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Damage Detection and Localization at the Jacket Support of an Offshore Wind Turbine Using Transformer Models

PROBLEM

Offshore wind turbine jacket structures are subjected to harsh marine environments, characterized by strong winds, waves, and currents, that accelerate fatigue and joint deterioration. Traditional inspection and maintenance approaches are largely reactive, involving costly access operations and extended downtime. Quiet failures such as hairline cracks or lost bolts may go undetected until they precipitate catastrophic shutdowns, underscoring the urgent requirement for a continuous, non-destructive monitoring methodology capable of early and precise damage detection.

GENERAL OBJECTIVE

Develop and evaluate a real-time structural health monitoring (SHM) methodology based on transformer neural networks to detect and localize cracks and missing bolts in the jacket support of an offshore wind turbine with high accuracy.

METHODOLOGY

Experimental Setup

A 1:10 scale jacket-type support (2.7 m) was excited by white-noise inputs at four amplitudes while eight triaxial accelerometers captured 24 vibration channels over 1140 tests. Four damage conditions (healthy, 5 mm crack, missing bolt, replica bar) were introduced at each of the jacket's four levels.

Data Preprocessing

Each experiment recorded 60 s of vibration at 330 Hz. Recordings were divided into 0.5 s windows to capture transient dynamics, reshaped into multivariate feature vectors, standardized and split into 65 % training, 20 % validation, and 15 % testing subsets.

Transformer Model

An encoder-only transformer (two layers, four-head self-attention, lightweight feed-forward sublayers with ReLU, dropout and residual connections) projects each segment into embeddings and classifies into 13 structural states.

Training Protocol

The network was trained with RAdam (learning rate = 0.001, batch size = 64) using early stopping (best at epoch 14/35).

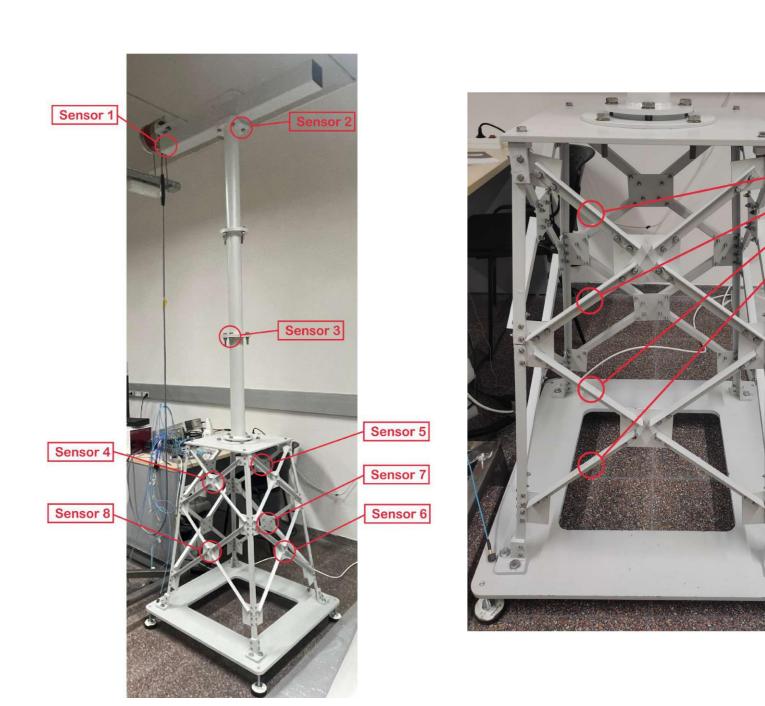


Figure 1: Location of the sensors and levels of the jacket support.

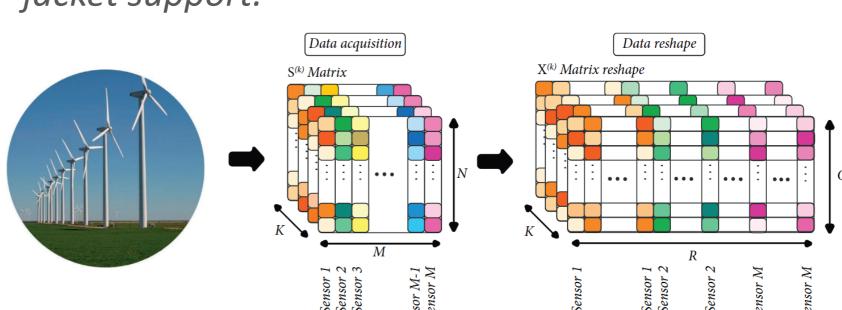


Figure 2: Data acquisition and reshaping flowchart.

RESULTS

Upon evaluation, the transformer-based SHM model achieved a test accuracy of 99.96 %, with precision, recall, and F1-score all averaging approximately 99.95 %. Inference on each 0.5 s window required only ~2.8ms, while total training time on an Apple M1 CPU was under six minutes. The confusion matrix revealed only nine misclassifications among 20520 test samples, all involving adjacent jacket levels without confusion of damage type.

Configuration number	Activation function	d_{ff}	d	h	e	Inference time (ms)	Avg training time (min)	Best epoch	Validation accuracy	Training accuracy	Test accuracy
1	ReLU	16	32	4	2	2.87	6.13	14	0.9994	0.9997	0.9996
2	ReLU	16	16	8	3	1.96	12.32	22	0.9996	0.9998	0.9998
3	ReLU	128	32	8	3	2.24	14.24	33	0.9997	0.9999	0.9994
4	ReLU	256	64	8	3	2.72	17.54	22	0.9994	0.9944	0.9996
5	GeLU	16	32	4	2	2.82	6.20	20	0.9995	0.9998	0.9993
6	GeLU	16	16	8	3	5.41	13.66	17	0.9996	0.9998	0.9994
7	GeLU	128	32	8	3	5.99	16.11	23	0.9995	0.9990	0.9994
8	GeLU	256	64	8	3	8.81	19.98	25	0.9995	0.9926	0.9995

Table 1: Results obtained by testing the methodology with different architecture configurations of the transformer model.

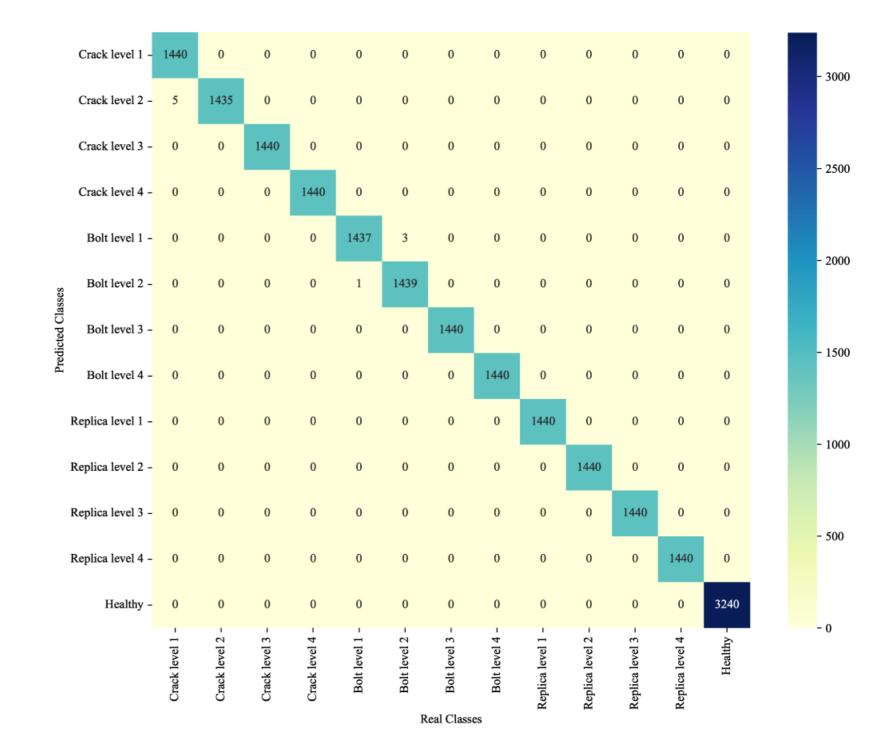


Figure 3: Confusion matrix on the testing data set using the best model.

CONCLUSIONS

- By leveraging the high parallelizability of the transformer architecture, this proof-of-concept demonstrates real-time damage detection and localization in offshore wind turbine jackets.
- The methodology's 99.96 % accuracy and millisecond-scale inference support its integration into continuous SHM systems, enabling predictive maintenance.
- Early identification of cracks and missing bolts promises reduced downtime, lower O&M costs, and extended turbine lifespan.