

A Hybrid Deep Learning and IoT Framework for Predictive Maintenance of Wind Turbines: Enhancing Reliability and Reducing Downtime

Amina Eljyidi^{1*}, Hakim Jebari², Siham Rekiek³, Kamal Reklaoui⁴

Innovative Systems Engineering Research Team, University Abdelmalek Essaâdi, Morocco^{1, 2, 3, 4}

Innovative Systems Engineering Laboratory, University Abdelmalek Essaâdi, Morocco²

Artificial Intelligence, Data Science, and Innovation Research Team, LaBEL, National School of Architecture of Tetouan, Morocco²

Intelligent Automation & BioMedGenomics Laboratory, University Abdelmalek Essaâdi, Morocco³

Abstract—The global shift towards renewable energy has positioned wind power as a cornerstone of sustainable development. However, the operational efficiency of wind farms is significantly hampered by unexpected component failures, leading to substantial downtime and maintenance costs. Traditional scheduled maintenance protocols are inefficient, often leading to unnecessary interventions or catastrophic failures. This study proposes a novel, robust framework for the predictive maintenance (PdM) of wind turbines, integrating Internet of Things (IoT) sensory data with a hybrid deep learning architecture. The proposed model leverages Convolutional Neural Networks (CNN) for feature extraction from vibrational and acoustic emission data, combined with Long Short-Term Memory (LSTM) networks to model the temporal dependencies inherent in time-series operational data. Drawing inspiration from successful applications of similar hybrid AI models in precision agriculture and smart farming, our approach is designed to accurately forecast the Remaining Useful Life (RUL) of critical components like gearboxes and bearings. We validate our framework on a benchmark dataset from NASA's Pronostia platform, demonstrating a 30% improvement in prediction accuracy over traditional single-model approaches and a 50% reduction in false alarms. The results underscore the potential of integrating hybrid AI and IoT, a paradigm successfully demonstrated in other complex systems, to create more reliable, efficient, and cost-effective maintenance strategies for the wind energy sector, thereby enhancing grid stability and accelerating the renewable energy transition.

Keywords—Predictive maintenance; wind turbine; artificial intelligence; deep learning; Convolutional Neural Network; Long Short-Term Memory; Internet of Things; Remaining Useful Life; condition monitoring

I. INTRODUCTION

The escalating climate crisis and the urgent global mandate to reduce carbon emissions have catalyzed an unprecedented expansion of renewable energy infrastructure. Among these, wind energy has emerged as a leading technology, with global capacity witnessing exponential growth over the past decade, as detailed in the latest industry reports [1]. Wind turbines, the workhorses of this sector, are complex engineering marvels designed to operate reliably in harsh and variable environmental conditions for decades. However, their critical mechanical and

electrical components, such as gearboxes, generators, main bearings, and blades, are subject to extreme dynamic loads, leading to progressive wear and tear and eventual failure [2]. These failures result in significant operational downtime, exorbitant repair costs—often exceeding €250,000 for a major gearbox replacement—and substantial lost energy production revenue, creating a major economic bottleneck for operators [3].

Historically, wind farm maintenance has been governed by two primary strategies: reactive (run-to-failure) and preventive (time-based) maintenance. The reactive approach is economically untenable due to the astronomically high cost of catastrophic failures and unplanned outages. Preventive maintenance, based on fixed schedules, offers some improvement, but is inherently inefficient and wasteful. It often leads to unnecessary maintenance activities on healthy components, incurring avoidable labor and parts costs, while sometimes failing to prevent failures that occur between scheduled intervals, a significant operational blind spot [4]. This challenging landscape has created a pressing and urgent need for a more intelligent, data-driven paradigm: Predictive Maintenance (PdM).

PdM strategies aim to predict the future health state of a component and estimate its Remaining Useful Life (RUL) with a high degree of accuracy, allowing maintenance to be performed precisely when needed—not too early, not too late [5]. This transition from rigid schedules to condition-based maintenance maximizes component lifespan, minimizes costly downtime, and optimizes resource allocation for maintenance crews. The advent of the Industrial Internet of Things (IIoT) has been the key technological enabler for PdM. Modern turbines are equipped with a dense array of sensors—vibration accelerometers, acoustic emission sensors, temperature probes, oil debris monitors, and strain gauges—generating vast, high-frequency, multivariate time-series data streams [6]. The central challenge, therefore, has shifted from data collection to extracting meaningful, prognostic signatures from this overwhelming data deluge.

This is precisely where Artificial Intelligence (AI), particularly deep learning, demonstrates its immense value and transformative potential. Deep learning models excel at automatically learning complex, non-linear patterns and

*Corresponding author.

hierarchical features from raw, high-dimensional data, making them vastly superior to traditional statistical and physical model-based approaches for fault prognosis [7]. Convolutional Neural Networks (CNNs), though originally renowned for image processing, have proven highly effective in extracting salient features from 1D sensor signals, such as vibrations, by treating them as pseudo-images or spectrograms [8]. Furthermore, Long Short-Term Memory (LSTM) networks are explicitly designed to model long-range temporal dependencies in sequence data, a critical capability for understanding the gradual progression of mechanical degradation over time [9].

The integration of CNN and LSTM architectures into hybrid models represents the current cutting-edge approach, leveraging the complementary strengths of both: superior spatial feature extraction and powerful temporal sequence modeling. Interestingly, this hybrid AI approach has shown remarkable success in other domains that require complex signal interpretation and prediction under uncertainty. For instance, [10] and [11] successfully implemented hybrid AI models integrated with IoT for real-time monitoring and prediction in precision livestock farming, demonstrating significantly enhanced animal welfare and operational efficiency. Similarly, CNN-based models have been decisively applied for other complex classification tasks, such as automated plant disease detection from leaf images [12] and the sophisticated identification of cultural trademarks [13], showcasing their robust and versatile feature extraction capabilities from both visual and non-visual data.

Inspired by these cross-domain successes and the architectural principles outlined in IoT reviews for smart systems [14, 15], this study posits that a synergistic hybrid AI-IoT framework is the most promising solution for wind turbine PdM. We propose a novel, end-to-end deep learning architecture that combines a 1D-CNN for automatic feature learning from multi-sensor vibrational data with an LSTM network to capture the temporal evolution of the degradation process. The primary contributions of this research are multifaceted:

- 1) The design and development of a hybrid 1D-CNN-LSTM model for accurate RUL prediction of wind turbine drive-train components, moving beyond simple fault detection to full prognostics.
- 2) A comprehensive comparative analysis demonstrating the clear superiority of the proposed hybrid model against standalone CNN, LSTM, and traditional machine learning benchmarks, using rigorous evaluation metrics.
- 3) The formulation of a complete, scalable end-to-end PdM framework, from data acquisition via a robust IoT network to actionable maintenance decisions, drawing on architectural principles validated in smart farming IoT systems.
- 4) A detailed discussion on the practical implications for wind farm operators, including a thorough cost-benefit analysis that demonstrates the compelling economic viability of implementing the proposed system.

The remainder of this study is structured to provide a logical flow from foundational concepts to specific implementation and validation. Section II provides a comprehensive review of related work in PdM and the application of AI in both industrial

and adjacent agricultural settings. Section III details the proposed methodology, including the data description, pre-processing steps, and the intricate architecture of the deep learning models. Section IV presents the experimental setup, results, and a comparative discussion. Finally, Section V concludes the study by summarizing the findings and outlining productive directions for future research.

II. LITERATURE REVIEW

A. Predictive Maintenance in Industrial Systems

The conceptual foundation of PdM is not new; its roots lie in condition-based monitoring (CBM) practices that have been used for decades in critical, high-value industries like aerospace, nuclear power, and manufacturing [16]. Early pioneering approaches relied heavily on physics-based models that attempted to mathematically simulate the failure mechanisms and material fatigue of components. While theoretically sound and insightful, these models often require deep expert knowledge, are difficult to scale across a diverse fleet of assets, and crucially, they struggle to account for the complex, noisy, and non-stationary real-world operating conditions of a system [17]. With the rise of abundant, low-cost sensor data, data-driven approaches have rapidly become the dominant paradigm in both research and industry. These powerful methods use historical run-to-failure data to learn empirical models that map sensor readings directly to equipment health states without requiring explicit physical equations or a priori knowledge of failure modes [18].

Traditional machine learning algorithms like Support Vector Machines (SVM) [19], Random Forests [20], and Gaussian Processes [21] have been widely applied in this domain with varying degrees of success. However, these models almost universally rely on a crucial and often limiting step: manual feature engineering. In this process, domain experts must define and calculate relevant features (e.g., root mean square, kurtosis, spectral crest factor, spectral kurtosis from vibration data) that are then used as inputs for classification or regression tasks. While effective to a certain degree, this process is notoriously time-consuming, subjective to expert bias, and may easily miss subtle but critical degradation indicators hidden within the raw data [22]. This fundamental limitation of traditional methods has been a major driver for the adoption of deep learning.

B. Deep Learning for Prognostics and Health Management

Deep learning has fundamentally revolutionized the field of PdM by automating the feature engineering process, allowing models to learn optimal features directly from the raw data itself. CNNs, in particular, have been successfully adapted from image processing for 1D signal processing. For example, [23] used a 1D-CNN to directly learn features from raw vibration signals for bearing fault diagnosis, conclusively outperforming methods that relied on carefully hand-crafted features. Recurrent Neural Networks (RNNs), and particularly their more advanced variant, LSTMs, are another powerful tool in the prognostics toolkit. Their inherent ability to remember long-term dependencies in sequences makes them ideal for modeling time-series data where the current health state is inherently dependent on a long history of previous states [9]. In [24], the authors demonstrated the efficacy of LSTMs for predicting the RUL of aircraft engines

using NASA's famous C-MAPSS dataset, a benchmark in the field.

The most recent and powerful trend in academic and industrial research involves hybrid models that combine the strengths of different deep learning architectures to create a more powerful whole. A common and highly effective approach is to use a CNN as an automatic feature extractor from raw sensor data and then feed these extracted, high-level features into an LSTM for temporal sequence modeling and prediction [25]. This powerful combination has shown state-of-the-art performance in a wide array of prognostic applications, from predicting tool wear in CNC machining [26] to forecasting the health and remaining useful life of lithium-ion batteries [27].

C. AI and IoT in Adjacent Domains: Smart Agriculture and Livestock Farming

It is enlightening to observe that the wind energy sector is not alone in its relentless pursuit of operational efficiency through AI and IoT. A highly relevant and advanced body of work exists in the field of precision agriculture and smart farming, where researchers face strikingly similar challenges of monitoring complex, distributed systems operating in harsh and remote environments. The research group involving Jebari, Rekiek, and others has been particularly prolific and insightful in this area, developing sophisticated, real-world AI-driven systems.

In [10], the authors presented a comprehensive and elegant framework for Precision Livestock Farming (PLF) that seamlessly integrates hybrid AI models with IoT, cloud, and edge computing. Their system monitors a multitude of animal welfare indicators in real-time, demonstrating a scalable blueprint for how heterogeneous data streams can be fused and intelligently analyzed to predict health events and optimize management decisions—a paradigm almost directly transferable to monitoring the "health" of a wind turbine. Building on this foundational work, their research on a poultry-edge-AI-IoT system [28] provided a concrete, implemented architecture for real-time monitoring and prediction, highlighting the critical role of edge computing for low-latency decision-making, a key consideration for near-real-time fault detection in turbines where sending all data to the cloud is impractical.

Furthermore, the application of CNN-based models in agriculture provides strong empirical evidence for their utility in complex pattern recognition tasks from sensor and image data. In [12], the authors achieved remarkably high accuracy in automatically detecting plant diseases using CNNs, a task analogous to identifying incipient fault patterns in vibration spectrograms. Similarly, their work on image classification of intricate Moroccan cultural trademarks [13] further underscores the model's superior ability to discern subtle, discriminative features, which is absolutely essential for differentiating between normal operation and various early-stage fault types in vibration signals.

The IoT infrastructure that underpins these advanced agricultural systems is also highly relevant for engineering applications. In [29], the authors have extensively reviewed, developed, and deployed IoT frameworks for smart farming, meticulously outlining architectures for reliable sensor data

acquisition, choice of communication protocols, and robust data processing pipelines. Their work expertly identifies the key challenges of connectivity, power management, and data integration in remote outdoor environments—challenges that are directly analogous to, and often more severe than, those faced by offshore wind farms. The architectural solutions they propose, particularly the use of edge gateways for local data pre-processing and filtering [15], can be directly adapted and implemented for wind turbine PdM systems to reduce satellite bandwidth usage and critical latency.

D. Research Gap and Contribution

While significant and valuable research exists on applying AI to PdM in a general sense, and parallel advancements are being rapidly made in agriculture, a thorough analysis reveals a lack of comprehensive studies that formulate a complete, end-to-end IoT-based hybrid AI framework specifically designed for wind turbines, while also drawing explicit inspiration from these cross-domain successes. Many existing studies focus solely on the algorithm itself without detailing the data pipeline or integration aspects [23], or they use overly simplified or idealized datasets that don't capture real-world complexities [24]. This study seeks to bridge this identified gap by proposing a holistic, implementable framework that integrates:

- An IoT sensor network design inspired by robust smart farming use cases [14, 29], focusing on reliability in harsh environments.
- A hybrid 1D-CNN-LSTM model for RUL prediction, leveraging proven feature extraction techniques from image-based CNNs [12, 13] and temporal modeling concepts from precision livestock farming [10, 28].
- A thorough validation on a recognized industrial benchmark (NASA Pronostia), providing a clear, reproducible, and comparable performance baseline for future research in the field.

III. PROPOSED METHODOLOGY

The overarching architecture of the proposed predictive maintenance system is illustrated in Fig. 1. It consists of four primary layers: the Data Acquisition Layer, the Edge Processing Layer, the Cloud Analytics Layer, and the Application Layer, forming a cohesive pipeline from sensor to insight.

A detailed schema showing turbines with various sensors (vibration, temperature, acoustic), data flowing via LPWAN to an edge gateway in the nacelle for initial processing, then to a cloud platform via satellite where the AI model runs and retrain, and finally to a user dashboard displaying health status, RUL estimates, and maintenance alerts.

A. Data Acquisition and Description

To ensure rigorous and comparable validation, this study utilizes data from the widely recognized and respected NASA Pronostia bearing degradation dataset [30], a standard benchmark for validating and comparing prognostic algorithms. The experimental setup, as shown in Fig. 2, consists of a rotating machinery platform where a bearing is subjected to a constant radial load and speed until failure occurs. Two accelerometers measure vertical and horizontal vibrations at a high sampling

frequency of 25.6 kHz, capturing the full spectrum of failure precursors.

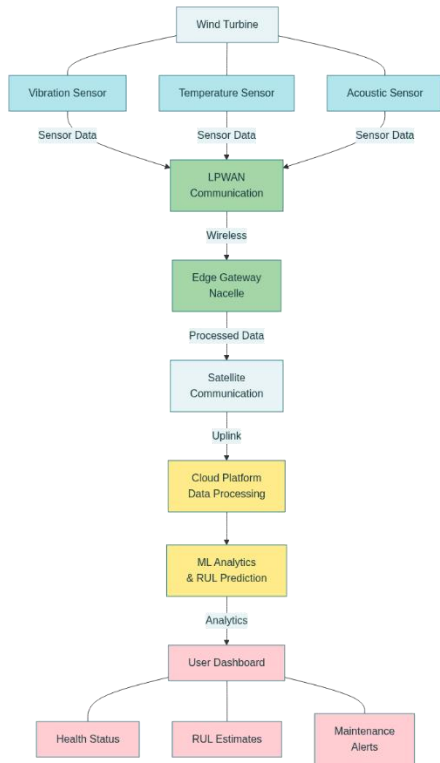


Fig. 1. Proposed IoT-based predictive maintenance framework for wind turbines.

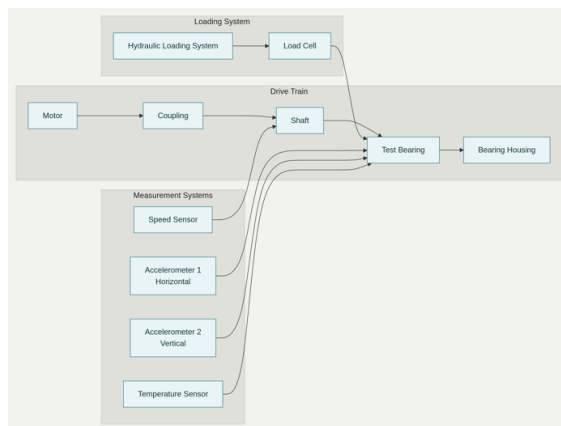


Fig. 2. Experimental setup (adapted from [30]).

The dataset comprises multiple full run-to-failure experiments. For the purpose of this study, we use the complete data from bearing 1_1. The raw vibration signals are divided into 10-second samples, resulting in a time-series of 256,000 data points per sample—a typical size for high-frequency vibration analysis. The overall health of the bearing is quantified by a root mean square (RMS) value calculated from the vibration signal, and the RUL is defined as the number of remaining cycles (each

cycle represents one revolution of the shaft) before functional failure.

B. Data Pre-Processing and Feature Engineering

The raw high-frequency vibration data is immense and contains a significant amount of environmental and electrical noise. Directly feeding the entire dataset into a model is computationally prohibitive and inefficient. Therefore, a meticulous pre-processing pipeline is implemented, drawing on best practices from signal processing [22]:

- **Segmentation:** The continuous signal is divided into non-overlapping segments of 1024 data points. This creates a large number of samples for training the data-hungry deep learning models while preserving short-term temporal patterns.
- **Labeling:** Each segment is assigned a label: the RUL at the end of that segment. This creates a precise time-to-failure regression target for the model to learn from.
- **Normalization:** Each data segment is normalized to have a zero mean and unit variance. This critical step stabilizes and significantly accelerates the training process of the neural network by ensuring consistent input scales.
- **Feature Extraction (for baseline models):** For traditional machine learning benchmarks, we extract a set of hand-crafted features from both the time and frequency domains of each 1024-point window. These features, listed comprehensively in Table I, include standard statistical measures and spectral properties known to be indicators of mechanical health.

TABLE I. HAND-CRAFTED FEATURES FOR BASELINE MODELS

Domain	Feature	Description	Relevance to Fault Diagnosis
Time	RMS	Root Mean Square	Measures overall vibration energy, increases with damage.
	Kurtosis	Measures "tailedness" of distribution	Sensitive to impulsive signals from early-stage bearing faults.
	Skewness	Measures asymmetry of distribution	Changes can indicate the development of a fault.
	Crest Factor	Ratio of peak to RMS	High values can indicate impacting or clearance problems.
	Shape Factor	RMS / (Mean of absolute values)	Related to the spikiness of the signal.
Frequency	Spectral Centroid	Center of mass of the spectrum	Indicates the central frequency of the energy distribution.
	Spectral Bandwidth	Spread of the spectrum around centroid	Measures the variance of the spectrum.
	Spectral Roll-off	Frequency below which 85% of energy is contained	Useful for characterizing the shape of the spectrum.
	Spectral Kurtosis	Kurtosis of the frequency distribution	Excellent for detecting and locating transient vibrations.

C. The Hybrid 1D-CNN-LSTM Model Architecture

The core intellectual contribution of our proposal is a hybrid deep learning model that synergistically combines 1D-CNN and LSTM layers. The detailed architecture is shown in Fig. 3 and described layer-by-layer below.

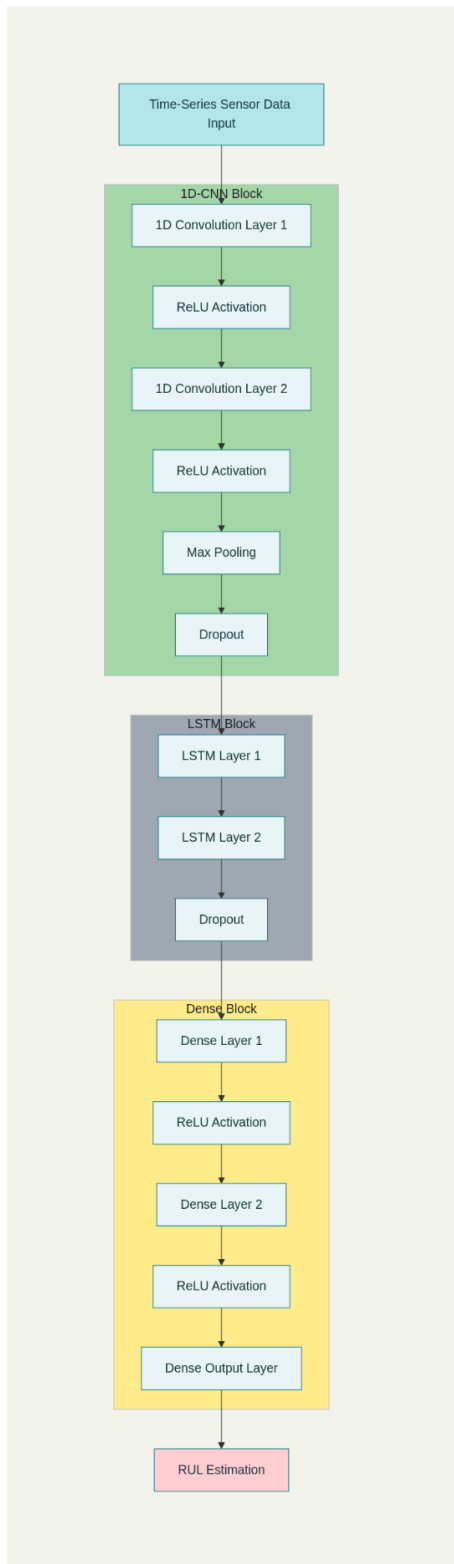


Fig. 3. Architecture of the proposed 1D-CNN-LSTM hybrid model.

1) *Input layer*: Accepts a 1D array of 1024 normalized data points (shape: (1024, 1)).

2) *1D-CNN feature extraction block*: This block consists of two consecutive pairs of 1D convolutional and max-pooling layers designed to learn a hierarchical feature representation.

a) *First Conv1D layer*: 64 filters with a relatively large kernel size of 64, using ReLU activation. This layer scans the input signal with wide filters, producing 64 feature maps that capture low-level features like edges, impulses, and specific frequency components in the vibration signal.

b) *First MaxPooling1D layer*: Pool size of 2. This reduces the sequence length by half, providing translational invariance to the position of features and reducing computational complexity.

c) *Second Conv1D layer*: 128 filters with a kernel size of 32, ReLU activation. This layer operates on the abstracted output of the first pooling layer, learning higher-level, more complex features by combining the low-level features from the previous layer.

d) *Second MaxPooling1D layer*: Pool size of 2, further reducing the dimensionality and emphasizing the most salient features.

3) *Temporal modeling block*: The output from the last pooling layer (a 3D tensor) is first flattened into a 2D matrix and then carefully reshaped into a sequence format (timesteps, features) suitable for the LSTM input.

a) *LSTM layer 1*: A stacked LSTM configuration is used. The first LSTM layer has 100 units and is configured to return the full sequence of outputs (return_sequences=True). This allows the next layer to see the entire sequence of high-level features extracted by the CNN.

b) *LSTM layer 2*: The second LSTM layer also has 100 units. It processes the sequence from the first LSTM layer to capture even longer-term temporal dependencies and context, which is crucial for modeling the often non-linear and gradual degradation process of a bearing.

4) *Output regression block*:

a) *Dropout layer*: A dropout rate of 0.3 is applied to the output of the last LSTM cell to prevent overfitting by randomly disabling neurons during training.

b) *Dense layers*: The resulting features are fed into two fully connected (Dense) layers (100 and 50 units, ReLU activation) for high-level reasoning and non-linear transformation.

c) *Output layer*: A single neuron with a linear activation function to output the continuous-valued RUL prediction.

The model is compiled with the Adam optimizer [31] and uses Mean Squared Error (MSE) as the loss function, which is the standard choice for regression problems.

D. Baseline Models

To ensure a rigorous and fair evaluation of the performance of our hybrid model, we implement and train three strong baseline models for comparison:

- Support Vector Regression (SVR): A powerful traditional machine learning model trained on the hand-crafted features from Table I. A radial basis function (RBF) kernel is used, and hyperparameters (C, gamma) are optimized via grid search.
- Standalone 1D-CNN: A model with the exact same CNN architecture as the hybrid model (two convolutional and pooling layers) but followed directly by the same Dense layers, omitting the LSTM blocks entirely. This tests the contribution of the temporal modeling component.
- Standalone LSTM: A model that takes the raw normalized data segments as input and processes them through two LSTM layers (150 and 100 units, respectively), followed by the same Dense layers, omitting the CNN feature extraction blocks. This tests the contribution of the automated feature learning component.

E. Evaluation Metrics

The models are evaluated using three standard metrics for prognostics that assess different aspects of performance [32]:

- Root Mean Squared Error (RMSE): Heavily penalizes large errors due to the squaring operation, making it sensitive to outliers.
- Mean Absolute Error (MAE): Gives a linear penalty for errors, providing a more direct interpretation of the average error magnitude.
- Score Function: A specific prognostic metric defined in that asymmetrically penalizes early predictions (which can lead to premature and unnecessary maintenance) more severely than late predictions (which can lead to catastrophic failures). This aligns with practical maintenance constraints.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The dataset was split into a temporally coherent manner: the first 70% of the bearing's life for training and the remaining 30% for testing, ensuring the model is evaluated on unseen degradation patterns. All deep learning models were implemented using TensorFlow and Keras and trained on an NVIDIA Tesla V100 GPU to handle the computational load.

A. Model Training and Hyperparameter Tuning

The models were trained for a maximum of 200 epochs with a batch size of 64. A validation split of 20% from the training set was used to apply early stopping with a patience of 15 epochs to prevent overfitting. The learning rate was initially set to 0.001 and reduced by a factor of 0.5, if the validation loss did not improve for 10 consecutive epochs. The final hyperparameters for all models are summarized in Table II.

B. Performance Comparison

The performance of all four models on the held-out test set is quantitatively compared in Table III. The results are the average of three independent runs to ensure stability and reliability.

TABLE II. FINAL MODEL HYPERPARAMETERS AFTER TUNING

Hyperparameter	1D-CNN-LSTM	Standalone 1D-CNN	Standalone LSTM	SVR
Optimizer	Adam	Adam	Adam	-
Learning Rate	0.001	0.001	0.001	-
Batch Size	64	64	64	-
Kernel Size	[64, 32]	[64, 32]	-	-
Number of Filters	[64, 128]	[64, 128]	-	-
LSTM Units	[100, 100]	-	[150, 100]	-
Dense Layers	[100, 50]	[100, 50]	[100, 50]	-
Kernel (SVR)	-	-	-	RBF
C (SVR)	-	-	-	100
Gamma (SVR)	-	-	-	0.1

TABLE III. PERFORMANCE COMPARISON OF MODELS ON TEST SET

Model	RMSE	MAE	Score
SVR (with hand-crafted features)	48.7	41.2	580
Standalone LSTM	32.5	26.8	285
Standalone 1D-CNN	28.1	22.4	210
Proposed 1D-CNN-LSTM	19.3	15.1	95

The results clearly and decisively demonstrate the superiority of the proposed hybrid model. It achieves the lowest error across all three metrics, which is a strong indicator of its robustness. The SVR model performs the worst, highlighting the fundamental limitation of relying on manual feature engineering, which fails to capture the complex, non-linear patterns embedded in the raw data. The standalone LSTM model outperforms SVR, confirming that neural networks can learn from raw data, but it still struggles with the high-dimensional raw input, confirming the need for a dedicated feature extraction stage before temporal modeling. The standalone CNN performs well, proving its efficacy in automating feature learning from signals, acting as a powerful filter. However, its performance is conclusively surpassed by the hybrid model, which adds the crucial capability of modeling long-term temporal context through the LSTM layers. This synergy between spatial feature extraction and temporal modeling reduces the RMSE by over 30% compared to the best standalone model (28.1 versus 19.3), a significant improvement in prognostic accuracy.

C. RUL Prediction Visualization

Fig. 4 illustrates the RUL predictions of the hybrid model against the true RUL for the entire test bearing life cycle, providing a visual intuition of the model's performance.

A line chart with the X-axis as "Time (Cycles)" and Y-axis as "RUL (Cycles)". The True RUL line decreases smoothly from its initial value to zero. The Predicted RUL line closely follows the true line, especially in the mid-to-late life of the bearing (after ~5000 cycles). Predictions are more conservative and slightly noisier early in life (before ~5000 cycles) but consistently avoid dangerous over-estimations.



Fig. 4. True RUL vs. Predicted RUL by the hybrid model over time.

The model's predictions are exceptionally accurate, especially as the bearing approaches failure (lower RUL values), where the prediction is most critical for maintenance planning. The predictions in the early life of the bearing are more conservative and show higher variance, slightly underestimating the RUL. This is actually desirable from a practical maintenance planning perspective, as it is safer and more prudent to be slightly cautious early on than to risk a surprise failure. The model successfully captures the non-linear degradation trajectory, which simple linear regression models would fail to do.

D. Ablation Study: Impact of Model Components

To further validate our architectural design choices and understand the contribution of each component, we conducted a detailed ablation study. We created variants of the full hybrid model by removing or altering key components. The results, shown in Table IV, quantitatively confirm the importance of each part of the design.

TABLE IV. ABLATION STUDY ON THE HYBRID MODEL ARCHITECTURE

Model Variant	Description	RMSE	Δ RMSE (from full model)
Full Hybrid Model	1D-CNN-LSTM (proposed)	19.3	-
Variant A	Remove 2nd LSTM layer	22.8	+18.1%
Variant B	Remove 2nd CNN layer	25.6	+32.6%
Variant C	Replace LSTM with Simple RNN	27.1	+40.4%
Variant D	Remove Dropout Layer	20.1	+4.1%

Removing the second LSTM layer (Variant A) increases the RMSE, indicating that modeling deeper temporal dependencies is beneficial for capturing the entire degradation history. Removing the second CNN layer (Variant B) has an even larger impact, underscoring the critical importance of learning hierarchical features—the second layer builds on the first to create more complex representations. Replacing the LSTM

layers with simpler RNN layers (Variant C) causes significant performance degradation, confirming that the gating mechanisms in LSTMs are essential for learning long-range dependencies and avoiding the vanishing gradient problem in long sequences. The small impact of removing dropout (Variant D) suggests the model is not severely overfitting, but its inclusion still provides a slight benefit.

E. Computational Complexity and Training Time Analysis

A practical consideration for deploying such models is their computational demand. Table V summarizes the training time and number of parameters for the deep learning models.

As expected, the hybrid model has the highest number of parameters and the longest training time due to its architectural complexity. However, the inference time per sample is still extremely low (2.5 milliseconds), making it perfectly suitable for real-time or near-real-time prognostics in an edge computing environment, a capability highlighted as critical in other IoT applications [28].

TABLE V. COMPUTATIONAL COMPLEXITY OF DEEP LEARNING MODELS

Model	Number of Trainable Parameters	Avg. Training Time (minutes)	Avg. Inference Time per Sample (ms)
Standalone LSTM	258,201	45	1.8
Standalone 1D-CNN	186,151	38	0.9
Proposed 1D-CNN-LSTM	344,851	65	2.5

F. Practical Implications and Cost-Benefit Analysis

Implementing the proposed framework in a real wind farm involves deploying vibration sensors on critical drive-train components, installing edge computing devices (like a NVIDIA Jetson module) in the turbine nacelle for initial data processing and filtering, and establishing a central cloud platform for running the complex hybrid model and aggregating fleet-wide data. Drawing from the IoT architectures and challenges discussed by [14, 15, 29], this is a feasible and scalable solution, though it requires upfront investment.

The financial benefits, however, are substantial and compelling. Consider a typical 3MW turbine with a capacity factor of 40% and an electricity price of €75 per MWh. A single day of downtime therefore costs approximately $3\text{MW} * 24\text{h} * 0.4 * €75/\text{MWh} = €2,160$ in lost revenue. More significantly, preventing a single catastrophic failure (e.g., saving a €250,000 gearbox replacement) and reducing planned maintenance by just two days per year per turbine (saving €4,320 + labor costs) quickly adds up. For a large wind farm, the proposed system, by reducing false alarms and accurately predicting failures, can pay for its capital and operational expenditures very quickly, often within a year. Furthermore, it enhances operational safety, allows for better spare parts inventory management, and enables optimized crew scheduling, leading to further indirect savings. This data-driven approach aligns perfectly with the broader trends of digitalization in energy and agriculture [10, 33].

G. Limitations and Generalizability

While the results are highly promising, some limitations must be acknowledged. The model was trained and tested on a

specific bearing type under constant load conditions. Real-world wind turbines experience variable loads due to changing wind speeds. Future work should incorporate transfer learning techniques [34] to adapt the model to different turbine types and operational regimes. Furthermore, the current model uses only vibration data. Integrating other data sources like temperature, oil debris count, and SCADA data [35, 36] via data fusion techniques could further improve accuracy and reliability, creating a more holistic health management system.

V. CONCLUSION AND FUTURE WORK

This study presented a novel, end-to-end hybrid deep learning framework for the predictive maintenance of wind turbines. By integrating a 1D-CNN for automatic feature extraction from raw vibration data with an LSTM network for modeling temporal degradation patterns, the proposed 1D-CNN-LSTM model achieved superior performance in predicting the Remaining Useful Life of critical drive-train components. Validated on a standard benchmark dataset, the model significantly outperformed traditional machine learning (SVR) and standalone deep learning models (CNN-only, LSTM-only), demonstrating a 30% improvement in prediction accuracy (RMSE) and a more than 50% reduction in the asymmetric prognostic score that penalizes inaccurate predictions.

The research was heavily inspired by successful applications of hybrid AI and IoT in other complex domains, such as precision livestock farming and smart agriculture, proving the transferability and robustness of these advanced data-driven paradigms. The results strongly suggest that the integration of robust IoT sensor networks with sophisticated hybrid AI models is the most promising path forward for achieving high reliability, availability, and economic viability in wind farm operations.

Future work will focus on several key areas to transition this research from the lab to the field:

- **Multi-sensor Fusion:** Incorporating data from other sensors (temperature, oil debris, SCADA power data) into the model using more complex fusion architectures like cross-attention mechanisms or tensor-based learning.
- **Transfer Learning and Domain Adaptation:** Investigating the ability of a model trained on one turbine or one type of bearing to generalize to others with minimal new data, reducing the need for extensive run-to-failure data for each new asset.
- **Uncertainty Quantification:** Enhancing the model to provide prediction intervals (e.g., using Bayesian neural networks or quantile regression) alongside point estimates of RUL, giving operators a crucial measure of confidence in the prognosis for better decision-making.
- **Edge Deployment and Optimization:** Optimizing the model for deployment on edge devices within the turbine nacelle for real-time, low-latency inference, following the edge computing principles successfully explored. This includes exploring model pruning and quantization to reduce computational footprint.

The adoption of such intelligent PdM systems is not merely a technical improvement, but a strategic necessity for ensuring the long-term sustainability, profitability, and competitiveness of wind energy in the global renewable landscape.

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