Enhancing the Reliability of Structural Health Monitoring for Bolted Joint Connections in Segmented Rotor Blades Using Data Fusion

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ABSTRACT

In the wind energy sector, the use of segmented rotor blades poses challenges for Structural Health Monitoring (SHM) systems due to the increasing high loads that can damage bolted joints. This paper investigates the potential of data fusion to improve the reliability of SHM systems for bolt connections in segmented rotor blades. Three CFRP structures with bolted joints are examined and monitored using both piezoelectric and electrical strain gauge sensors. A passive low-frequency monitoring system is built using strain measurements and neural networks to model the relations between measurement data. An additional active high-frequency monitoring system is designed using piezoelectric sensors and guided waves in combination with a subsequent principal components analysis. The results show that the data fusion system successfully detected the damages with an accurate damage occurrence probability prediction even if one monitoring system provided unreliable predictions. By combining two independent monitoring systems that complementarily cover different frequency bands, the data fusion system improved the reliability of the monitoring task and reduced the occurrence of false positive alarms. The approach presented in this study can also be applied to other monitoring systems in various industries, further expanding the impact of the research.

INTRODUCTION

Data fusion is a powerful approach that integrates different data types to gain deeper insights from combined data sets, rather than analyzing them in isolation [1]. In structural health monitoring (SHM), data fusion is used to improve decision-making in evaluating structural health. It reduces uncertainty by augmenting information completeness through synergistic integration of diverse data sources. Data fusion can occur at different levels: data-level, feature-level, and decision-level [2]. Previous studies have applied data fusion in SHM using various sensor systems, such as piezoelectric transducers, op-

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tical fibers, acoustic emission, and digital image correlation [3–6].
In this study, data integration is used to enhance damage detection certainty in joint bolted connections of segmented rotor blades. Composite rotor blades with bolt connections are prone to various types of damage, which can reduce the economic efficiency of wind turbines. To obtain complementary information, strain gauge sensors monitor low-frequency variations, while piezoelectric sensors monitor high-frequency variations, covering different frequency ranges. Strain measurements are effective in providing a local assessment and suitable for detecting fatigue cracks and delamination. However, they may not be optimal for detecting internal or small-scale damages and can be sensitive to environmental, electrical, and mechanical factors, leading to false positive alarms. On the other hand, guided waves are more sensitive to different types of damages, including hidden ones, and can cover a large monitoring area, complementing the limitations of strain measurements and reducing false positive alarms. Decision-level fusion is applied by linearly combining the indices obtained from both monitoring systems, considering their heterogeneity. This integrated approach enhances the robustness of the monitoring system for rotor blades and reduces maintenance requirements during operation.

THEORETICAL BACKGROUND

Damage detection using Neural Networks

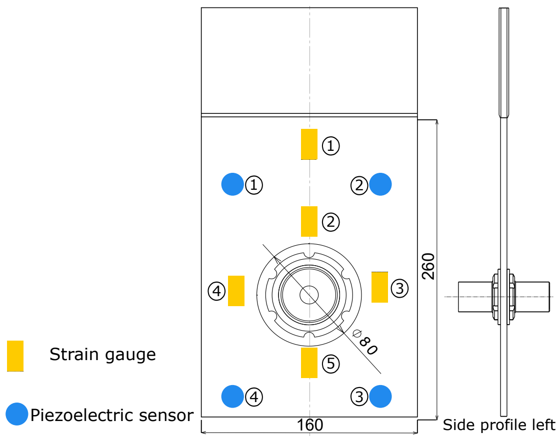
Neural Networks (NNs) are models in machine learning that can be used to model relations between the data points of two or more time series. They consist of interconnected neurons organized in layers and can be trained on labeled data to learn patterns. The relations between two time series, denoted as S_i and S_j, can be modeled using a NN by determining a function f such as $\hat{s}_i(t) = f(s_j(t))$, where $\hat{s}_i(t)$ is the predicted value of $s_i(t)$ using $s_j(t)$ and f is determined using a NN trained on measurements from the intact structure. Changes in the relations between n sensor pairs can be detected by monitoring the prediction error, calculated as

$$\epsilon_i = \frac{1}{n} \sum_{i=1}^{n} |\hat{s}_i(t) - s_i(t)| \tag{1}$$

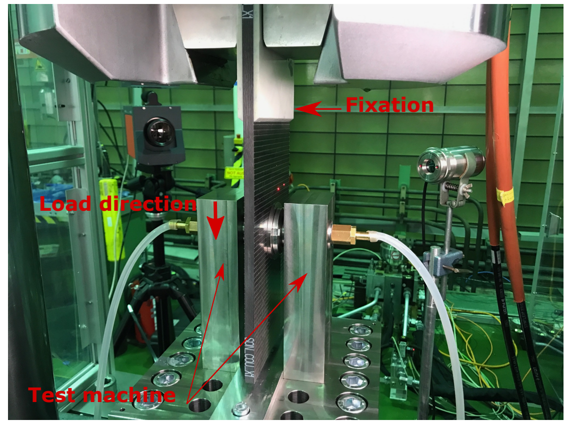
which can serve as a damage indicator.

Damage detection using Q-Index

Principal Component Analysis (PCA) is a statistical approach used for reducing the dimensionality of multivariate data while preservinginformation [5]. It involves transforming a normalized input matrix X $(n \times l)$ into a reduced matrix T $(n \times \tilde{l})$ using the loading matrix $\tilde{P}$ $(l \times \tilde{l})$, which contains $\tilde{l}$ orthogonal vectors called principal components. The reduced input space T can be obtained by multiplying X with $\tilde{P}$ as $T = X\tilde{P}$, where $\tilde{l}$ represents the desired reduced dimensionality. The loading matrix $\tilde{P}$ can be obtained from the eigenvectors of the covariance matrix Σ of X, where Σ is calculated as $\Sigma = \frac{1}{n} X^T X = PEP^T$, with P being the complete eigenvector matrix and E being a diagonal matrix with eigenvalues as diagonal elements.



(a) Instrumentation plan of the bolted joint.



(b) Photograph of a coupon mounted on the test machine.

Figure 1: Experimental setup for the static coupon tests.

The reconstructed data $\tilde{X}$ can be obtained from T and $\tilde{P}$ as $\tilde{X} = T\tilde{P}^T$. Changes in the data properties lead to changes in the principal components and thus to an increased reconstruction error. The Q-index is a measure of the residual or difference between the original sample and its reproduction from the reduced space. It can be calculated as

$$Q_i = \|e_i\|^2 = x_i(I - \tilde{P}\tilde{P}^T)x_i^T \tag{2}$$

where $e_i = (x_i - x_i\tilde{P}\tilde{P}^T)$ is the residual vector, I the identity matrix, and $\tilde{P}$ the loading matrix calculated by using measurements from the intact structure. Careful consideration of $\tilde{l}$ is important to ensure minimal information loss and avoid noise effects [5].

Fusion of damage indices

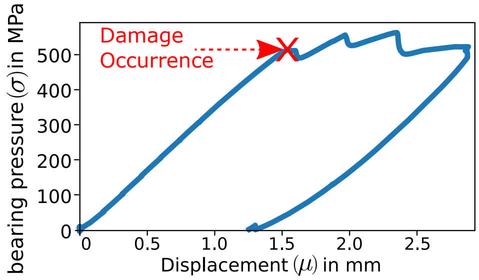
The first step in predicting the state of the structure is to map the damage indices (Q and ϵ) to a probability between 0 and 1, where 0 indicating intact and 1 indicating damaged. This is done by defining the probability P_i for each monitoring system by:

$$P_i(x) = \begin{cases} 0 & \text{if } x \leq a \\ \frac{x-a}{b-a} & \text{if } a < x < b \\ 1 & \text{if } x \geq b \end{cases} \tag{3}$$

Here, a and b represent the maximum and minimum values, respectively, that the damage index can have when the structure is known to be intact or damaged. The values of a and b are extracted from one coupon and than tested on the other two coupons.
A final damage probability is that obtained $P_{\text{fusion}} = \sqrt{P_Q(Q)P_\epsilon(\epsilon)}$. The fusion of probabilities by product mean amplifies the impact of low values in the predictors, making it useful to handle rare or extreme events and avoid false positives.

EXPERIMENTAL SETUP

In this study, three carbon fiber-reinforced polymer (CFRP) bearing test specimens measuring 260 mm × 160 mm × 10 mm with 39 mm bolted joints were examined. The



(a) stress-strain diagram of coupon no. 1

	μ(mm)	σ(MPa)
Mean	1.5	507.5
S. deviation	0.05	14

(b) Failure statistics of static coupon tests

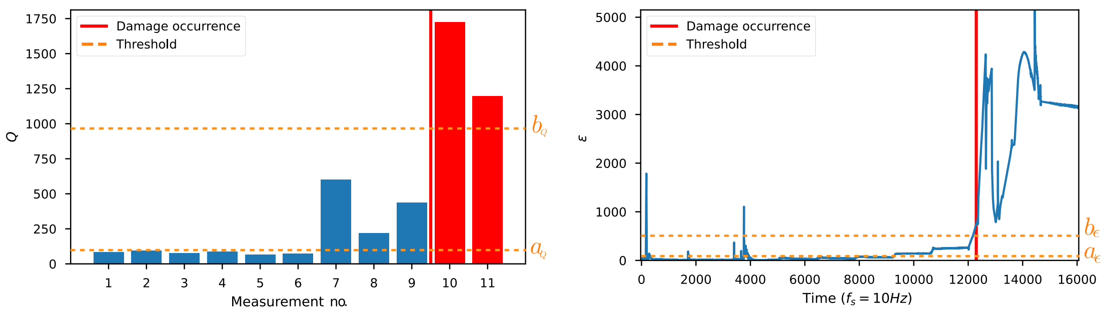
Figure 2: Mechanical properties of the coupons.

test specimens were each instrumented with 5 strain gauges (SGs) and 4 piezoelectric sensors (PZTs) as shown in Figure 1a. The mechanical load was introduced using a bearing fixture and a servohydraulic testing machine with a load capacity of 1000 kN (Figure 1b). The load profile is defined by a sequence of ramps with holding stages, where the load increases from 0 to 120 kN. The load is ramped up in steps of 20 kN and each ramp is held at its maximum for a duration of 140, 120, and 80 seconds, respectively, for the three plates. Subsequently, the load is increased linearly for all coupons until the point of failure load is reached. All sensors are mounted around the bolted connection, where the highest stresses are expected and potential damage may occur. SG 1, positioned relatively far from the stress region, serves as a reference sensor, and its relation with the other sensors is used as a damage indicator. SGs signals are recorded continuously during the test at a sampling rate of 10 Hz. PZT 1 serves as an actuator. As excitation signal, a 50 kHz 5-cycle Hann-filtered sine wave is used, measured in a round-robin fashion with a sample rate of 10 MHz. The ultrasonic based monitoring system is activated eleven times with each coupon in different conditions. Damage occurs when the applied static stress exceeds the linear elastic limit, causing irreversible deformation due to progressive damage. The failure statistics for the static tests of three coupons are summarized in table (b) in Figure 2.

RESULTS

The condition of the coupon is classified into three states: healthy, uncertain, and damaged, as defined in Eq. 3 and the accompanying Figure. The healthy state refers to the bolt connection being fully functional, with no limitations. The uncertain state is characterized by the bolt connection still being intact, but there is a growing risk of damage occurring as the applied stress increases. The damaged state is reached when the bolt connection can no longer perform its function due to irreversible deformations. Measurement data of the intact condition with a maximum load of 60 kN are used as training data for both monitoring systems. The borders of each damage index (a and b) are determined for the first coupon, and then tested on the other two coupons. The results of the damage detection on the first coupon are shown in Figure 3.

The Q index is initially small as the first measurements are used to determine principal components. However, as the load increases, the damage index also increases. When damage occurs, the Q index reaches higher values, facilitating the identification of the



(a) Evolution of Q-index.
(b) Evolution of ϵ-index.

Figure 3: Monitoring results of the first coupon.

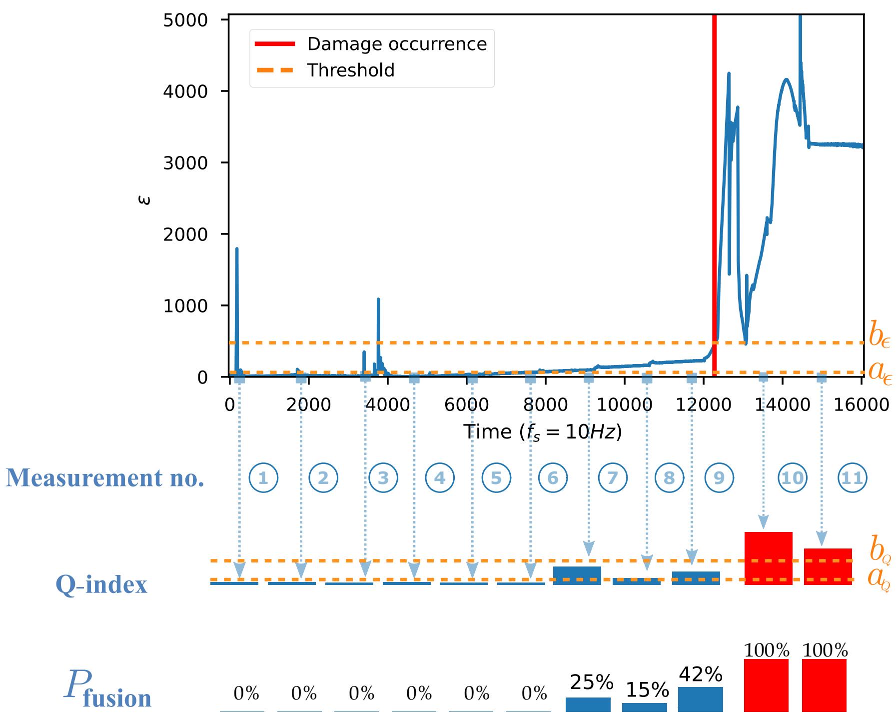


Figure 4: Damage detection on the first coupon (load ramp every 140 s) by fusion the output of the monitoring systems.

a_Q and b_Q borders. Similarly, the ϵ index exhibits low values initially and a peak at the time of damage. Nonetheless, the latter is very sensitive to changes of the internal stress, leading to sudden spikes that could trigger false positive alarms. Based on the initial evaluations, the determined thresholds are $a_Q = 150$, $b_Q = 990$, $a_\epsilon = 25$, and $b_\epsilon = 460$. The results for a fused index according to Eq. 3 are depicted in Figure 4. The resulting damage probability categorizes into three distinct states: intact state with a low probability of damage ($\approx 0\%$), damaged state with a high probability of damage (over 99%), and uncertain state with intermediate values. Higher values for P_{fusion} correspond to higher damage occurrence probabilities. By merging the predictions of both monitoring systems, the output is adjusted based on the confidence set of the other system

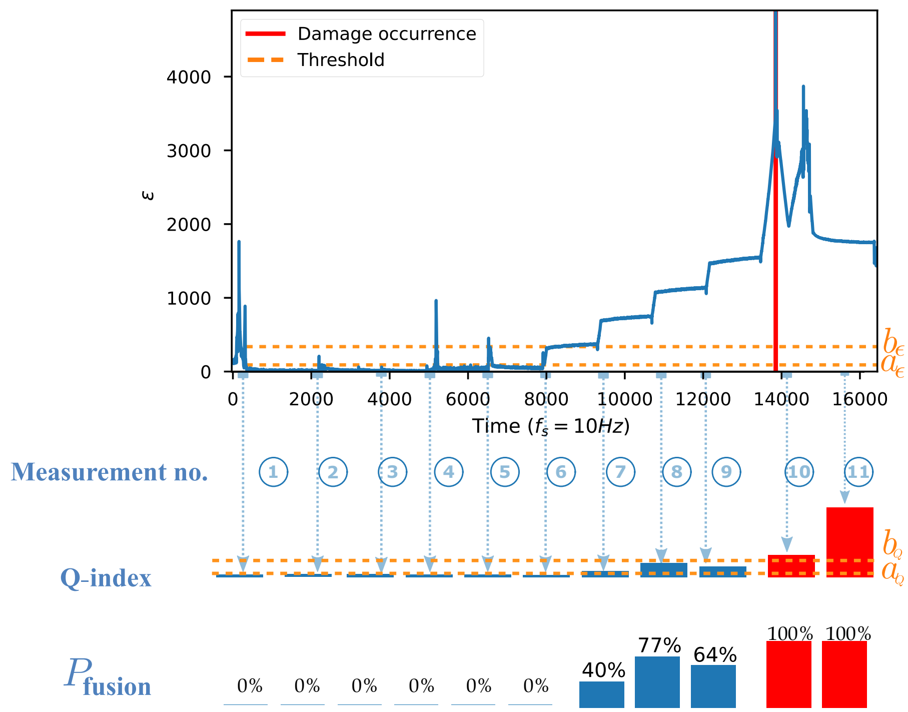


Figure 5: Damage detection on second coupon (load ramp every 120 s) by fusion the output of the monitoring systems.

(the system with low damage probability). For instance, when ϵ indicates damage (with a value exceeding the preset threshold and a damage probability of 100% as observed in measurement no. 1) and 3) while Q indicates a normal state (damage probability close to 0%), the damage occurrence probability is $P_{\text{fusion}} = 0\%$. The overall likelihood only increases when both indices predict non-zero damage probabilities. This enhances the stability of the probability against sudden spikes from the strain-based monitoring system, thus providing a more reliable monitoring of damage progression. Moreover, an overall likelihood of 100% is obtained only when both systems agree on the presence of damage. The threshold values a and b are tested on the remaining plates, and the results of the damage detection are presented in Figures 5 and 6. The changes in the load bearing behavior were found to be inadequately addressed by the selected thresholds for the low-frequency monitoring system, namely a_ϵ and b_ϵ. This can be attributed to the high sensitivity of the damage index ϵ to the internal stress and the local sensor placement, which limits the reliability of the defined thresholds. While ϵ reflects the changes in the internal stress and exhibits a similar trend to the probability of damage occurrence, determining universal thresholds for distinguishing between the various states of all analyzed plates presents a daunting challenge. For instance, the strain-based monitoring system indicates damage presence when bearing stress increases to 154 MPa in the second coupon (failure pressure: 520.2 MPa), and 337 MPa in the third coupon (failure pressure: 514.2 MPa). Although adjusting the threshold values may mitigate the issue, determining the appropriate threshold values in advance remains challenging due to tiny differences in sensor placement leading to different measurement values with similar trends and, consequently, different thresholds. Furthermore, SG 5 exhibits

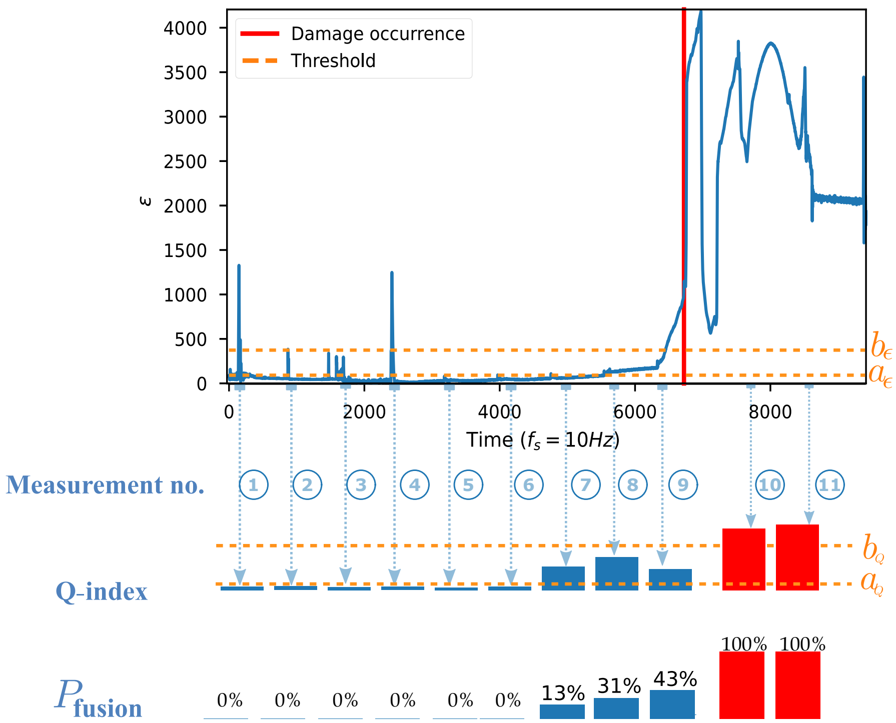


Figure 6: Damage detection on third coupon (load ramp every 80 s) by fusion the output of the monitoring systems.

higher dependency on the actual stress than other sensors, as it is directly connected to the joint in the load direction, increasing its contribution to ϵ. To reduce the impact of stress changes on the damage index, examining the relationships between the sensors separately is a possible solution.

The appropriateness of the chosen threshold for the ultrasonic-based monitoring system was confirmed for the second and third coupons. The high-variance features in the high-frequency domain were extracted by the PCs, which remained unaffected by load changes. Additionally, the placement of PZTs around the joint connection and the removal of PCs with minor variance made the monitoring system responsive to global changes in the plate and less sensitive to minor variations in sensor placement. Consequently, the Q index exhibited a similar variation range across all coupons, rendering the active monitoring system more reliable in this study. It is, therefore, possible to rely exclusively on this monitoring system to detect damage and activate it permanently. However, while the Q index effectively detected damage, it did not show a clear correlation with the trend of the damage occurrence likelihood, making it challenging to track damage occurrence probability before the damage occurred. It should be noted that insufficient measurements were taken before the damage to better estimate this point.

The effectiveness of the combined monitoring systems has been demonstrated in accurately and reliably predicting the coupon's state. The ultrasonic-based system was found to be more reliable in detecting damage due to its insensitivity to load changes, and the strain-based system was found to have a similar trend to the load exerted. The advantages of both systems were fused to correct any inaccuracies in damage detection and provide trustworthy predictions about the probability of damage occurrence. False negatives did not occur in this study since both systems could detect damage effectively. The system fusion was particularly successful in mitigating false positive alarms, primarily caused by the strain-based monitoring system, thus improving the overall accuracy of the damage detection process and the monitoring of the joint connection's state.

CONCLUSION AND OUTLOOK

In this study, the effectiveness of data fusion on the decision level was performed to enhance the reliability of SHM systems for joint connections in segmented rotor blades. The combination of two independent monitoring systems, a low-frequency passive system and a high-frequency active system, was proved to be successful in detecting damages at an early stage and reducing false positive alarms, as well as providing a reliable monitor of the damage occurrence probability. Future work should focus on validating the merged system under dynamic loads and applied to multiple joint connections, as well as exploring alternative fusion strategies and damage detection methods.

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