



EURODINAME III - An International Symposium on Dynamic Problems of Mechanics
June 8-11, 2026 - Giens Peninsula, FR

EURODINAME-2026-13517

ONE-DIMENSIONAL CONVOLUTIONAL AUTOENCODER-BASED MONITORING FOR FAULT DETECTION IN WIND TURBINES

Amanda Aryda Silva Rodrigues de Sousa

Marcela Rodrigues Machado

Department of Mechanical Engineering, University of Brasilia, Brasília, 70910-900, Brazil
eng.amandaaryda@gmail.com

Emmanuel Ramasso

Rafael Teloli

Université Marie et Louis Pasteur, SUPMICROTECH, CNRS, FEMTO-ST Institute, Department of Applied Mechanics, 26 Rue de l'Épithaphe, Besançon, 25000, France

Abstract. As global wind energy capacity grows, ensuring the operational reliability and economic viability of wind turbines remains a critical challenge due to their susceptibility to unexpected faults that can compromise structural integrity and safety. Unsupervised deep learning has shown great promise in structural health monitoring, enabling automated fault detection through data-driven approaches. This work introduces an unsupervised approach to anomaly detection in wind turbines using accelerometer-based vibration signals throughout the turbine. The methodology uses a one-dimensional convolutional autoencoder trained solely on healthy-state vibration data. By learning a compact latent representation of normal dynamic behavior, the autoencoder captures complex temporal patterns in vibration responses. Consequently, it exhibits a low reconstruction error (RE) on seen, healthy data but a significantly higher RE on unseen, anomalous data. This RE is used as a health index, with higher RE values indicating potential degradation. It is applied to an onshore wind turbine and evaluated under diverse operational scenarios, including normal conditions and fault states. By combining unsupervised deep learning with vibration analysis, the proposed methodology offers an efficient and flexible solution for early fault detection in wind turbines.

Keywords: Structural Health Monitoring, Wind Turbines, one-dimensional convolutional Autoencoder, unsupervised Learning

1. INTRODUCTION

Wind turbines operate in harsh environments, facing dynamic loads, heavy precipitation, ice accumulation, and lightning strikes. Minor manufacturing imperfections and aerodynamic asymmetries can further compromise structural stability and performance, especially in critical components such as the main bearing, blades, shafts, gearbox, generator, and power converter (Catelani *et al.*, 2020; Liu and Zhang, 2020; Jahani *et al.*, 2022; Nejad *et al.*, 2022). Mechanical subsystems account for over 75% of operational downtime, while maintenance and operational costs account for 10–30% of the Levelized Energy Cost in wind energy projects (Turnbull and Carroll, 2021; IREA, 2023).

Structural Health Monitoring (SHM) is essential for preventing faults, improving efficiency, and reducing maintenance costs throughout a wind turbine's lifespan (Farrar and Worden, 2013; Avci *et al.*, 2021). Current SHM techniques include acoustic emission sensors, vibration and strain monitoring, thermal analysis, computer vision, and aerodynamic response methods (Ding *et al.*, 2023; Lydia and Kumar, 2023). However, early damage detection remains difficult, particularly for offshore installations (Mourad *et al.*, 2023; Cuesta *et al.*, 2025).

Deep learning (DL) addresses these challenges by processing large volumes of multiphysical data, such as vibration, temperature, and strain, to identify patterns associated with early-stage faults (Weijtjens *et al.*, 2017; Nguyen *et al.*, 2017; Kim *et al.*, 2017). These models automatically extract relevant features from raw or minimally processed data, reducing reliance on manual feature engineering. Architectures such as convolutional neural networks (CNNs) (Jiang *et al.*, 2019), recurrent neural networks (RNNs) (Yu *et al.*, 2020), and autoencoder (AE) (Chen *et al.*, 2021; Wang *et al.*, 2025) are increasingly used for fault detection. Khazaei *et al.* (2022) applied CNNs to structural damage detection, while Dervilis



et al. (2014b,a) demonstrated robust anomaly detection using Autoassociative Neural Networks and radial basis functions (RBFs). For bearing and gear faults, Gao *et al.* (2021) demonstrated the effectiveness of CNNs. Further advancements, such as cyclostationary feature extraction (Amin *et al.*, 2023) and unsupervised CNN-based strategies (Meyer, 2022), highlight the potential of integrating signal processing with learning algorithms.

Researchers have continually advanced AE architectures to improve wind turbine fault detection. Li *et al.* (2023) proposed a generalized autoencoder combined with statistical pattern recognition. Using power cepstral coefficients from acceleration signals as damage-sensitive features, their method outperformed traditional autoencoders and Principal Component Analysis (PCA). Similarly, Wang *et al.* (2022) developed an enhanced autoencoder to increase fault-detection accuracy, and Liu *et al.* (2022) proposed CNN conditional variational autoencoder (CNN-CVAE) models, which are considered advanced hybrid frameworks that integrate AEs with other deep learning methods.

Despite these advances, many approaches still rely on feature extraction or labeled fault data, limiting real-world applicability, while statistical threshold-based classification remains underexplored. This work proposes a one-dimensional convolutional autoencoder (1D-CAE) an unsupervised approach to anomaly detection that learns directly from raw vibration signals and requires only healthy data for training. By learning a compact latent representation of normal dynamic behavior, the autoencoder captures complex temporal patterns in vibration responses. A statistical threshold based on the RE is then applied to distinguish normal from anomalous conditions for classification.

2. METHOD DESCRIPTION

The proposed framework for fault classification follows a structured workflow organized into five main stages, as illustrated in Figure 1. The complete process comprises: (1) data acquisition; (2) signal processing and data preparation; (3) training the 1D-CAE model; (4) RE and threshold Definition; and (5) model evaluation. The final stage also provides an estimation of the structural condition, indicating the presence or absence of operational faults. The workflow is described in Algorithm 1.

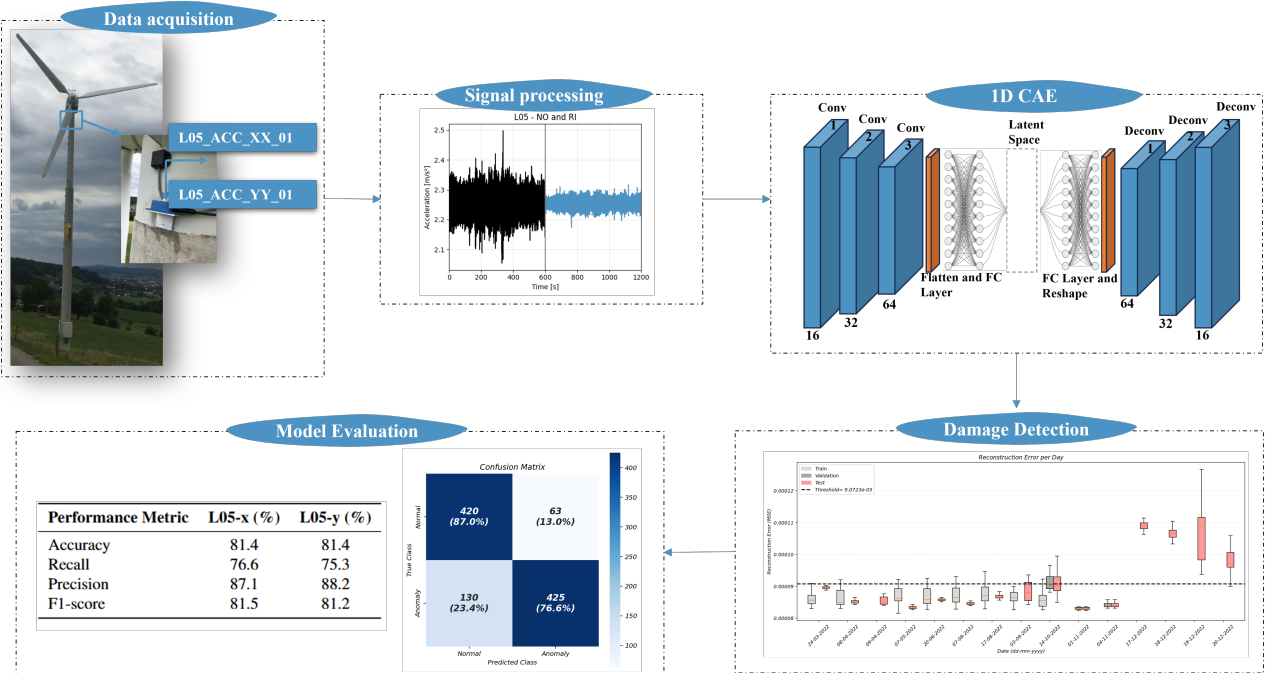


Figure 1: Pipeline representation of 1D-CAE for fault classification on the Aventa 6.7 kW wind turbine.

2.1 Data acquisition

The monitored wind turbine is the Aventa AV-7 (Aventa AG, Switzerland), installed in Taggenberg, Switzerland, and commissioned by ETH. It has a rated power of 6.7 kW, a 12.8 m rotor with three blades, and operates between 2 m/s and 14 m/s, with a hub height of 18 m, reaching a maximum rotational speed of 63 RPM. Instrumentation described in Eleni Chatzi (2023) includes 14 accelerometers along the tower, nacelle frame, main bearing, and generator, as well as two full-bridge strain gauges at the tower base for bending moment estimation. Acceleration and strain signals are sampled at 200 Hz.

The sensor was selected based on its sensitivity to a specific fault mechanism: rotor icing (RI). The analysis focuses on the x- (side-to-side) and y- (fore-aft) acceleration components. The selected tower sensor (L05 ACC) exhibits clearly

Table 1: 1D-CAE Algorithm for Wind Turbine Fault Detection

Algorithm Steps
1: Data Acquisition: Acquire time-domain vibration signals $x(t)$ from accelerometers installed on the wind turbine under different operational conditions.
2: Signal Processing and Dataset Preparation: • Standardize signal length by truncating all records to the minimum available length across the dataset. • Split dataset into training, validation, and test sets.
3: 1D-CAE Training: Initialize encoder $\mathcal{E}_\phi$ and decoder $\mathcal{D}_\theta$. for epoch in range(epochs): for batch in GetBatches(training_data, batch_size): $z = \mathcal{E}_\phi(x(t))$ $\hat{x}(t) = \mathcal{D}_\theta(z)$ Compute reconstruction loss and update network parameters.
4: RE Computation and Threshold Definition: Compute RE for validation and test samples: $RE_i = \ x_i(t) - \hat{x}_i(t)\ _2^2$ Define statistical threshold for anomaly detection: $\tau = \mu_{healthy} + \sigma_{healthy}$
5: Model Evaluation and Operational State Estimation: Classify each sample: Healthy if $RE_i \leq \tau$ Faulty if $RE_i > \tau$ Evaluate performance using Accuracy, Precision, Recall, F1-score, and Confusion Matrix.

distinguishable temporal responses under healthy and faulty operating conditions, with rotor icing leading to noticeable reductions in amplitude. Figure 1 presents the raw temporal signals used in data processing, in the acceleration plot, the black line represents normal operation, and the blue lines indicate faulty conditions. All signals were collected on the same day to minimize the impact of changing environmental conditions and ensure consistent comparisons.

Although the turbine’s operational history includes scheduled maintenance and various fault events, this study focuses only on the period affected by ice-induced damage. A naturally occurring blade icing event was recorded during a cold-weather period from December 17 to December 20, 2022, as shown in Figure 2. Ice accumulation on the blades altered the aerodynamic profile and created an asymmetric mass distribution along the rotor. These changes reduced aerodynamic efficiency, modified load distribution, and increased rotational imbalance, which directly affected energy production and the turbine’s dynamic response. This scenario was chosen for its practical relevance and the complex effects it has on turbine dynamics in real operating conditions.

2.2 Signal processing and data preparation

Vibration signals from the selected accelerometer were compiled into a structured dataset suitable for deep learning applications. Each record includes the measurement date, sensor identifier, and an operational-condition label indicating whether the turbine was operating under healthy or faulty conditions. Signals along the x- and y-axes were grouped by acquisition session, preserving temporal order. Each session was segmented into 10-minute blocks to ensure uniformity. The dataset supports flexible filtering and assignment to training, validation, and test sets.

Table 2: Example records from the L05-ACC dataset. Each record contains 10 minutes of vibration data.

Sensor	Date	Hours	x-axis (signals)	y-axis (signals)
L05 ACC	09-04-2022	00:05:36	Array[...]	Array[...]
L05 ACC	09-04-2022	00:15:59	Array[...]	Array[...]
L05 ACC	10-04-2022	01:20:15	Array[...]	Array[...]
L05 ACC	10-04-2022	01:30:50	Array[...]	Array[...]

Note: Signals are recorded in the x- and y-axes of the accelerometer.

Since 1D-CAE requires fixed-length input sequences for stable convolution operations and efficient optimization,

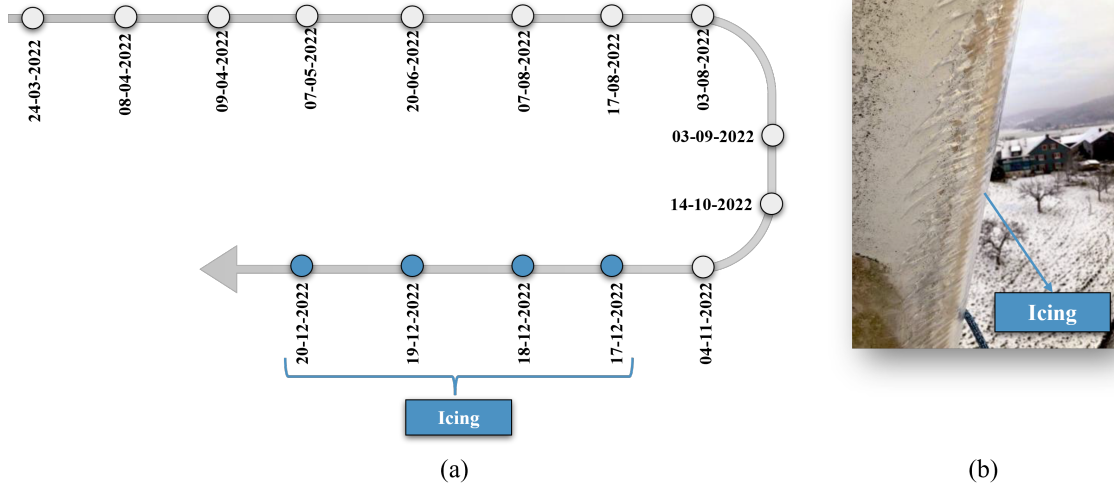


Figure 2: (a) Timeline of recorded fault of the Aventa AV-7 ETH Zurich research wind turbine; (b) Illustration of the blade icing event affecting the turbine during the analyzed period.

all vibration records were standardized to 10-minute durations. To mitigate minor length discrepancies arising from acquisition variability, signals were truncated to the minimum available length within the selected dataset. This strategy ensured uniform dimensionality without introducing artificial padding or interpolation artifacts.

The proposed 1D-CAE was trained exclusively using healthy operational data from the L05 accelerometer in both x- and y-axes, comprising 386 training signals, 97 validation signals, and 1,038 test signals. After preprocessing, each sample contained 42,122 temporal points. For anomaly detection, the decision threshold was set to the mean RE of the healthy training set plus one standard deviation, providing a data-driven criterion for distinguishing normal from fault operating conditions.

2.3 1D-CAE Architecture

Within the unsupervised framework, AE are widely employed for anomaly detection due to their ability to learn compact representations of normal operating conditions. When trained exclusively on healthy data, the model minimizes RE for normal patterns, while fault conditions typically result in higher RE (Goodfellow *et al.*, 2016). The proposed model is a 1D-CAE designed to extract representative latent features from time-domain vibration signals acquired by accelerometers installed on the wind turbine. Given an input signal $x(t) \in R^L$, the encoder performs successive nonlinear transformations,

$$z = \mathcal{E}_\phi(x(t)), \quad (1)$$

where $z \in R^d$ is a latent feature vector with reduced dimensionality $d \ll L$, and ϕ denotes the encoder parameters. The decoder reconstructs the signal as

$$\hat{x}(t) = \mathcal{D}_\theta(z), \quad (2)$$

where θ represents the decoder parameters. The network is trained by minimizing the reconstruction loss defined as

$$\mathcal{L} = \|x(t) - \hat{x}(t)\|_2^2, \quad (3)$$

The encoder compresses the input vibration signals through three one-dimensional convolutional layers with progressively increasing numbers of filters (16, 32, and 64). Each convolutional layer is followed by a ReLU activation function, enabling nonlinear feature extraction while reducing temporal dimensionality through strided operations. The resulting feature maps are flattened and projected into a compact latent representation of dimension 16 via a fully connected layer.

The decoder reconstructs the signal by first expanding the latent vector through a fully connected layer and reshaping it to match the convolutional feature dimensions. The reconstruction is then performed using three transposed convolutional layers arranged symmetrically with respect to the encoder (64–32–16–1 channels). ReLU activations are applied after the first two transposed convolutional layers. Table 3 summarizes the complete network configuration.

The network was trained using the Adam optimizer with a learning rate of 10^{-3} . The RE was computed as the mean squared error between the input and reconstructed signals. For anomaly detection, a statistical threshold was defined as the mean RE of the healthy training set plus one standard deviation. This criterion enables the identification of

Table 3: Architecture of the proposed 1D-CAE.

Layer	Channels	Kernel	Stride	Padding
<i>Encoder</i>				
Conv1D + ReLU	$1 \rightarrow 16$	64	4	32
Conv1D + ReLU	$16 \rightarrow 32$	7	2	3
Conv1D + ReLU	$32 \rightarrow 64$	5	2	2
Fully Connected (Latent)	16	–	–	–
<i>Decoder</i>				
Fully Connected	16	–	–	–
ConvTranspose1D + ReLU	$64 \rightarrow 32$	5	2	2
ConvTranspose1D + ReLU	$32 \rightarrow 16$	7	2	3
ConvTranspose1D	$16 \rightarrow 1$	64	4	32

fault operational conditions based on deviations from the learned healthy-state representation. The optimal architecture was determined empirically by evaluating multiple configurations and hyperparameter settings. Model performance was assessed using standard metrics, including accuracy, precision, recall, F1 score, and the confusion matrix.

3. DETECTION OF ICE-INDUCED DAMAGE

To ensure accurate fault detection, the analysis focused on the sensor: the top-tower L05 accelerometer. The study evaluated the turbine under healthy operating conditions and blade-icing faults. A 1D-CAE was trained exclusively on healthy data from the L05 sensor along both x- and y-axes (386 training, 97 validation, and 1,038 test signals, each containing 42,122 temporal samples). The anomaly-detection threshold was derived from the RE statistics of the training set. As illustrated in Figure 3, the thresholds were 9.072×10^{-5} for the x-axis and 2.137×10^{-4} for the y-axis.

Daily boxplot analyses show consistent increases in RE during icing events, indicating that the 1D CAE effectively captures dynamic deviations due to changes in mass and stiffness. Figures 3 illustrate the RE evolution. The model was trained and validated on healthy operational data, while the test set included both normal and faulty conditions. Reconstruction results confirm the robustness of the model and the suitability of the chosen thresholds, which successfully distinguish normal operation from blade-icing events occurring from December 17 to December 20, 2022, as indicated by the operational timeline (Figure 2).

According to Table 4, the 1D-CAE achieved similar accuracy for both axes, reaching 81.4%, indicating that operational states were correctly classified. Precision for the x- and y-axes was 87.1% and 88.2%, respectively, showing that most detected faults correspond to actual blade-icing events. This high precision demonstrates strong robustness against false alarms, which is critical for practical monitoring systems and helps avoid unnecessary maintenance interventions.

Recall values were 76.6% and 75.3% for the x- and y-axes, indicating that roughly three-quarters of the actual icing events were successfully identified. The presence of false negatives suggests that some ice-affected states exhibited vibration patterns only slightly different from those in normal operation, possibly corresponding to early-stage or low-severity ice accumulation. The F1 scores of 81.5% (x-axis) and 81.2% (y-axis) reflect a balanced trade-off between detection sensitivity and reliability.

Table 4: Performance metrics for sensor L05 in the x- and y-axes.

Performance Metric	L05-x (%)	L05-y (%)
Accuracy	81.4	81.4
Recall	76.6	75.3
Precision	87.1	88.2
F1-score	81.5	81.2

The figure 4 shows the confusion matrices were subsequently analyzed to evaluate classification performance. Values along the diagonal correspond to correctly classified samples, whereas off-diagonal entries indicate misclassifications. For the x-axis, the model correctly identified 420 normal samples and 425 anomaly samples, with 63 false positives and 130 false negatives. For the y-axis, 427 normal samples and 418 anomaly samples were correctly classified, with 56 false positives and 137 false negatives. Overall, the confusion matrix for the y-axis shows slightly higher precision, suggesting that the tower's longitudinal dynamics are more sensitive to aerodynamic disturbances caused by ice accumulation.

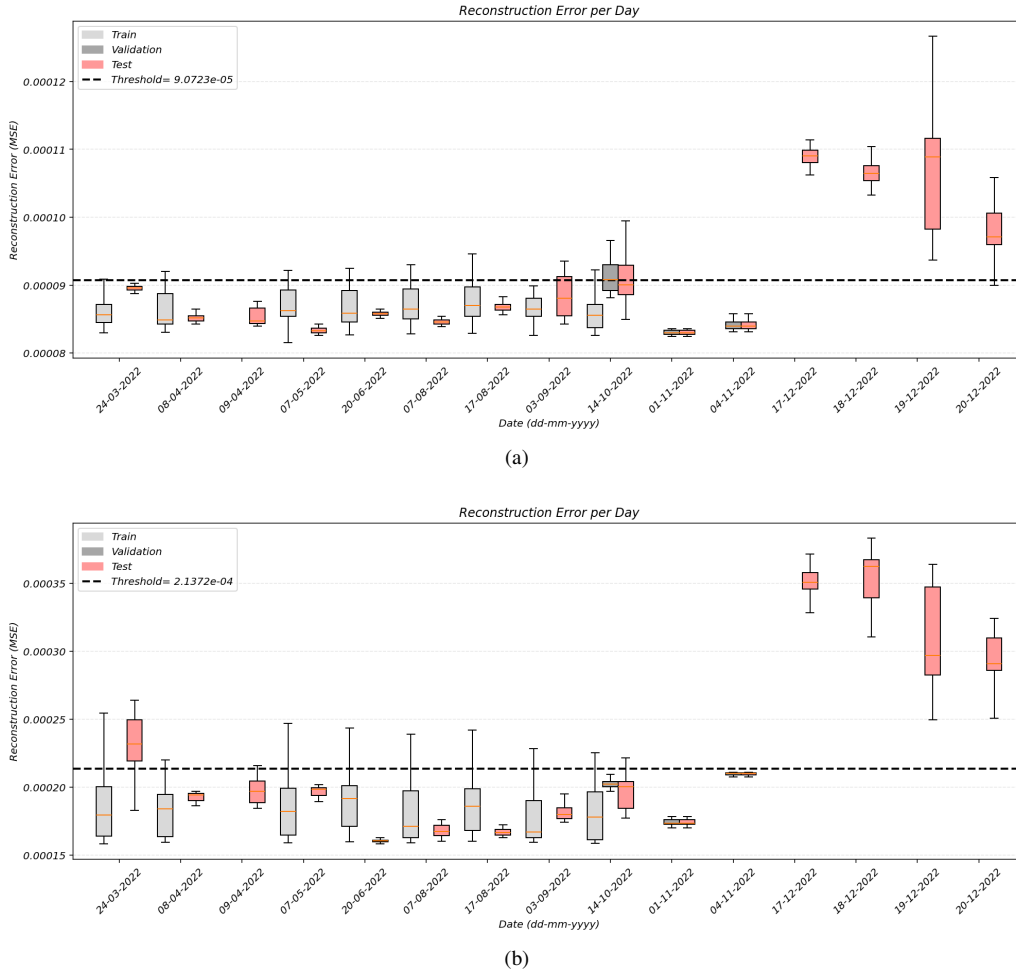


Figure 3: RE per 10-minute record for the L05 sensor: (a) x-axis, (b) y-axis.

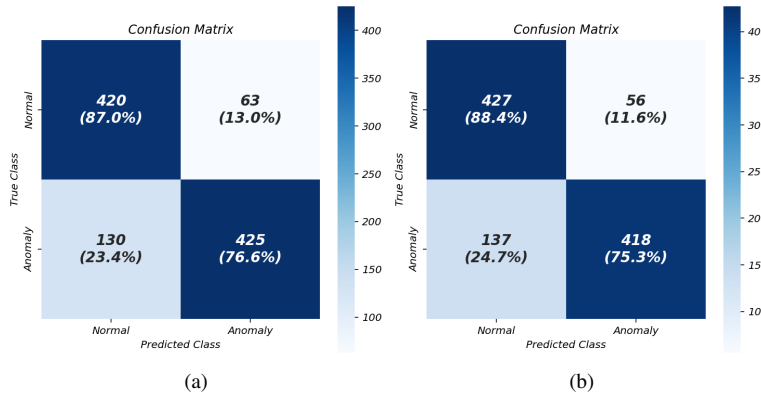


Figure 4: Confusion matrices for L05 sensor: (a) x-axis, (b) y-axis.

As aerodynamic loads primarily act along the wind-aligned axes, variations in lift and drag due to ice formation are expected to influence longitudinal structural responses more strongly than lateral ones. These results demonstrate that the proposed reconstruction-error-based approach can reliably detect naturally occurring icing events under realistic operational variability. Unlike supervised classifiers that require labeled fault data, the unsupervised 1D CAE adapts to healthy structural dynamics and flags deviations without prior knowledge of fault signatures.

4. CONCLUSION

This study presented an unsupervised fault-detection framework based on a 1D-CAE for identifying ice-induced anomalies in a small-scale wind turbine. The model was trained exclusively on healthy operational data from the top-

tower L05 accelerometer, capturing intrinsic dynamic patterns in the x- (side-to-side) and y- (fore-aft) axes. Deviations due to blade-icing events were detected using statistically defined RE thresholds. Performance metrics confirmed robust classification, with accuracy above 81%, precision between 87–88%, and balanced F1-scores around 81%. Daily boxplots and confusion matrices demonstrated the model’s sensitivity to dynamic deviations, with slightly higher responsiveness along the y-axis, consistent with longitudinal tower dynamics affected by aerodynamic disturbances. These results indicate that RE-based unsupervised learning provides a reliable, data-driven approach for early fault detection in wind turbines, without requiring labeled fault data, supporting preventive maintenance under realistic operational conditions.

5. REFERENCES

- Amin, A., Bibo, A., Panyam, M. and Tallapragada, P., 2023. “Vibration based fault diagnostics in a wind turbine planetary gearbox using machine learning”. *Wind Engineering*, Vol. 47, No. 1, pp. 175–189. doi:10.1177/0309524X221123968. URL <https://doi.org/10.1177/0309524X221123968>.
- Avci, O., Abdeljaber, O., Kiranyaz, S., Hussein, M., Gabbouj, M. and Inman, D.J., 2021. “A review of vibration-based damage detection in civil structures: From traditional methods to Machine Learning and Deep Learning applications”. *Mechanical Systems and Signal Processing*, Vol. 147, p. 107077. ISSN 08883270. doi:10.1016/j.ymssp.2020.107077. URL <https://doi.org/10.1016/j.ymssp.2020.107077> <https://linkinghub.elsevier.com/retrieve/pii/S0888327020304635>.
- Catelani, M., Ciani, L., Galar, D. and Patrizi, G., 2020. “Optimizing maintenance policies for a yaw system using reliability-centered maintenance and data-driven condition monitoring”. *IEEE Transactions on Instrumentation and Measurement*, Vol. 69, No. 9, pp. 6241–6249. doi:10.1109/TIM.2020.2968160.
- Chen, H., Liu, H., Chu, X., Liu, Q. and Xue, D., 2021. “Anomaly detection and critical scada parameters identification for wind turbines based on lstm-ae neural network”. *Renewable Energy*, Vol. 172, pp. 829–840. doi:10.1016/j.renene.2021.03.078. URL <https://ideas.repec.org/a/eee/renene/v172y2021icp829-840.html>.
- Cuesta, J., Leturiondo, U., Vidal, Y. and Pozo, F., 2025. “A review of prognostics and health management techniques in wind energy”. *Reliability Engineering System Safety*, Vol. 260, p. 111004. ISSN 0951-8320. doi:<https://doi.org/10.1016/j.res.2025.111004>.
- Dervilis, N., Choi, M., Antoniadou, I., Farinholt, K.M., Taylor, S.G., Barthorpe, R.J., Park, G., Farrar, C.R. and Worden, K., 2014a. “Machine learning applications for a wind turbine blade under continuous fatigue loading”. *Key Engineering Materials*, Vol. 588, pp. 166–174. ISSN 16629795. doi:10.4028/www.scientific.net/KEM.588.166.
- Dervilis, N., Choi, M., Taylor, S., Barthorpe, R., Park, G., Farrar, C. and Worden, K., 2014b. “On damage diagnosis for a wind turbine blade using pattern recognition”. *Journal of Sound and Vibration*, Vol. 333, No. 6, pp. 1833–1850. ISSN 0022-460X. doi:<https://doi.org/10.1016/j.jsv.2013.11.015>. URL <https://www.sciencedirect.com/science/article/pii/S0022460X13009528>.
- Ding, S., Yang, C. and Zhang, S., 2023. “Acoustic-signal-based damage detection of wind turbine blades—a review”. *Sensors*, Vol. 23, No. 11. ISSN 1424-8220. doi:10.3390/s23114987.
- Eleni Chatzi, Imad Abdallah, M.H.O.B.S.B.Y.M., 2023. “Aventa av-7 eth zurich research wind turbine scada and high frequency structural health monitoring (shm) data [data set]”. *Zenodo*. doi:<https://doi.org/10.5281/zenodo.8229750>.
- Farrar, C.R. and Worden, K., 2013. *Structural Health Monitoring: A Machine Learning Perspective*. ISBN 9781119994336. doi:10.1002/9781118443118.
- Gao, Y., Zhai, P. and Mosalam, K.M., 2021. “Balanced semisupervised generative adversarial network for damage assessment from low-data imbalanced-class regime”. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 36, No. 9, p. 1094 – 1113. doi:10.1111/mice.12741. URL <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85112382339&doi=10.1111%2fmice.12741&partnerID=40&md5=c7963ef0a16a450caff9397c3afc395c>.
- Goodfellow, I., Bengio, Y. and Courville, A., 2016. *Deep Learning*. MIT Press. <http://www.deeplearningbook.org>.
- IREA, 2023. “Renewable power generation costs 2022”. In *International Renewable Energy Agency*.
- Jahani, K., Langlois, R.G. and Afagh, F.F., 2022. “Structural dynamics of offshore wind turbines: A review”. *Ocean Engineering*, Vol. 251, p. 111136. ISSN 0029-8018. doi:<https://doi.org/10.1016/j.oceaneng.2022.111136>. URL <https://www.sciencedirect.com/science/article/pii/S0029801822005467>.
- Jiang, G., He, H., Yan, J. and Xie, P., 2019. “Multiscale convolutional neural networks for fault diagnosis of wind turbine gearbox”. *IEEE Transactions on Industrial Electronics*, Vol. 66, No. 4, pp. 3196–3207. doi:10.1109/TIE.2018.2844805.
- Khazaee, M., Derian, P. and Mouraud, A., 2022. “A comprehensive study on structural health monitoring (shm) of wind turbine blades by instrumenting tower using machine learning methods”. *Renewable Energy*, Vol. 199, pp. 1568–1579. ISSN 0960-1481. doi:<https://doi.org/10.1016/j.renene.2022.09.032>. URL <https://www.sciencedirect.com/science/article/pii/S0960148122013829>.
- Kim, W., Yi, J.H., Kim, J.T. and Park, J.H., 2017. “Vibration-based structural health assessment of a wind turbine tower using a wind turbine model”. *Procedia Engineering*, Vol. 188, pp. 333–339. ISSN 1877-7058. doi:

- <https://doi.org/10.1016/j.proeng.2017.04.492>. URL <https://www.sciencedirect.com/science/article/pii/S1877705817320441>. Structural Health Monitoring - From Sensing to Diagnosis and Prognosis.
- Li, L., Morgantini, M. and Betti, R., 2023. "Structural damage assessment through a new generalized autoencoder with features in the quefreny domain". *Mechanical Systems and Signal Processing*, Vol. 184, p. 109713. ISSN 0888-3270. doi:<https://doi.org/10.1016/j.ymssp.2022.109713>. URL <https://www.sciencedirect.com/science/article/pii/S0888327022007889>.
- Liu, J., Yang, G., Li, X., Hao, S., Guan, Y. and Li, Y., 2022. "A deep generative model based on cnn-cvae for wind turbine condition monitoring". *Measurement Science and Technology*, Vol. 34. URL <https://api.semanticscholar.org/CorpusID:253789518>.
- Liu, Z. and Zhang, L., 2020. "A review of failure modes, condition monitoring and fault diagnosis methods for large-scale wind turbine bearings". *Measurement*, Vol. 149, p. 107002. ISSN 0263-2241. doi:<https://doi.org/10.1016/j.measurement.2019.107002>. URL <https://www.sciencedirect.com/science/article/pii/S0263224119308681>.
- Lydia, M. and Kumar, G.E.P., 2023. "Condition monitoring in wind turbines: a review". In *Non-Destructive Testing and Condition Monitoring Techniques in Wind Energy*, Academic Press, Wind Energy Engineering, pp. 229–247. ISBN 978-0-323-99666-2. doi:<https://doi.org/10.1016/B978-0-323-99666-2.15003-8>. URL <https://www.sciencedirect.com/science/article/pii/B9780323996662150038>.
- Meyer, A., 2022. "Vibration fault diagnosis in wind turbines based on automated feature learning". *Energies*, Vol. 15, No. 4. ISSN 1996-1073. doi:10.3390/en15041514. URL <https://www.mdpi.com/1996-1073/15/4/1514>.
- Mourad, A.H.I., Almomani, A., Sheikh, I. and Elsheikh, A., 2023. "Failure analysis of gas and wind turbine blades: A review". *Engineering Failure Analysis*, Vol. 146, p. 107107. ISSN 1350-6307. doi:<https://doi.org/10.1016/j.engfailanal.2023.107107>.
- Nejad, A.R., Keller, J., Guo, Y., Sheng, S., Polinder, H., Watson, S., Dong, J., Qin, Z., Ebrahimi, A., Schelenz, R., Gutiérrez Guzmán, F., Cornel, D., Golafshan, R., Jacobs, G., Blockmans, B., Bosmans, J., Pluymers, B., Carroll, J., Koukoura, S., Hart, E., McDonald, A., Natarajan, A., Torsvik, J., Moghadam, F.K., Daems, P.J., Verstraeten, T., Peeters, C. and Helsen, J., 2022. "Wind turbine drivetrains: state-of-the-art technologies and future development trends". *Wind Energy Science*, Vol. 7, No. 1, pp. 387–411. doi:10.5194/wes-7-387-2022.
- Nguyen, T.C., Huynh, T.C., Yi, J.H. and Kim, J.T., 2017. "Hybrid bolt-loosening detection in wind turbine tower structures by vibration and impedance responses". *Wind and Structures, An International Journal*, Vol. 24, No. 4, pp. 385–403. ISSN 15986225. doi:10.12989/was.2017.24.4.385.
- Turnbull, A. and Carroll, J., 2021. "Cost benefit of implementing advanced monitoring and predictive maintenance strategies for offshore wind farms". *Energies*, Vol. 14, No. 16. ISSN 1996-1073. doi:10.3390/en14164922.
- Wang, A., Qian, Z., Pei, Y. and Jing, B., 2022. "A de-ambiguous condition monitoring scheme for wind turbines using least squares generative adversarial networks". *Renewable Energy*, Vol. 185, pp. 267–279. ISSN 0960-1481. doi: <https://doi.org/10.1016/j.renene.2021.12.049>. URL <https://www.sciencedirect.com/science/article/pii/S0960148121017699>.
- Wang, S., Vidal, Y. and Pozo, F., 2025. "An unsupervised approach to early fault detection and performance degradation assessment in bearings". *Advanced Engineering Informatics*, Vol. 68, p. 103620. ISSN 1474-0346. doi: <https://doi.org/10.1016/j.aei.2025.103620>. URL <https://www.sciencedirect.com/science/article/pii/S1474034625005130>.
- Weijtens, W., Verbelen, T., Capello, E. and Devriendt, C., 2017. "Vibration based structural health monitoring of the substructures of five offshore wind turbines". *Procedia Engineering*, Vol. 199, pp. 2294–2299. ISSN 1877-7058. doi:<https://doi.org/10.1016/j.proeng.2017.09.187>. URL <https://www.sciencedirect.com/science/article/pii/S1877705817336305>. X International Conference on Structural Dynamics, EUROLYN 2017.
- Yu, W., Kim, I.Y. and Mechefske, C., 2020. "An improved similarity-based prognostic algorithm for rul estimation using an rnn autoencoder scheme". *Reliability Engineering and System Safety*, Vol. 199, p. None. doi:10.1016/j.ress.2020.106926. URL <https://ideas.repec.org/a/eee/reensy/v199y2020ics0951832019307902.html>.