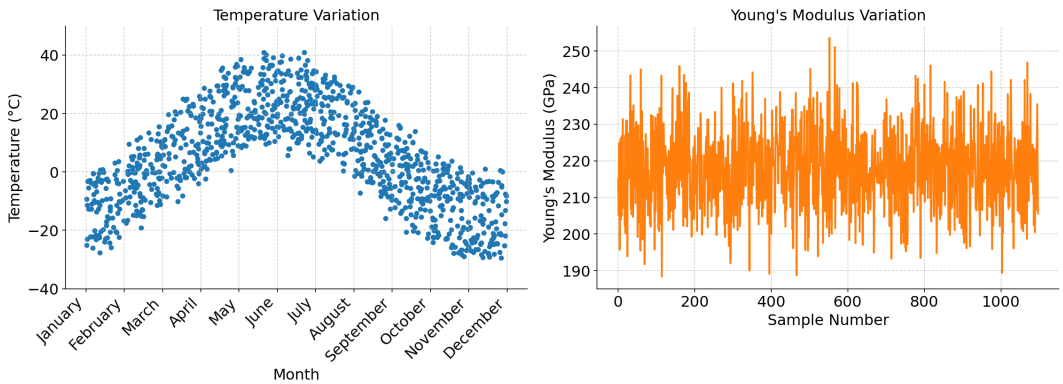

Figure 2. Representative subset (1098 samples) of Norwegian simulated temperature profile and corresponding Young Modulus values.

for one year (8760 samples). To reduce computational load while preserving temporal and statistical features, a random subset of 1098 samples ($\sim$3 per day) was chronologically sorted (Figure 2). Then the effect of temperature on the structural elements was incorporated by assuming a non-linear temperature-dependent Young's modulus [11]:

$$E(T) = E_0 \left[1 - 0.005(T - 20)^{(-0.01T)} + 0.05\,\text{rand}[\mathcal{N}(0,1)]\right] \tag{1}$$

Using the 1098 temperature samples, corresponding Young's modulus values were calculated, enabling 1098 modal analyses and yielding natural frequencies for the healthy state (Figure 3). To assess outlier detection under uncertainty, these baseline frequencies were contaminated with 1% and 3% random noise. Damage scenarios were then simulated by reducing the calibrated spring stiffness by 1% increments up to 40%, producing 40 additional sets of 1098 frequencies per damage level. These datasets form the basis for computing damage indices, as described in the next subsection: "Outlier Detection Methods".

METHODOLOGY

Outlier Detection Methods

The frequency sets obtained from both healthy and damaged states form an $M \times N$ matrix, denoted as $\mathbf{A}$, where N represents the number of modal analyses performed using the updated FE model, and M is the number of natural frequencies extracted in each analysis. Each column $n \in N$ of matrix $\mathbf{A}$ corresponds to a frequency vector $\mathbf{f}_n = [f_n^1, f_n^2, \ldots, f_n^M]^T$. The matrix $\mathbf{A}$ derived from the healthy state ($\mathbf{A}_{healthy}$) will serve as the baseline for comparison with damaged states ($\mathbf{A}_{damaged}$), considering damage severities ranging from $\kappa = 1\%$ to $\kappa = 40\%$. To compare and detect damage, four outlier detection methods will be employed to represent each column n as a scalar index, resulting in a cloud of scalar indices derived from $\mathbf{A}$, as follows:

Mahalanobis distance: This method measures the multivariate distance of a point from the center of a distribution, taking into account the covariance structure of the data.

The Mahalanobis distance of a data point $\mathbf{x}$ to a distribution with mean vector $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$ is given by:

$$D_M(\mathbf{x}) = \sqrt{(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu})} \tag{2}$$

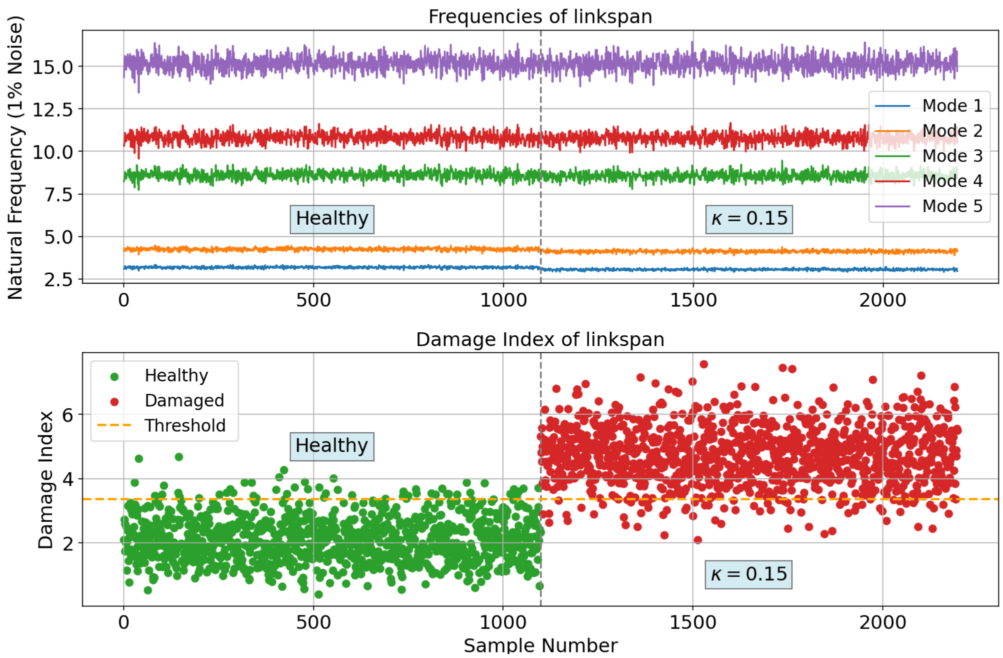

Figure 3. Natural frequencies and damage index for healthy and damaged linkspan states. $\kappa = 0.15$ indicates a 15% reduction in lifting towers' spring stiffness.

where: $\mathbf{x}$ is a vector $\mathbf{n} \in \mathbf{N}$ from $(\mathbf{A}_{damaged})$, $\boldsymbol{\mu}$ is the mean vector of $(\mathbf{A}_{healthy})$, $\boldsymbol{\Sigma}$ is the covariance matrix of $(\mathbf{A}_{healthy})$, $\boldsymbol{\Sigma}^{-1}$ is the inverse of the covariance matrix.

Local Outlier Factor (LOF): extends the idea of k-nearest neighbors by not just looking at the distance to neighbors but also comparing the local density of a point to the local densities of its neighbors. A point in a sparse region compared to its neighbors in denser regions will have a higher LOF. The frame work and mathematical background of this method can be found in [12, 13].

LOF is applied to assess the "outlierness" of each frequency vector. Specifically, the healthy state frequency matrix $(\mathbf{A}_{healthy})^T$ is transposed and used to fit a Local Outlier Factor model. Subsequently, for each frequency vector $\mathbf{n} \in \mathbf{N}$ derived from a damaged state (representing a transposed column in $(\mathbf{A}_{damaged})^T$), this vector is also scored using the pre-fitted LOF model. The resulting score quantifies the local density deviation of the damaged state's frequency vector relative to its neighbors in the healthy state frequency space.

Isolation Forest: isolates instances by randomly selecting a feature and then randomly selecting a split value between the minimum and maximum values of the selected feature. Instances that require fewer splits to be isolated are more likely to be outliers. The anomaly score is related to the path length of a sample in the isolation trees. The frame work and mathematical background of this method can be found in [13, 14].

The Isolation Forest method is applied to discern damaged states by evaluating the "isolatability" of their modal frequency sets relative to the baseline healthy state. Given the $M \times N$ frequency matrix $\mathbf{A}$, where each column represents a frequency vector $\mathbf{n} \in \mathbf{N}$ from a single modal analysis, Isolation Forest aims to identify frequency vectors that are easily isolated, which are indicative of anomalies or damage. Specifically, the healthy state frequency matrix $(\mathbf{A}_{healthy})^T$ is transposed and used to train an Isolation Forest model. Subsequently, for each frequency vector $\mathbf{n} \in \mathbf{N}$ obtained from a damaged state (corresponding to a transposed column in $(\mathbf{A}_{damaged})^T$), this vector is also scored using the trained model.

Grubbs' test: is typically used to detect a single outlier in a univariate dataset assumed to be normally distributed. This implementation extends it to multivariate data by calculating the standardized score (z-score) for each feature and then taking the maximum absolute z-score across all features for each data point. A higher score suggests a potential outlier.

For a data point $\mathbf{x} = (x_1, x_2, \ldots, x_p)$ which is the vector $\mathbf{n} \in \mathbf{N}$, the DI is calculated as:

$$DI_{Grubbs}(\mathbf{x}) = \max_{j=1}^{p} \left| \frac{x_j - \mu_j}{\sigma_j} \right| \tag{3}$$

where: μ_j is the mean of the j-th feature in $(\mathbf{A}_{healthy})$, σ_j is the standard deviation of the j-th feature in $(\mathbf{A}_{healthy})$.

PFA-driven Alarm Thresholds and Minimum Detectable Damage

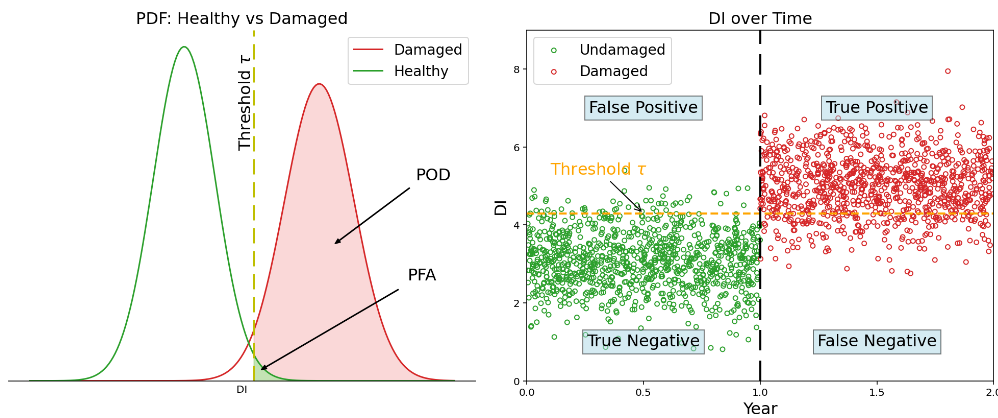

Figure 4. PFA-driven alarm thresholds using DI: PFA, POD distribution and damage detection classification. [4]

Once the scalar indices for both healthy and damaged states have been computed, the crucial question is how to differentiate between damaged and healthy scalar points. A common approach involves employing a threshold based on the PFA. This method dictates that for a given pre-defined threshold value, any DI exceeding this threshold is classified as damaged. Specifically, when examining the cloud of scalar DI indices representing a healthy state, we can establish a threshold τ such that only 5% of the damage indices surpass this value (resulting in a False Positive), while the remaining 95% fall below it (True Negative), thus setting the PFA at 5%. Applying this same threshold τ to the scalar clouds of a damaged state allows us to identify values above τ as correctly detected damages (True Positive). Conversely, values below τ, despite being derived from damaged data, are incorrectly classified as undamaged (False Negative) - see Figure 4 for graphical explanation. In essence, the PFA represents the percentage of damage indices exceeding the threshold τ in the healthy state, whereas the POD represents the percentage of damage indices exceeding the threshold τ in the damaged state.

If a fixed threshold τ is established for the healthy state such that PFA = 5%, an increase in the damage level will result in an increase in POD. This increase will continue until a specific damage level is reached where POD = 95%. This particular damage level can be defined as the minimum detectable damage for the predefined criteria of PFA = 5% and POD = 95%. Utilizing a predefined PFA and POD, the MDD for the Magerholm linkspan lifting towers (considering spring stiffness reductions from 1% to 40%) will be established through the application of each of the four mentioned outlier detection methods.

RESULTS AND DISCUSSION

Figure 5 illustrates the DIs calculated for the Magerholm linkspan, when the stiffness of the lifitng towers was reduced. These DIs were derived using the four previously mentioned methods, applied to the raw natural frequencies (without noise). The DIs for various damage levels are plotted alongside the healthy state for comparison. Figure 6 displays the corresponding DI values, but derived from natural frequencies contaminated with 1% noise. Figure 7 illustrates the POD curves for each of the four methods, including the 95% detection probability threshold to identify the MDD for each method.

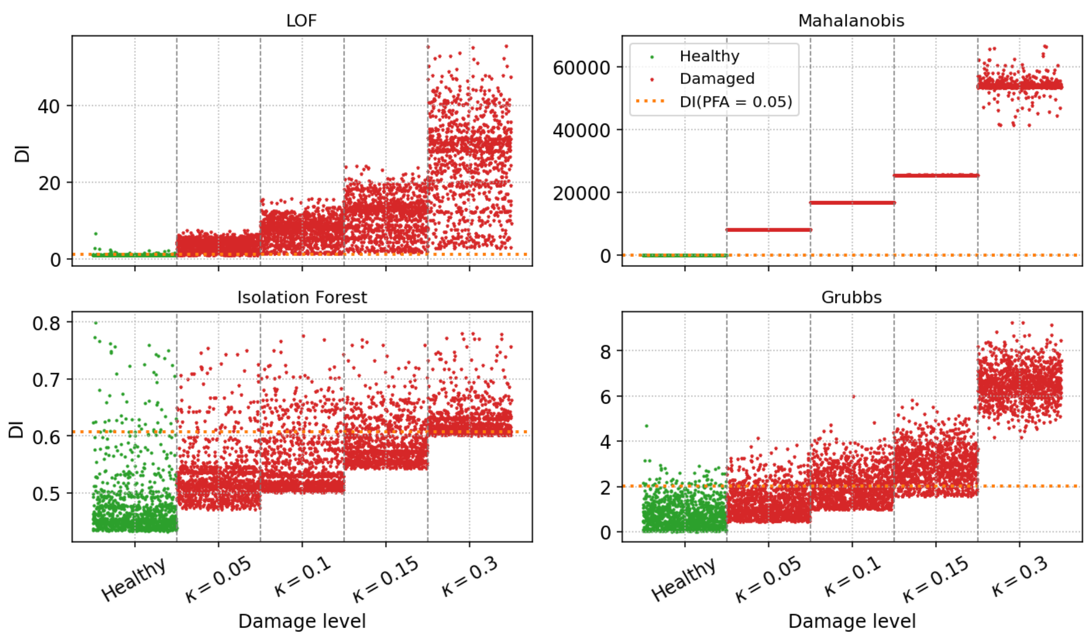

Figure 5. Damage indices of 4 outlier detection methods with different damage levels using raw frequencies.

The damage index increases with increasing damage levels. However, the rate of this increase varies significantly across the different methods, particularly when using raw frequencies (Figure 5). For the LOF method, as damage severity escalates, the DI not only increases in magnitude but also exhibits a widening range between its minimum and maximum values. In contrast, the Mahalanobis method demonstrates a remarkably significant increase in DI with each damage level, resulting in a clear separation between the point clouds representing different damage states. The Isolation forest method also demonstrates a clear separation between the point clouds representing different damage levels, particularly when considering the minimum DI within each level. Notably, the maximum DI value observed in the healthy state is comparable to the maximum values across all damage states. This similarity in maximum DI value makes the application of the mentioned threshold-based damage detection method inefficient. The Grubbs test method displays a consistent increase in DI, with a gradual rise in the average DI value corresponding to increasing damage levels, while maintaining a relatively stable range between the minimum and maximum DI values.

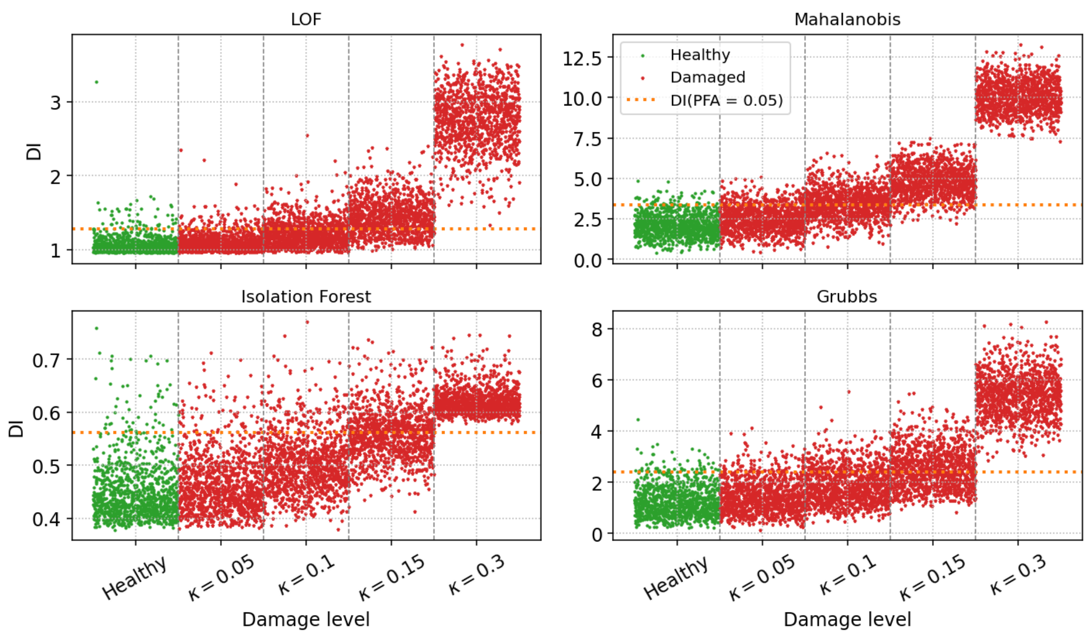

Figure 6. Damage indices of 4 outlier detection methods with different damage levels using frequencies with 1% noise added.

Figure 6 illustrates the impact of using natural frequencies contaminated with 1% noise as input data for the outlier detection methods. Compared to the results without noise added, the increase in DI with increasing damage levels is less pronounced. The LOF method still exhibits an increase in the mean DI value, but the standard deviation of the DI distribution reduces with added noise. The Mahalanobis method's sensitivity is greatly reduced and its supremacy has been diminished. The Isolation Forest method continues to present the same limitation observed with raw frequencies: the maximum DI values for the healthy state and high damage levels remain similar. In contrast, the Grubbs method demonstrates robustness, maintaining a stable performance even with the introduction of noise in the input data.

Figure 7 evaluates the performance of the four methods at different noise levels using three types of input data: raw natural frequencies, frequencies corrupted with 1% noise and frequencies corrupted with 3% noise. For the data without noise (solid lines), both the LOF and Mahalanobis distance methods exhibit MDD values below $\kappa = 5\%$ (POD above the 95% threshold at $\kappa = 5\%$). The Grubbs test follows with an MDD of 17%, and the Isolation Forest method has the highest MDD at 20%.

When considering the data with 1% noise (dashed lines), the relative performance of the four methods remains consistent. The Mahalanobis distance method achieves the

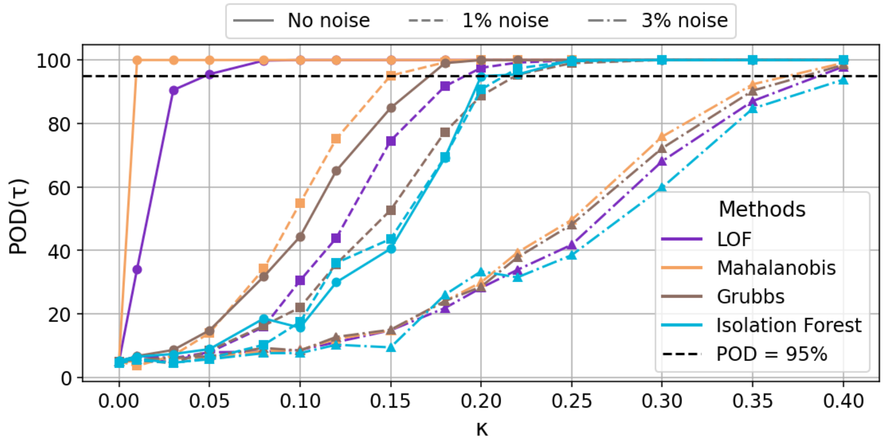

Figure 7. Probability of detection over damage damage levels using different methods at different noise levels.

lowest MDD at 15.5%, followed by LOF at 19%, the Grubbs test at 22.5%, and the Isolation Forest method with MDD at 22%. The MDD increases significantly, exceeding 37% for all methods, when the frequencies are contaminated with 3% noise (dashed-dotted lines). At this noise level, the performance difference between the four methods becomes negligible. This trend suggests that the introduction of noise to the input frequencies generally reduces the ability to detect minimum damage, as evidenced by the increased MDD values across all methods. A possible explanation for this finding is that the temperature variation does not significantly affect the structure's natural frequencies, as the corresponding changes in Young's modulus are not substantial. Consequently, the changes in the damage indices calculated by the four methods are likely predominantly driven by the added noise.

In short, the Isolation Forest method appears to be the least effective, further compounded by its lack of robustness, as it yields varying DI values across different calculations. The remaining three methods each present their own strengths and weaknesses. The Mahalanobis distance and LOF methods demonstrate comparable performance, with LOF showing slightly greater resilience to noise compared to the Mahalanobis distance. The Grubbs test appears to be the most robust in the presence of noise, exhibiting the smallest difference in MDD values between the raw and noise-added datasets.

CONCLUSIONS

In summary, this study evaluated the effectiveness of four outlier detection methods (LOF, Mahalanobis, Isolation Forest, and Grubbs) within a MDD framework for identifying reduction in stiffness of lifting towers in the Magerholm linkspan. The authors utilized an updated FE model to extract 5 natural frequencies corresponding to measurement frequencies for each modal analysis as a basis for damage index calculation. Damaged indices derived using the four mentioned methods are then evaluated using PFA-driven alarm threshold to detect damages. The results show that Mahalanobis and LOF are the two best methods if there is no present of noise in the natural frequencies. Alternatively, in the case of contaminated frequencies as input data, Grubbs test show highest robustness in identifying damages. Finally, in all cases, Isolation forest show to poorest performance.

Since temperature changes induce only minor variations in the structure's Young's modulus and natural frequencies, the alterations seen in the damage indices calculated by the four methods are most likely a result of the added noise. Building on this observation, future research should expand beyond solely considering temperature variations as the primary environmental factor influencing damage detection in linkspans. Specifically, the impact of tide levels, which directly affect the stiffness of the lifting towers, warrants investigation. Moreover, future studies should not only focus on defining the MDD in lifting tower stiffness but also explore other common types of linkspan damage. These could include loosened bolts, cracks in the front beam, and other structural degradations that may manifest differently in the dynamic response of the linkspan.

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