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RESEARCH ARTICLE OPEN ACCESS

Data-Driven Damage Detection on a Temperature-Varying Turbine Blade Using Multiple Sensor Modalities

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ABSTRACT

This study investigates vibration-based structural health monitoring (SHM) of a small-scale wind turbine blade using multiple sensor types to evaluate the performance of an output-only, data-driven and semisupervised damage detection framework. The primary objective is to assess how different sensing modalities influence damage detection and localisation and to demonstrate the robustness of the proposed SHM approach across diverse sensor configurations in a wind turbine composite material blade. To this end, experimental accelerometer and strain-gauge time series are considered in this study. The method integrates multivariate autoregressive (MAR) modelling, principal component analysis (PCA), Mahalanobis distance-based dissimilarity metrics, and K-means clustering. This hybrid framework requires no labelled damage data and minimal user input, offering a transparent, interpretable and computationally efficient solution suitable for real-world applications. The blade was experimentally tested under progressive damage, which was introduced as sequential cracks at three locations, and under varying temperature conditions. Results show that the method reliably detects damage across sensor configurations, highlighting its potential as a practical and cost-effective tool for continuous SHM. Notably, both sensor types were able to detect damage using only one sensor as input in the model; however, strain gauges proved more effective than accelerometers for damage localisation.

1 | Introduction

Wind turbine blades (WTBs) are among the most critical and costly components of a wind energy system, both in terms of manufacturing and maintenance [1, 2]. Their failure can lead to significant operational losses. Common damage types in WTBs—such as surface and internal cracks, debonding and delamination—are especially concerning given the composite, anisotropic and heterogeneous nature of blade materials, which complicates both detection and prediction of damage progression.

Structural health monitoring (SHM) aims to address these challenges by enabling early detection and prognosis of damage through sensor-based surveillance systems [3, 4]. While several nondestructive testing (NDT) techniques—including acoustic

emission, ultrasonic testing, machine vision and vibration-based methods—have been proposed for blade inspection, their widespread application to WTBs is limited due to accessibility issues, complex geometries and the influence of variable environmental and operational conditions [5, 6]. As a result, hybrid SHM approaches that combine multiple methods are increasingly recommended to improve robustness and fault-detection accuracy [3].

Among data-driven approaches, vibration-based SHM methods have shown great promise by using operational response data to infer structural condition [7]. Autoregressive (AR) models and their variants (e.g., ARMA and ARX) are widely used in this context as damage-sensitive feature extractors, generally in the time-domain [8–13]. However, univariate AR models treat each

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sensor independently and do not account for cross-sensor interactions that naturally arise in multisensor SHM systems. In contrast, multivariate autoregressive (MAR) models (also referred to as vector AR models in the literature) provide a natural extension by capturing temporal dependencies and spatial correlations between multiple sensor signals. These intersensor correlations can enhance both the sensitivity to damage and the ability to localise it, particularly in distributed sensing networks. As a result, MAR models often outperform their univariate counterparts in detecting subtle structural changes, especially in cases where damage manifests globally across multiple locations. Despite their advantages, most existing applications of MAR models have focused on relatively simple structures such as beams, steel truss bridges and small-scale buildings [14–16]. Their application to more complex, composite systems, particularly WTBs, remains limited. Moreover, the influence of environmental variability and the integration of different sensing modalities in MAR-based SHM frameworks are still underexplored.

While studies such as Goi and Kim's [15] have shown that MAR models outperform univariate AR models when applied to accelerometer data, the generalisability of this improvement to other sensor types, such as strain gauges, is not yet well understood. Moreover, few SHM studies have systematically compared the effectiveness of different sensing modalities within vibration-based frameworks. Notably, Yang et al. [17] proposed a frequency response transmissibility analysis using both strain gauges and accelerometers in a lab setting, though without considering environmental effects. As Li et al. [4] emphasised, both sensor types represent cost-effective and technologically mature options for SHM, each with distinct advantages and limitations depending on the application context. However, they are also susceptible to electrical disturbances and noise, underscoring the need for careful evaluation of sensing strategies in real-world conditions.

In this study, we use experimental data from a 1.75-m small-scale composite WTB tested by Ou et al. [18] to evaluate damage detection and localisation under varying temperature conditions. The damage was simulated in the experiments as cracks of increasing length (5, 10 and 15 cm) at three locations along the blade's longitudinal axis (17%, 30% and 50%). Previous work on this dataset employed deep learning methods such as variational autoencoders [19] and neural extended Kalman filters [20]. While these studies demonstrated the potential of advanced data-driven techniques, they required large sensor arrays, five strain gauges and eight accelerometers, respectively, which may not be practical for many SHM deployments. Furthermore, these approaches did not explicitly address temperature variability and overlooked progressive damage scenarios, instead performing detection only against the initial undamaged baseline. Such constraints limit their applicability to real-world continuous monitoring, where the current structural state may already be damaged.

To overcome these challenges, the present work develops a hybrid, semisupervised SHM framework that compares the performance of accelerometers and strain gauges while tracking changes sequentially between damage stages and accounting for temperature variability in both the training and testing phases. The methodology integrates MAR and AR models for feature

extraction, principal component analysis (PCA) for temperature compensation and Mahalanobis distance (MD) for sensor-wise damage quantification, enabling progressive and environmentally robust damage detection in composite WTBs. However, given that the proposed damage detection framework relies on extracted strain or acceleration response features without assumptions on sensing modality, it is well-suited for integration with other sensing technologies. Noticeably, fibre-optic cables for these also measure delta strains [21, 22].

To the best of the authors' knowledge, this is the first study to apply multivariate feature extraction techniques for SHM of composite blades under environmental variation using both accelerometers and strain gauges. The main contributions of this work are as follows: (i) develop and evaluate a multivariate feature extraction method for detecting and localising damage in composite WTBs and comparing it with univariate approaches; (ii) comparing the performance of the methodology across different sensor networks, including accelerometers and strain gauges; (iii) accounting for environmental variability, specifically temperature changes, in the damage detection framework and (iv) enable progressive damage detection, comparing each damage state with the blade's immediately preceding structural condition, including already damaged states.

2 | Description of the Experimental WTB Benchmark

The experimental small-scale WTB benchmark consists of a 1.75-m long and 5.0-kg blade part of a Windspot 3.5-kW wind turbine model. It has a layered sandwich structure, consisting of (i) a 0.93-mm-thick outer shell of double-layered composite material, composed of plain-weave fabric and chopped strand mat made of *E*-glass fibres and (ii) a low-stiffness polyurethane foam core for internal reinforcement. This small-scale blade was tested as part of an experimental campaign by Ou et al. [18] for the development of damage detection algorithms. The experiment setup, temperature variations and damage considerations are briefly described in the next paragraphs, and a general overview is provided in Figure 1.

The blade was fixed at one end using a steel frame secured by four bolts, subjected at the same time by three concrete columns. The tests were conducted in a climate-controlled chamber, maintaining a constant humidity of 60%, while temperature varied between -15°C and $+40^{\circ}\text{C}$. Experimental dynamic tests were carried out for measuring the different responses of the blade. The blade was excited using an electromechanical shaker, applying two types of excitations: (i) white noise signals with an effective frequency range of 0–400 Hz and (ii) sine sweeps with frequencies from 1 to 300 Hz. Noticeably, this pseudo-white noise was intended to mimic a scenario where operational modal analysis (OMA) techniques can be applied, as these require a broadband stationary excitation, usually referred to as “ambient” excitation. The laboratory setup included a total of eight PCB Piezotronics accelerometers ($\pm 10\text{ g}$ working range) and 21 strain gauges arranged unidirectionally and in form of rosettes, as shown in Figure 2. Two distinct strain gauges configurations were tested, each one indicated through Superscripts (1) and (2) in Figure 2, setting them along the different axes in each case.

Progressive damage was introduced into the blade in the form of cracks, induced as surface cuts, as outlined in Table 1.



FIGURE 1 | Summary of the experimental campaign elements: (a) blade inside the climate chamber; (b) climate controller; (c) electromechanical shaker; (d, e) strain gauges on the low- and high-pressure sides; (f) climate sensor; (g, h) introduced cracks [18].

Additionally, point masses were added to simulate icing loads; however, these are not considered in this analysis, as the primary focus is on structural damage. The healthy state is denoted as R , while damaged cases ($D-L$) correspond to increasing crack lengths and additional crack's introduction. Each crack had a uniform depth of 4 mm and width of 1.5 mm. In the healthy (undamaged) state, a total of 20 white noise tests and one sine sweep excitation performed, while each damage case was tested with one sine sweep and five white noise excitations, while temperature varied between -15°C and $+40^{\circ}\text{C}$ in 5°C increments for each case. Data were sampled at 1666.7 Hz in 2-min windows.

3 | Damage Detection Algorithm

The damage detection algorithm is an output-only, data-driven, semisupervised approach with four main steps following the collection of acceleration data from sensors installed along the structural element under monitoring: (i) feature extraction, (ii) feature modelling, (iii) feature fusion and (iv) feature discrimination and clustering, as schematised in Figure 3. The proposed algorithm builds upon the methods introduced in Meixedo et al.'s study [11] which relied exclusively on AR models, but significantly extending them to account for the interdependency of measured signals by employing MAR models for feature

extraction. This approach leverages the correlation between multiple signals (i.e., multiple sensors in the network of the installed monitoring system) to describe the behaviour of the system, detecting damage through variations in their correlation rather than changes in individual signal behaviour.

The MAR predicts the next value in a D -dimensional time series, y_i , as a linear combination of the N previous vector values. The model is expressed as follows:

$$y_i = \sum_{j=1}^N y_{i-j} A_j + e_i, \quad (1)$$

where D represents the number of sensors, N is the MAR model order, $y_i = [y_i^{(1)}, y_i^{(2)}, \dots, y_i^{(D)}]$ is the i -th sample of a D -dimensional time series, $A_j \in \mathbb{R}^{D \times D}$ are coefficient matrices capturing interdependencies between signals and e_i is the residual error vector. The coefficients A_j are estimated using the least-square method, minimising the residual error across all samples. In contrast, univariate AR models operate on scalar time series. In this case, each coefficient A_j reduces to a scalar a_j , and both y_i and e_i become scalar values, modelling only the temporal relationship within a single signal without accounting for cross-sensor interactions.

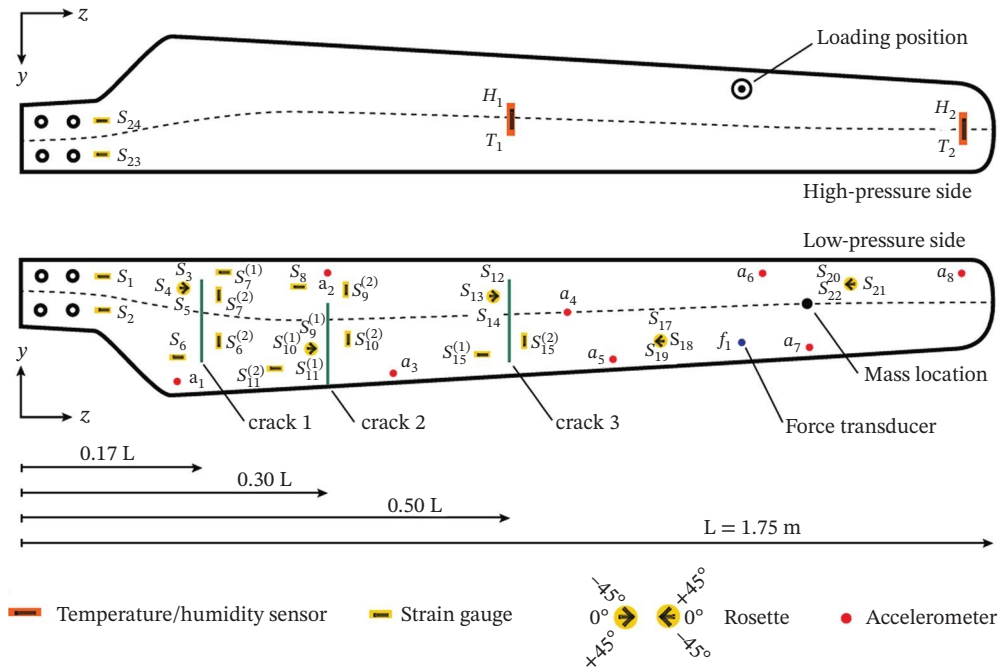


FIGURE 2 | Experimental setup of accelerometers and strain gauges on the tested blade [18].

TABLE 1 | Damage configuration tested by Ou et al. [18].

Case	Crack 1	Crack 2	Crack 3	# of experiments
R (Undamaged)	—	—	—	504 (20 WN + 1 SS)
D	5 cm	—	—	144 (5 WN + 1 SS)
E	5 cm	5 cm	—	144 (5 WN + 1 SS)
F	5 cm	5 cm	5 cm	144 (5 WN + 1 SS)
G	10 cm	5 cm	5 cm	144 (5 WN + 1 SS)
H	10 cm	10 cm	5 cm	144 (5 WN + 1 SS)
I	10 cm	10 cm	10 cm	144 (5 WN + 1 SS)
J	15 cm	10 cm	10 cm	144 (5 WN + 1 SS)
K	15 cm	15 cm	10 cm	144 (5 WN + 1 SS)
L	15 cm	15 cm	15 cm	144 (5 WN + 1 SS)

Abbreviations: SS = sine sweep and WN = white noise.

Environmental variability, such as changing wind and wave conditions, affects the structural response, demanding data normalisation. PCA addresses this by filtering environmental effects without requiring additional data. PCA transforms standardised feature space X into orthogonal principal components based on the covariance matrix C , retaining components that capture the desired variance threshold:

$$X' = XV_m, \quad (2)$$

where V_m contains the eigenvectors corresponding to the largest m eigenvalues, retaining a predefined variance threshold. To normalise the features, the first components associated with the environmental variability are removed [23]. This reduces false positives caused by environmental changes when applying the damage detection algorithm [24]. Nevertheless, the algorithm must still be trained with data covering a wide range of temperatures to ensure robustness.

Following normalisation, the MD quantifies deviations of each sensor's behaviour from the baseline condition. The MD for a sensor is defined as

$$MD_s = \sqrt{(x_s - \bar{x}) \cdot S_x^{-1} \cdot (x_s - \bar{x})^T}. \quad (3)$$

Here, x_s is the vector of features for a given sensor, and $\bar{x}$ and S_x are the mean vector and covariance matrix of baseline data, respectively. The MD values for all sensors are combined to compute the dissimilarity between simulations using the Euclidean distance:

$$dis_{ij} = \sqrt{\sum_{d=1}^D (MD_{s=i} - MD_{s=j})^2}. \quad (4)$$

The dissimilarity matrix serves as input for a K-means clustering algorithm, which partitions simulations into K clusters by minimising the intracluster dissimilarity:

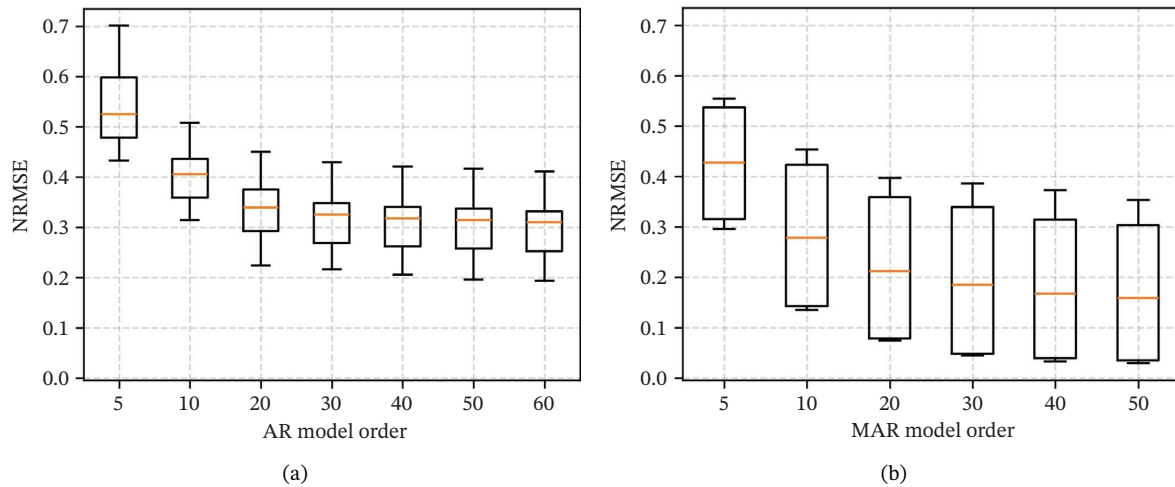


FIGURE 4 | Boxplots of NRMSE values using accelerometers for (a) AR model orders and (b) MAR model orders with two sensors.

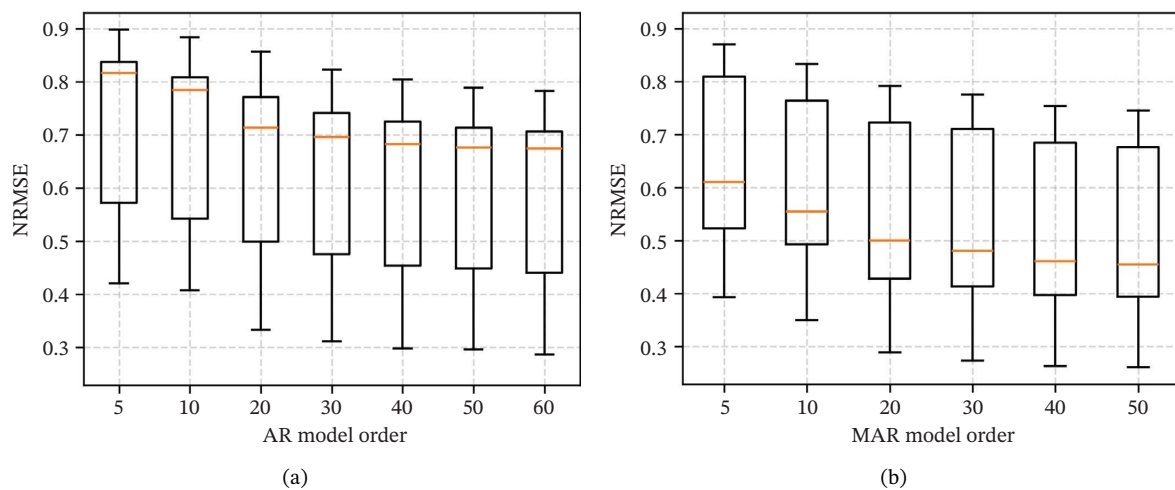


FIGURE 5 | Boxplots of NRMSE values using strain gauges for (a) AR model orders and (b) MAR model orders with two sensors.

that are often overlooked or attenuated in traditional OMA, which typically fails to resolve higher-order modes. Therefore, all results presented in this study are based on full-bandwidth signals sampled at 1666 Hz.

Although several methods for the selecting model order have been proposed in the literature—such as the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) or direct analysis of model errors [25]—no universally optimal method exists. These criteria primarily serve as heuristics to balance model accuracy with parsimony, aiming to minimise error while avoiding overfitting. Consequently, the selected model order may not correspond to the absolute best-performing solution for damage detection applications. Some attempts to overcome this issue have been presented in the literature [26, 27], but they still rely on a primary order selection based on AIC or NRMSE convergence. Since the primary goal of this paper is to evaluate the capabilities of the proposed methodology rather than to identify the optimal model order or the most informative features (a topic reserved for future work), the final choices are made based on trial and error based on the accuracy of the model and better algorithm's performance.

5 | Detectability

This subsection evaluates the detectability of progressive structural damage using time-series features derived from AR and MAR models applied to accelerometer and strain data. By analysing MD, dissimilarity measures and clustering performance, we assess the sensitivity of these features to different damage stages. Both single- and multisensor configurations are examined, with a focus on quantifying how model complexity and sensor redundancy affect the ability to detect and track evolving damage conditions. The training of the damage detection algorithm is made with 75% of the baseline data, while testing is made with the rest 25% together with samples from the new damage condition, with both stages incorporating samples across all temperature conditions in the range of -15°C to $+40^{\circ}\text{C}$.

5.1 | Damage Detection Based on One Sensor Measurements

Recent studies on the same benchmark dataset have explored deep learning-based approaches [19, 20, 28]. For instance, Z. Yang et al. [19] proposed a variational autoencoder with a neural ordinary differential equation, while Liu et al. [20]

employed neural extended Kalman filters. Although these methods achieved promising results, they require large sensor arrays and generally neglect environmental variability, such as temperature effects. Moreover, they primarily focus on detecting deviations from the initial undamaged state without addressing the progression of damage. In contrast, the transition-based MD analysis presented here provides a framework for detecting incremental damage stages with fewer sensors while maintaining sensitivity to structural changes.

For visualisation, one accelerometer (a_8) and one strain gauge (s_{13}) are selected for the subsequent figures. Results are later extended to all sensors to allow a comprehensive performance comparison. An offline comparison is performed in the first place. Figure 6 presents a boxplot of MD values for all damaged cases, using the undamaged condition R as a baseline. Figure 6 subplot (a) shows the results while using one accelerometer, while subplot (b) shows results using the single-strain gauge. In both cases, MD values generally increase as the level of damage in the blade structure progresses. The most pronounced increase occurs during the first damage transition $R \rightarrow D$, whereas subsequent transitions show more gradual rises. This trend indicates that the MD metric effectively captures progressive structural degradation, particularly when assessed relative to the initial undamaged state.

However, in practical scenarios, a damage detection algorithm aims to identify changes progressively. Therefore, each stage is assessed relative to its immediate predecessor rather than the original undamaged condition. This transition-based framework aligns more closely with real-time monitoring needs. Figure 7 shows MD values for each damage transition, using the preceding state as the baseline: subplot (a) corresponds to the accelerometer, and subplot (b) to the strain gauge. Black bars represent the baseline (previous) condition resulting MD values, while coloured bars indicate the new damaged state MD values.

Among the transitions, $J \rightarrow K$ —one of the final stages, where the crack at 30% of the blade length is enlarged to 15 cm—produces the highest indices, indicating the greatest detectability. By contrast, the early stages $R \rightarrow D$ and $E \rightarrow F$ (introducing 5 cm of cracks at 17% and 50% of the blade's length,

respectively) yield the lowest MDs, making them more challenging to detect with both sensor types. For both sensors, the closest crack is located at 50% of the blade length, yet the associated damage scenarios ($E \rightarrow F$, $H \rightarrow I$ and $K \rightarrow L$) are not consistently easier to detect. This suggests that detectability is influenced more by the severity and progression of the damage, as well as experimental factors, than by simple proximity to the sensor.

The dissimilarity data exhibited an exponential trend and, consequently, was logarithmically scaled before being used as input for K-means clustering. The results, presented in Figure 8, show clear separation between two clusters corresponding to pre- and postdamage transition conditions: (a) for the accelerometer and (b) for the strain gauge. This indicates that even a single sensor—accelerometer or strain gauge—provide sufficient information to distinguish structural states. Similar performance was observed across other one-sensor configurations (not shown for brevity), highlighting the effectiveness of the approach even with minimal sensing.

Mean specificity (E) and sensitivity (S), which are the probabilities of correctly identifying negative and positive cases, were computed over 20 random trials for AR-40 models using 25% test data from a single sensor at various locations. For clarity, Figures 9 and 10 present the equivalent false positive rate ($1-E$) and false negative rate ($1-S$) for the accelerometers and strain gauges, respectively.

Accelerometer results show consistent detection of structural transitions, with only minor false positives during the $D \rightarrow E$ and $E \rightarrow F$ stages (approximately 10%-11% error in both $1-S$ and $1-E$), which is consistent with the low detectability observed in Figure 7. In contrast, strain gauge results show more frequent misclassifications, particularly for transitions $D \rightarrow E$, $E \rightarrow F$ and $H \rightarrow I$, with errors reaching up to 37% for $1-S$ and 30% for $1-E$.

Strain gauge performance also exhibits a strong dependence on sensor placement: gauges located near the blade root yield poorer results, whereas those positioned farther away achieve more reliable detection. This trend may be explained by the larger

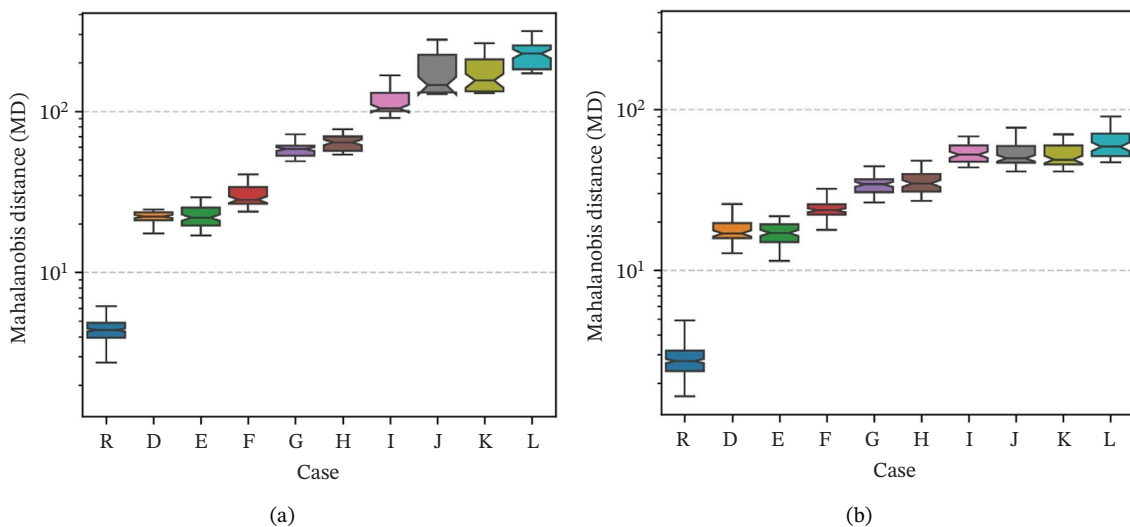


FIGURE 6 | Boxplot of the MD values across all damage cases using AR-40 models for (a) accelerometer a_8 and (b) strain gauge s_{13} .

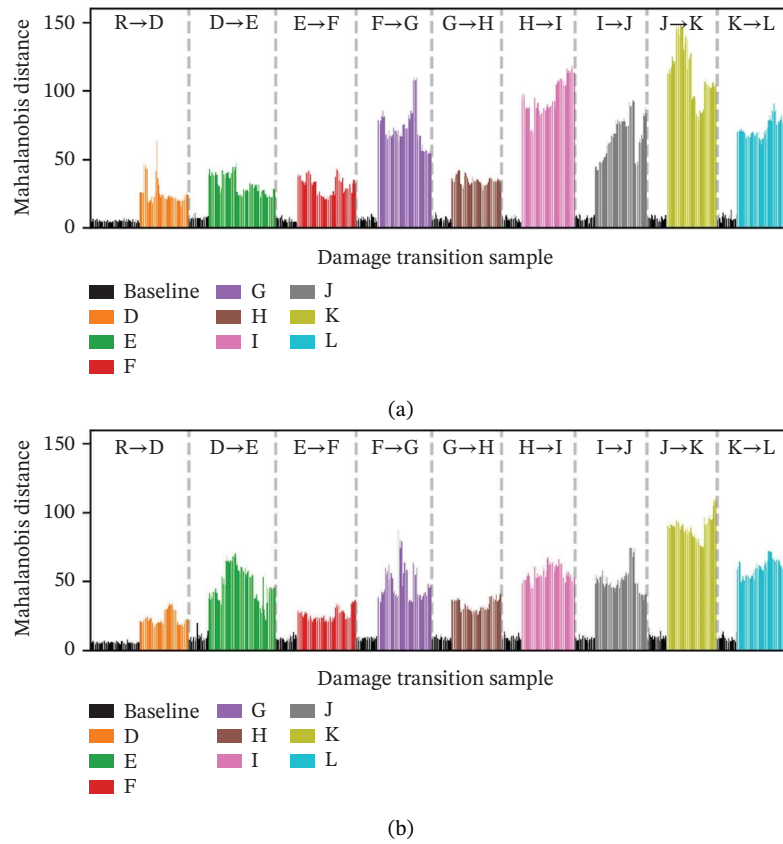


FIGURE 7 | Mahalanobis distance across damage stage transitions using AR-40 models for (a) accelerometer a_8 and (b) strain gauge s_{13} .

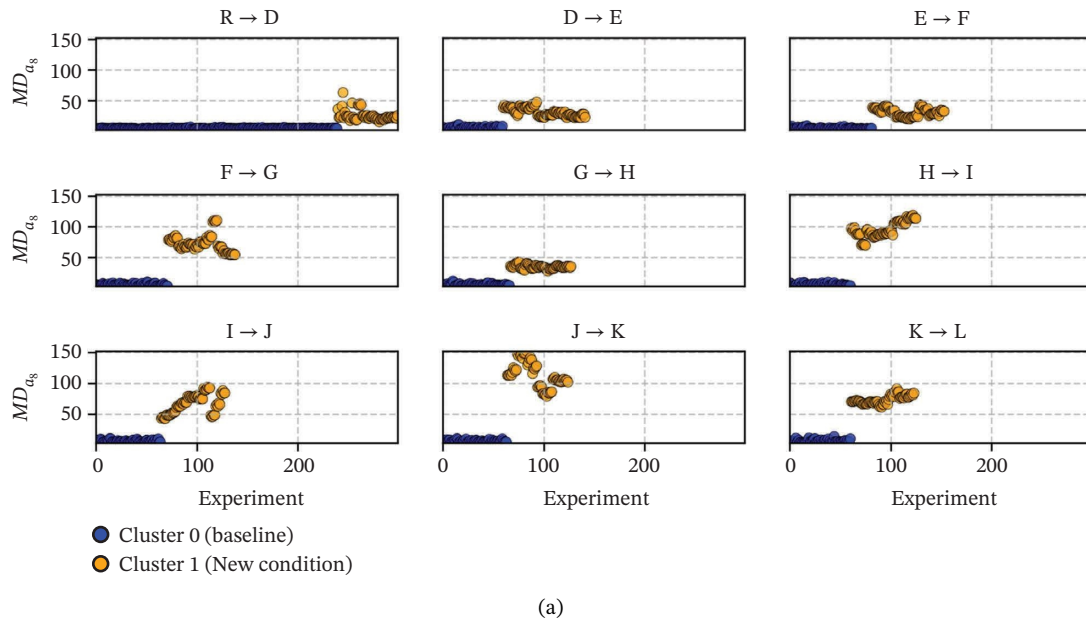


FIGURE 8 | (Continued)

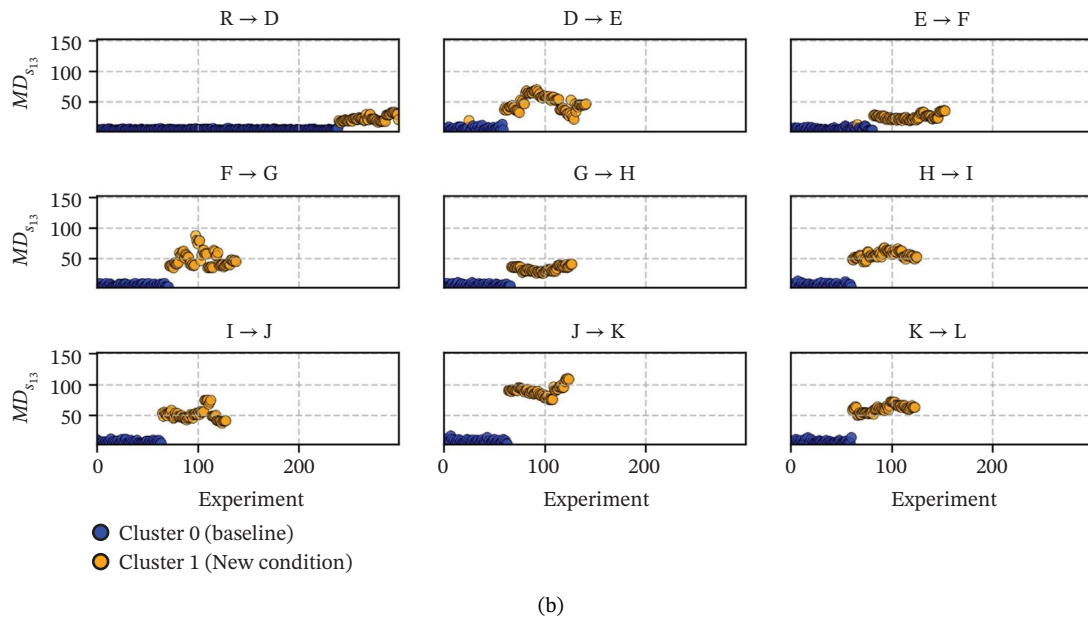


FIGURE 8 | Clustering performance of *K*-means using AR-40 models for (a) accelerometer a_8 and (b) strain gauge s_{13} .

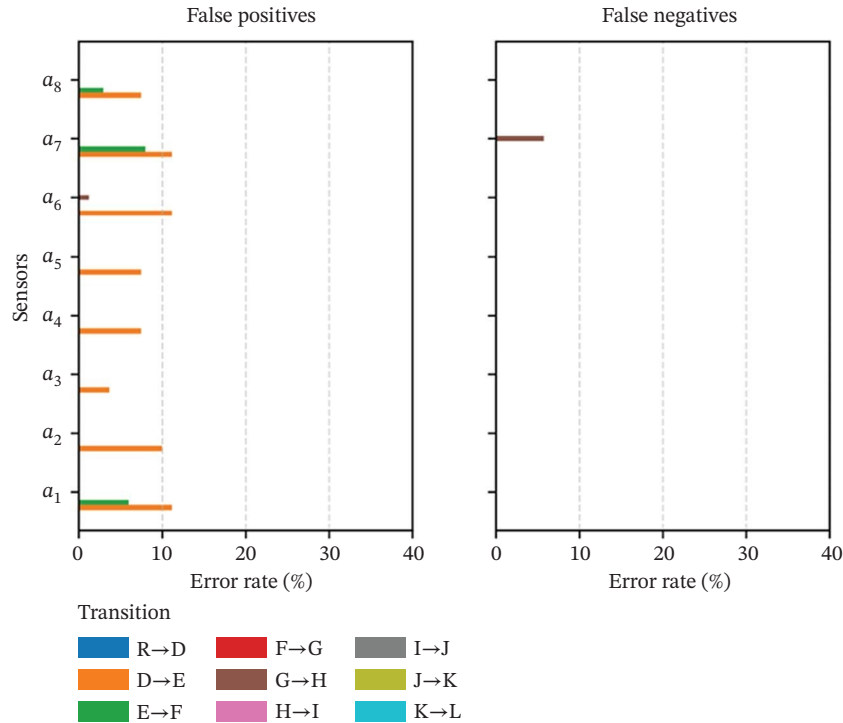


FIGURE 9 | False positive (1-E) and false negative (1-S) rates across the structural condition transitions using a single accelerometer with AR-40 models.

deformations occurring farther from the root, which make structural changes more pronounced and thus easier to detect.

5.2 | Two-Sensor Analysis

The algorithm's performance is next evaluated using two arbitrarily selected sensors. Figure 11 compares the MDs computed from AR-40 to MAR-40 models for accelerometers a_1 and a_8 . The MAR model produces MD higher values than

those from the AR model—up to 600% higher during the $J \rightarrow K$ transition (enlargement of the crack at 30% of the blade length to 15 cm) and up to 700% higher in early transitions such as $E \rightarrow F$ with first incorporations of cracks. These results highlight the improved feature quality achieved by incorporating intersensor correlations. For accelerometers, this demonstrates that exploiting correlations between multiple sensors substantially enhances the detectability of structural transitions.

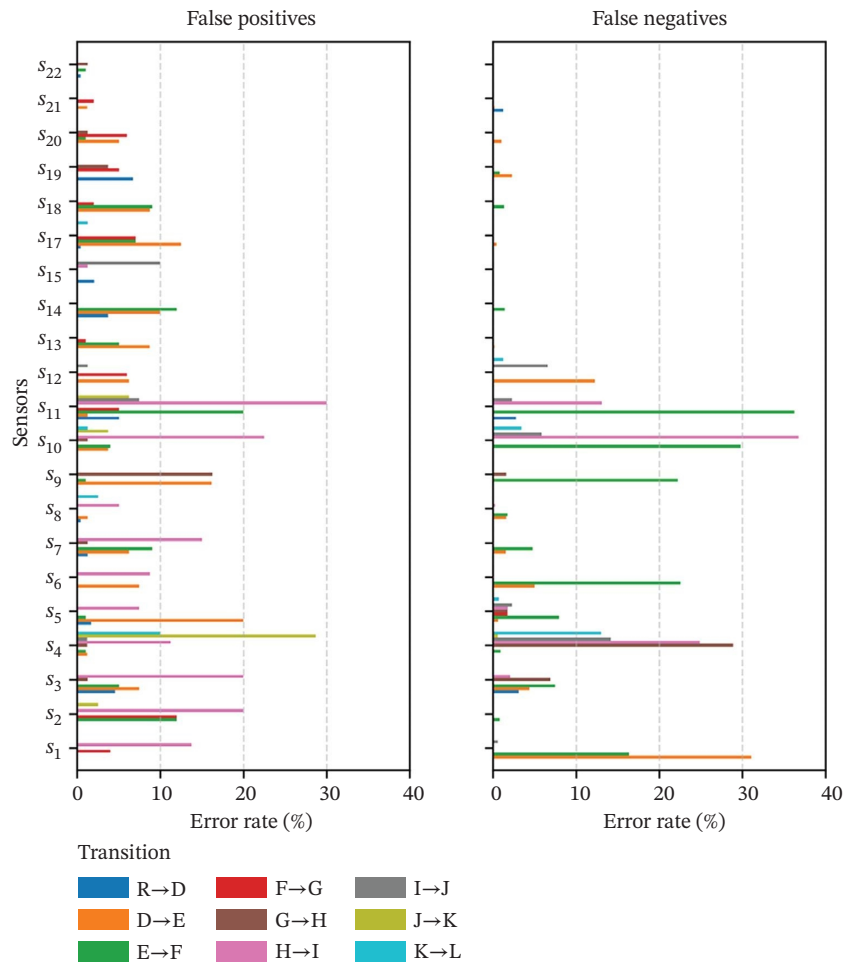


FIGURE 10 | False positive (1-E) and false negative (1-S) rates across structural condition transitions using a single-strain gauge with AR-40 models.

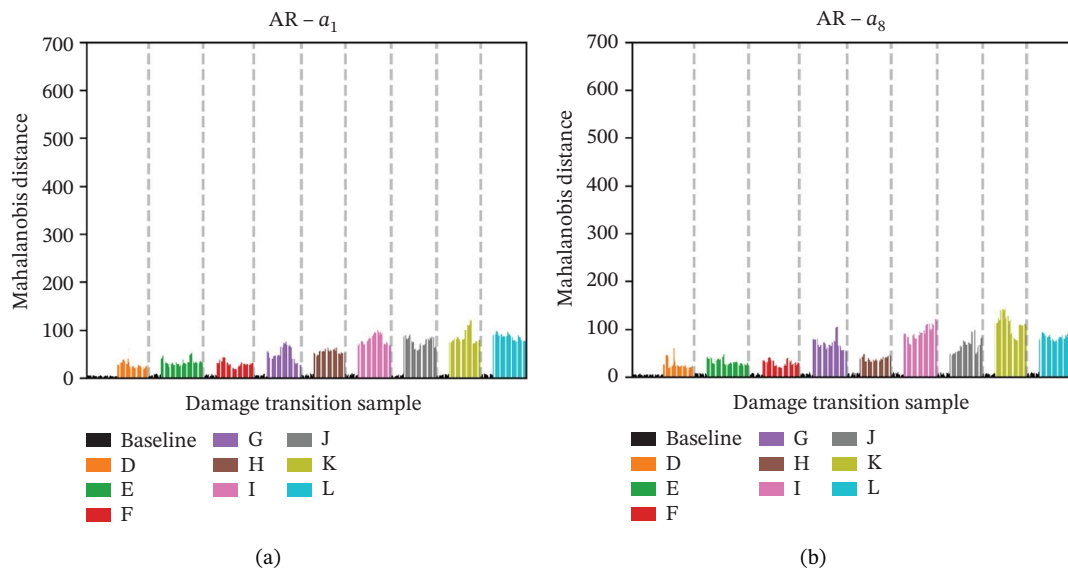


FIGURE 11 | (Continued)

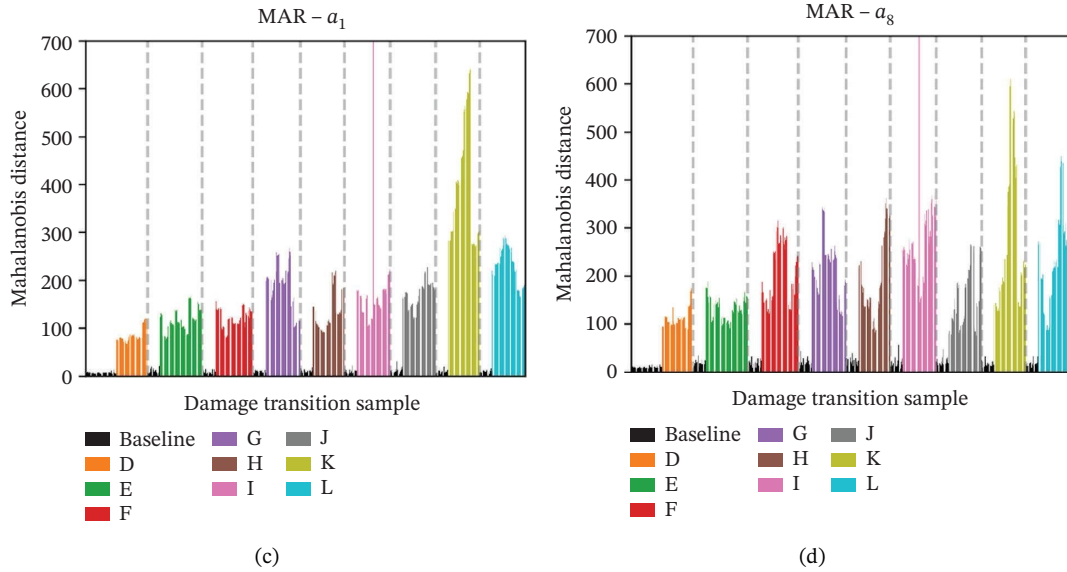


FIGURE 11 | Mahalanobis distances between consecutive structural conditions for (a) AR-40 with accelerometer a_1 , (b) AR-40 with accelerometer a_8 , (c) MAR-40 with accelerometer a_1 and (d) MAR-40 with accelerometer a_8 .

Figure 12 presents MDs computed using AR-40 and MAR-20 models for strain gauges s_4 and s_{13} . Unlike the accelerometer case, the MAR model does not significantly improve feature quality for strain gauges (excepting transition $F \rightarrow G$ for sensor s_{13} , by 500%). This suggests that intersensor correlations among strain gauges are less informative, likely because these sensors capture more localised strain effects compared to the broader vibration patterns (i.e., global dynamic) detected by accelerometers. This observation is further discussed in the following sections.

The improvement in feature quality is quantified using the change in mean dissimilarity of the experiments across damage stages, defined as

$$\Delta \overline{\text{dis}} = \overline{\text{dis}}^{(z)} - \overline{\text{dis}}^{(z-1)}, \quad (7)$$

where $z \in \{R, D, E, \dots, L\}$ denotes the structural condition. In this formulation, transitions are penalised when the MD values for the baseline condition are inflated, thus enhancing the robustness of the indicator.

The mean dissimilarity change $\Delta \overline{\text{dis}}$ across transitions is shown in Figure 13(a) for two accelerometers and Figure 13(b) for two strain gauges, comparing AR and MAR models. This provides a more compact representation of the behaviours observed in Figures 11 and 12. For accelerometers, the MAR model consistently produces larger dissimilarity changes, indicating that incorporating intersensor correlations improve feature quality and enhances discrimination of structural transitions. Because similar levels of new damage are introduced at each stage, comparable differences between transitions would be expected; deviations from this trend likely reflect experimental variability.

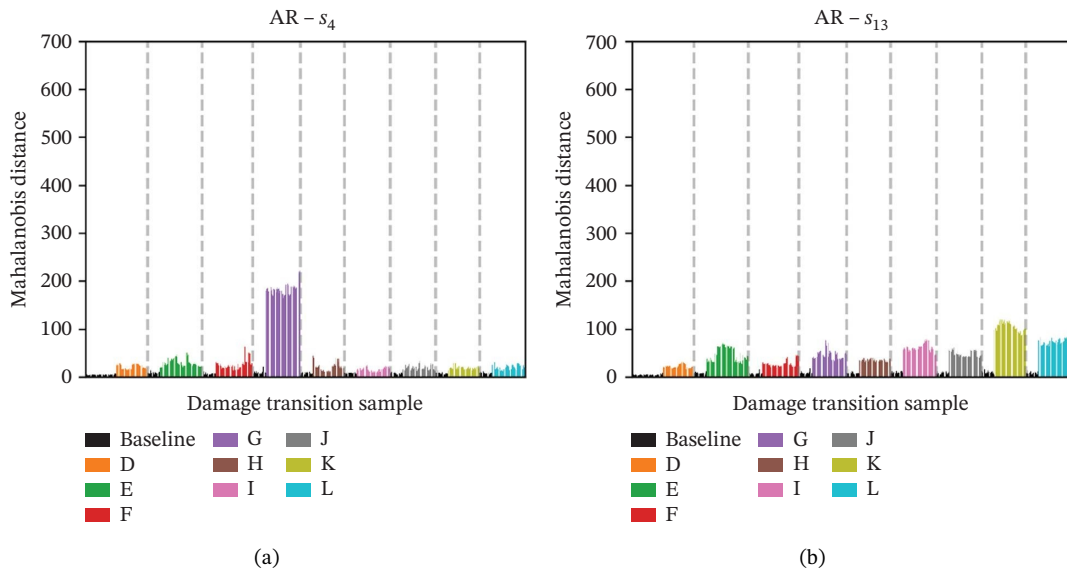


FIGURE 12 | (Continued)

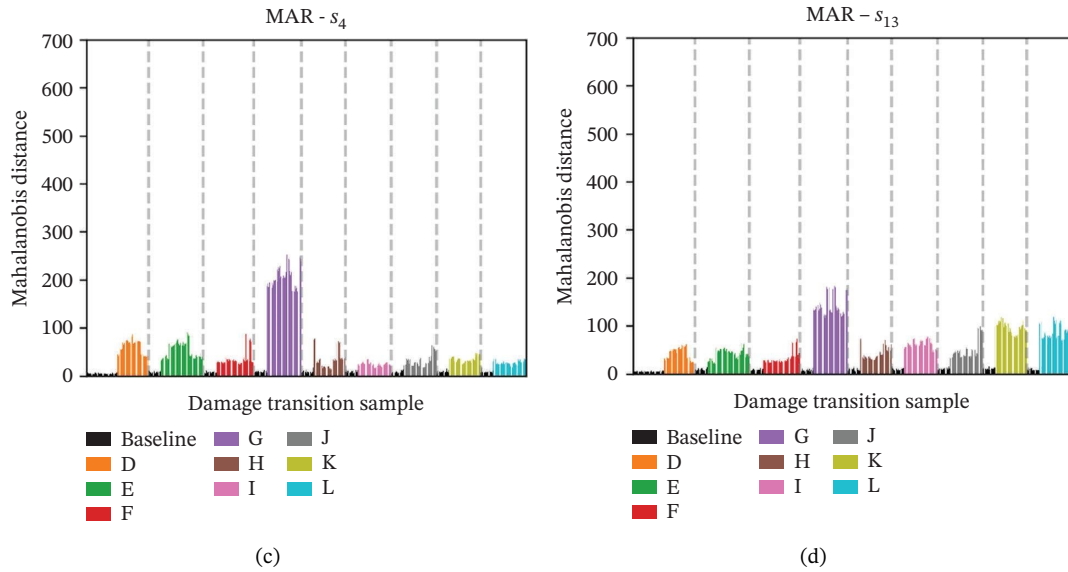


FIGURE 12 | Mahalanobis distances between consecutive structural conditions for (a) AR-40 with strain gauge s_4 , (b) AR-40 with strain gauge s_{13} , (c) MAR-20 with strain gauge s_4 and (d) MAR-20 with strain gauge s_{13} .

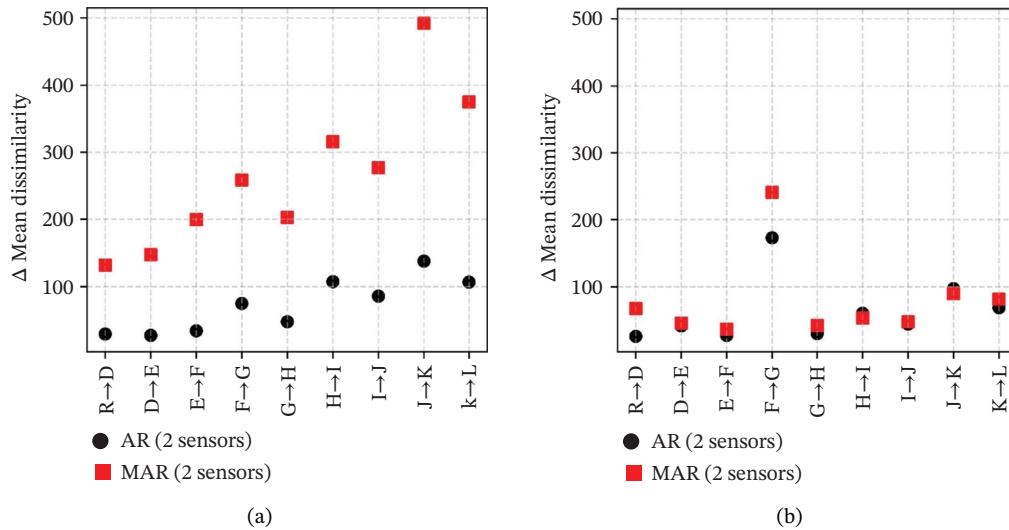


FIGURE 13 | Change in mean dissimilarity for each structural transition, comparing results from (a) AR-40 and MAR-40 models with accelerometers a_1 and a_8 and (b) AR-40 and MAR-20 models with strain gauges s_4 and s_{13} .

Nevertheless, the overall pattern supports the robustness of the dissimilarity metric. In contrast, the strain-gauge data show no clear trend to suggest that incorporating correlation information improves detectability within the algorithm.

5.3 | Dissimilarity vs. Number of Sensors

To investigate the influence of the sensor count on performance, Figure 14 presents the evaluation of Δdis for AR and MAR models, as additional sensors are included: (a) accelerometers and (b) strain gauges. In the MAR models, the total number of features is fixed at 80 for accelerometers and 40 for strain gauges, regardless of the sensor count. Each boxplot contains nine data points, corresponding to the values for each transition shown in Figure 13 for the two-sensor case. For consistency, the same

sensor combinations are used for both MAR and AR models; results may vary slightly with different combinations.

As shown in Figure 14, the mean dissimilarity increases with the addition of sensors for both models, but performance tends to plateau after 5-6 sensors in both scenarios (accelerometers and strain gauges), indicating diminishing returns in feature quality beyond this point. For accelerometers, MAR models consistently outperform univariate models when using two or more sensors. In contrast, for strain gauges, no clear trend is observed—while MAR models show a slight performance gain with 2–12 sensors; the difference is not statistically significant. This plateau suggests that, in practical terms, deploying more than six sensors may offer limited diagnostic benefit relative to the added cost and complexity for damage detection in the analysed structure.

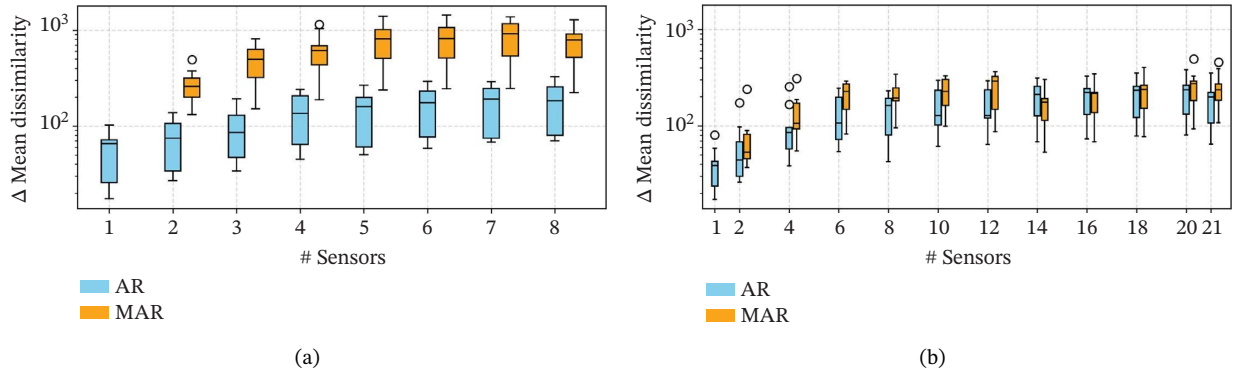


FIGURE 14 | Boxplots of $\Delta \overline{\text{dis}}$ for AR-40 and MAR models across different numbers of sensors: (a) accelerometers and (b) strain gauges.

6 | Locatability

This section examines the ability to localise structural damage using acceleration and strain gauge measurements from sensors distributed along the blade. MD values derived from AR and MAR models are analysed to determine whether the spatial distribution of damage can be inferred from sensor responses. Comparisons between model types and sensing modalities identify configurations that support accurate localisation across different damage transitions. For this analysis, all sensors along the blade are used to perform localisation. While the results from AR models can be directly extrapolated to other sensor combinations due to their independence, the localisation capability of MAR models may vary with the number of sensors employed.

To evaluate the contribution of each sensor to damage detection across different damage stages, we compute the change in MD values between a damaged condition and its corresponding baseline (or previous condition) using the Fisher criterion [29], as applied in Mosavi et al. [16]. This approach allows the locatability of damage signals to be assessed at the sensor level.

For each damage stage z , and each sensor i , the Fisher criterion $FC_i^{(z)}$ is computed as

$$FC_i^{(z)} = \frac{(m_i^{(z)} - m_i^{(z-1)})^2}{\sigma_i^{(z)^2} + \sigma_i^{(z-1)^2}}, \quad (8)$$

where

- $m_i^{(z)}$ and $m_i^{(z-1)}$ are the means of the MD value for sensor i under the damaged condition at stages z and $z-1$, respectively.
- $\sigma_i^{(z)}$ and $\sigma_i^{(z-1)}$ are the corresponding standard deviations.

This metric quantifies the increase in anomaly indication for each sensor due to the damage progression. High values of $FC_i^{(z)}$ suggest that sensor i is sensitive to the damage introduced in Stage z , hence contributing potentially to its localisation.

6.1 | Accelerometers

Figure 15 presents heatmaps of FC values obtained from accelerometers placed along the blade for each damage transition, with the red line marking the location of newly introduced damage (i.e., cracks). Results from AR-40 and MAR-10 models are shown, alongside a quantitative summary in Table 2. For

direct comparison with the following section, the heatmap colour scale is held invariable.

From Figure 15, it can be observed that the highest FC values do not consistently correspond to sensors located near the actual damage, indicating limited localisation capability when relying solely on acceleration data. While certain damage transitions, such as $D \rightarrow E$ and $K \rightarrow L$, show higher FC values for sensors close to the damage, no clear pattern emerges. This limitation is likely due to the global response characteristics of acceleration signals.

These findings contrast with those of Mosavi et al. [16], who reported higher FC values for sensors close to the damage when applying multivariate models to accelerate data from a laboratory-tested beam, also using the Fisher criterion. It should be noted, however, that the analysed systems differ substantially: The composite blade exhibits nonlinear and complex behaviour, whereas the beam used in Mosavi et al's study is made from a mostly linear steel material.

6.2 | Strain Gauges

To assess whether more localised measurements can improve damage localisation, the analysis was repeated using strain gauge data. Figure 16 presents heatmaps of FC values obtained from AR-40 and MAR-2 models. The red line marks the new damage location for each damage transition. Table 3 summarises the maximum FC values and corresponding sensors.

As observed, strain-gauge data yield superior localisation performance, with lighter colours appearing closest to the damage site on the heatmaps, indicating higher FC values. This confirms that strain gauges provide a more direct mapping of damage locations than accelerometers, as sensors positioned near the damage consistently register the highest FC values. The results also highlight that the effectiveness of strain gauges depends on their placement relative to the damage site, offering valuable insight for the future sensor network design.

While damage transitions with lower detectability—such as $R \rightarrow D$ and $E \rightarrow F$ —produce lower FC values, localisation accuracy is not compromised. In terms of model comparison, MAR models do not substantially improve localisation in this scenario, likely because the high spatial resolution of strain-gauge measurements already provides sufficient information, leaving little added value from multivariate correlations. Nevertheless, MAR models demonstrate greater robustness, as seen in the $J \rightarrow K$ transition, where AR models fail to identify the damage location.

TABLE 2 | Sensor-wise FC per damage stage using accelerometers with AR-40 and MAR-10 models.

Transition	AR-40 models		MAR-10 models	
	Max FC	Sensor with max FC	Max FC	Sensor with max FC
R $\rightarrow$ D	24.5	a_4	21.0	a_2
D $\rightarrow$ E	48.7	a_3	42.0	a_3
E $\rightarrow$ F	41.4	a_3	48.2	a_6
F $\rightarrow$ G	40.8	a_4	27.4	a_2
G $\rightarrow$ H	70.3	a_1	35.7	a_5
H $\rightarrow$ I	54.1	a_2	7.7	a_3
I $\rightarrow$ J	70.6	a_1	40.6	a_3
J $\rightarrow$ K	127.3	a_2	45.3	a_1
K $\rightarrow$ L	83.3	a_6	107.8	a_4

7 | Discussion

Based on the results of this study, several key findings and implications for future research can be identified. Regarding the detectability of damage using both MAR and AR models, and with both accelerometers and strain gauges, the main findings are as follows:

1. The proposed algorithm detects damage using both acceleration and strain gauge data from the studied dataset, and a single sensor is sufficient to capture all investigated damage transitions, demonstrating efficiency with minimal instrumentation.
2. Across all examined scenarios, accelerometers show greater robustness for damage detection than strain gauges, achieving the lowest false positive and false negative rates when using a single sensor, and the highest MD values when multiple sensors are deployed in the blade's detection network.
3. Increasing the number of accelerometers enhances the accuracy and robustness of detection by providing richer dynamic information from across the structure, although beyond six sensors, the benefits diminish due to redundancy.

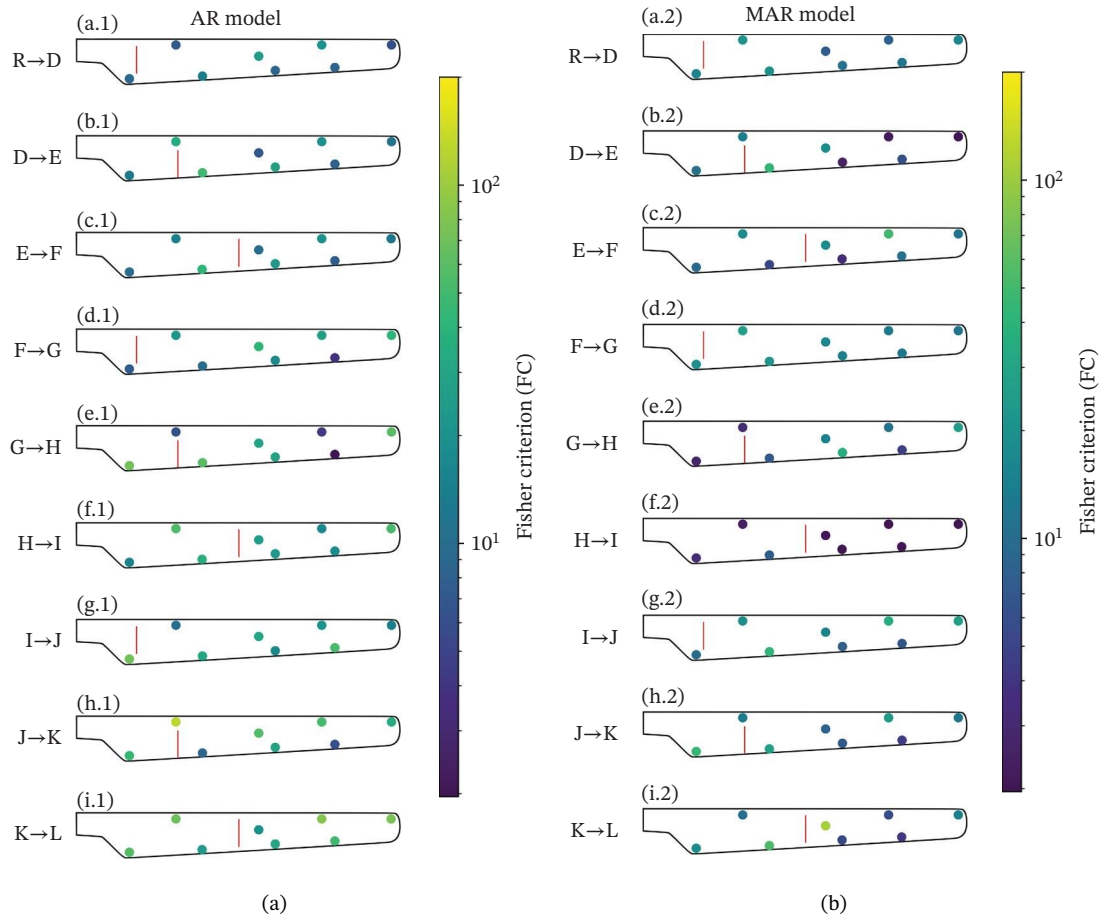
**FIGURE 15** | Heatmaps of FC values along the blade using accelerometer measurements, with (a.1)-(i.1) showing AR-40 model results in the left column and (a.2)-(i.2) MAR-10 models in the right column. The red line marks the new damage location for each damage transition.

TABLE 3 | Sensor-wise FC per damage stage using strain gauges with AR-40 and MAR-2 models.

Transition	AR-40 models		MAR models	
	Max FC	Sensor with max FC	Max FC	Sensor with max FC
R $\rightarrow$ D	60.5	s_5	41.4	s_6
D $\rightarrow$ E	127.1	s_{11}	83.1	s_{11}
E $\rightarrow$ F	21.5	s_{15}	42.1	s_{15}
F $\rightarrow$ G	367.7	s_4	389.3	s_3
G $\rightarrow$ H	93.9	s_9	203.3	s_9
H $\rightarrow$ I	321.6	s_{14}	373.4	s_{14}
I $\rightarrow$ J	179.2	s_6	152.5	s_6
J $\rightarrow$ K	603.1	s_{21}	189.2	s_8
K $\rightarrow$ L	432.9	s_{15}	246.6	s_{15}

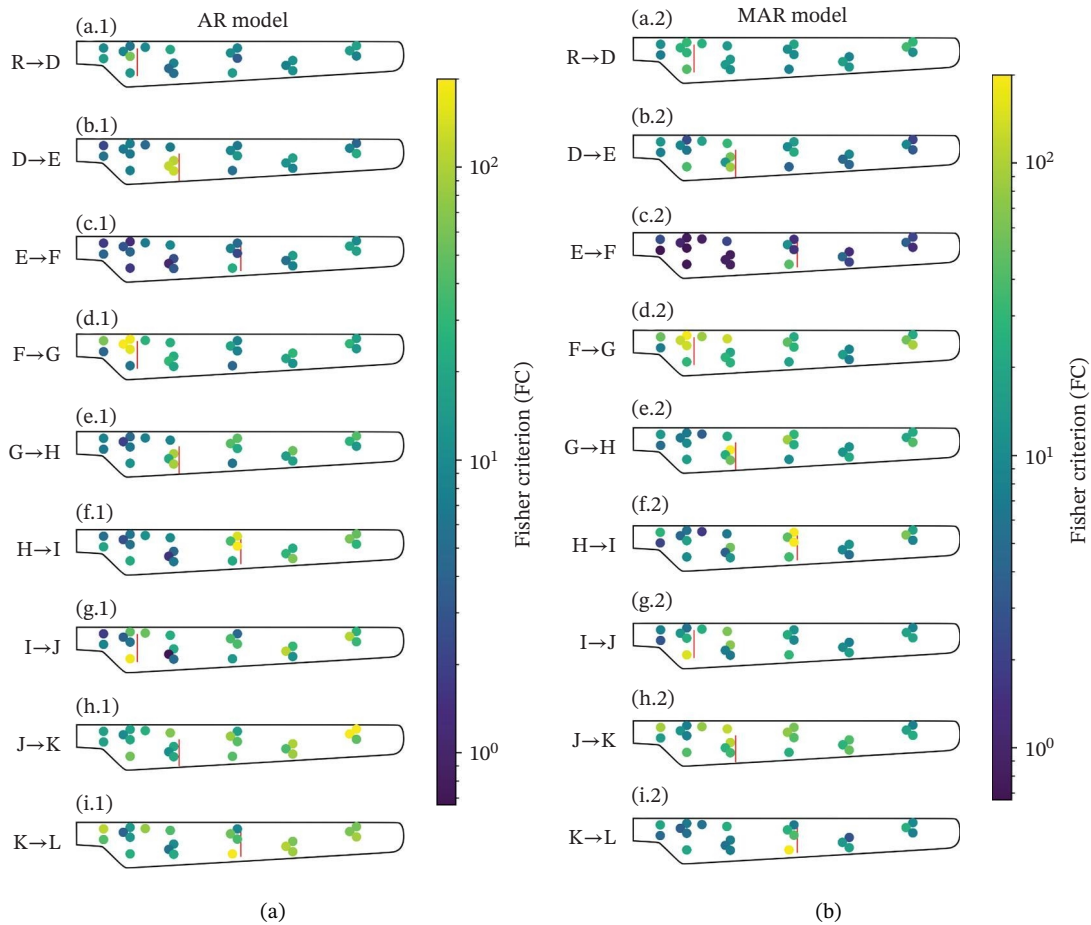


FIGURE 16 | Heatmap of FC values along the blade using strain gauge measurements, with (a.1)-(i.1) showing AR-40 model results in the left column and (a.2)-(i.2) MAR-2 models in the right column. The red line marks the new damage location for each damage transition.

4. MAR models outperform univariate AR models when two or more accelerometers are used, indicating that incorporating spatial correlations between sensors improves feature quality and sensitivity to damage, whereas for strain gauges, MAR models provide no significant improvement over AR.
1. Strain-based Fisher criterion values exhibit a strong correlation with damage location, highlighting their potential for accurate spatial localisation of anomalies. Acceleration data, by contrast, show weaker direct correlation with location, likely because accelerations capture the global dynamic response, whereas strains are more sensitive to localised deformations in composite blades.

In contrast, for the locatability of damage, the following conclusions can be drawn:

2. MAR models do not substantially enhance localisation accuracy for either accelerometers or strain gauges, although they may improve robustness in certain scenarios.

8 | Conclusions

This study presented a semisupervised, data-driven framework for SHM of a small-scale composite wind turbine blade subjected to progressive damage and varying temperatures. The methodology combined MAR modelling, PCA, MD metrics and *K*-means clustering and was tested using two sensor types: accelerometers and strain gauges. Experimental data from a blade with sequentially introduced cracks at multiple locations served as the basis for validating the proposed damage detection and localisation approach.

The detectability analysis confirms that both AR and MAR models, particularly when applied to accelerometer data, provide robust indicators of structural degradation. Single-sensor AR models already capture early damage transitions, although with limited sensitivity at initial stages. In contrast, two-sensor MAR models significantly enhance detectability by leveraging inter-sensor correlations, resulting in higher MDs and clearer dissimilarity changes across damage transitions. These findings suggest that a minimal yet strategically placed sensor array can achieve high sensitivity to damage the progression, offering a balanced trade-off between performance and instrumentation cost—supporting the feasibility of lightweight, output-only SHM solutions for in-service monitoring.

The results also indicate that while MAR models improve damage detectability, the capacity for damage localisation is more dependent on the type of measurement. Accelerometers, which reflect global structural dynamics, offer limited spatial resolution, making it difficult to pinpoint damage locations. In contrast, strain gauges, more sensitive to local deformation, enable a clearer spatial correlation between the damage and sensor response. Notably, the use of MAR models does not significantly improve localisation when applied to strain data, suggesting that strain-based AR models already provide sufficient fidelity for this purpose. These insights underscore the critical role of sensor modality in the SHM design, especially when localisation is a key monitoring objective.

Therefore, for detectability aims, the selection of accelerometers using MAR models should be the best option, while for localisation, using strain gauges with AR models provide acceptable results. Thus, a combination of those sensor types provides relevant information of the system's health. For detectability specifically, if strain gauges are preferred, farther positions from the blade root might be more suitable, while similar performance is expected using accelerometers over the blade.

Building on the insights from this study, future research should address several remaining challenges and opportunities. First, the maximum effective distance between a sensor and the damage site for reliable localisation remains uncertain, particularly for strain gauges, whose performance is highly dependent on placement—knowledge that could directly guide the optimisation of future sensor network designs. Second, although the optimal selection of AR coefficients has been investigated in the literature (e.g., Hoell and Omenzetter [26]), its targeted evaluation for

damage-detection applications warrants further exploration. Finally, extending the proposed methodology to full-scale WTBs operating under realistic and variable environmental and operational conditions would provide valuable validation. Such work could also integrate additional environmental variables—including humidity, loading history and rotational speed—and assess a broader spectrum of damage types, thereby strengthening the robustness, adaptability and real-world applicability of the approach. Advancing these research directions would not only refine the methodology itself but also contribute to the development of more resilient, efficient and scalable SHM systems for the next-generation of offshore wind energy infrastructure.

Author Contributions

Maria E. Quiroz: writing-review and editing, writing-original draft, visualisation, validation, software, methodology, investigation, formal analysis, data curation and conceptualisation. Eshwar Kuncham: writing-review and editing. Sathiskumar A. Ponnusami: writing-review and editing. Miguel A. Bravo-Haro: writing-review and editing, validation, supervision, resources, methodology and conceptualisation.

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Disclosure

Any opinions, findings, conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect those of the sponsors.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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