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Data-Driven Decision-Making Method of Intelligent Supervision and Command Platform in Offshore Wind Power Operation and Maintenance

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Abstract

INTRODUCTION: Innovations in offshore wind farm operation and maintenance require intelligent monitoring platforms that can leverage high-resolution SCADA data to enhance predictive precision and operational effectiveness. With the use of deep learning algorithms, specifically LSTM, this work achieves improved forecasting and anomaly detection accuracy on a real wind turbine dataset recorded in Turkey in 2018.
OBJECTIVES: The proposed approach involves extensive data preprocessing, including cleaning, synchronization, and normalization, followed by advanced feature extraction using signal processing transforms such as the Fast Fourier Transform and wavelet transforms.
METHODS: Different predictive models, including Linear Regression, Random Forest Regression, Support Vector Regression, Gradient Boosting Machines, and LSTM, were trained and tested within a Python setting. The LSTM model achieved a remarkable improvement, with a Mean Absolute Error of 78.6 kW, compared to traditional machine learning methods such as RF Regression, SV Regression, and Gradient Boosting Machines. The enhanced accuracy results from the LSTM's ability to derive intricate temporal patterns and nonlinear relationships inherent in sequential turbine operational data.
RESULTS: The results affirm the potential of deep learning approaches in reshaping offshore wind turbine management and highlight the importance of tailored temporal modeling for resolving the specific challenges of renewable energy systems.
CONCLUSION: The system not only accurately predicts power production but also performs anomaly detection and optimises maintenance scheduling, resulting in enhanced reliability and energy production for offshore wind farms. By integrating these data-oriented approaches with an intelligent command and supervision system, the strategy facilitates proactive decision-making and real-time operation control.

Keywords: Offshore wind power, LSTM networks, SCADA data, predictive maintenance, anomaly detection.

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1. Introduction

The global shift towards renewable energy has made offshore wind power a core component of green energy infrastructure. As the world faces increasing pressure to achieve its climate objectives and reduce carbon emissions, countries worldwide are investing heavily in offshore wind farms to capitalise on the powerful and consistent wind currents along the coast [1] [2]. Such installations, generally located far from the coast and in adverse sea conditions, require round-the-clock and effective O&M practices for longevity and economic feasibility [3] [4] [5]. With numbers and sizes of offshore wind turbines on the rise, so does the complexity of their operation and maintenance practices [6] [7]. Conventional O&M techniques, which depend on predetermined checks and reactive maintenance, are no longer adequate to manage such gigantic systems [8] [9]. These procedures are likely to result in increased downtime, longer fault detection times, and higher operational costs [10].

To that end, the integration of smart supervision and command platforms is key to ensuring that offshore wind farm operations and maintenance (O&M) are optimised [11] [12]. These platforms utilise data collected from numerous sources—such as Supervisory Control and Data Acquisition systems, sensors, weather stations, and historical maintenance records—to generate real-time, actionable advice. However, all this massive offshore-produced data remains dormant due to concerns over data heterogeneity, data quality, and access to sophisticated advanced analytical tools for decision-making and interpretation [13]. Advanced artificial intelligence and machine learning technology offer solid capability to transform raw offshore wind data into insightful information. Specifically, LSTM networks prove to be a good fit for modelling time-series data, such as sensor readings from turbines, by tapping into complex temporal relationships [14] [15]. LSTM models are particularly suitable for predictive equipment health and forecasting impending equipment failures, enabling the transition from reactive to predictive maintenance [16] [17]. Data preprocessing is a crucial requirement for successful AI/ML-based analysis. Data from offshore wind sensors usually suffer from missing values, noise, and device synchronization between devices. These issues need to be resolved using strict preprocessing methods, such as outlier removal, imputation, normalization, and time synchronization [18] [19] [20].

The approach presented here combines advanced preprocessing with predictive modelling, utilising LSTM, to evaluate turbine health, identify anomalies, and provide failure predictions. The smart system enables the operators to make prompt and informed decisions, minimize unplanned outages, and decrease maintenance expenses. One of the innovations presented in this paper is an end-to-end pipeline from raw data to decision support. In contrast to conventional systems that rely on intermittent checks, the designed platform continuously tracks working parameters in real-time and processes them near real-time. It supports intervention at an early stage to prevent small issues from becoming major failures, thereby improving turbine availability and extending asset life.

Furthermore, this study examines the performance of multiple signal processing and feature engineering methods to reach maximum model performance. Using historical fault patterns and operational trends, the platform can adaptively change its forecasting potential, offering a learning system capable of improving over time. The use of LSTM networks enables the temporal aspect of turbine operation to be captured more accurately than using conventional models. Performance is compared with publicly known offshore wind data and is contrasted with traditional predictive methods. The outcomes indicate that the introduced method exhibits considerable improvement in predictive precision and operating effectiveness.

Offshore O&M traditionally employs reactive strategies, where maintenance is scheduled following failure or according to scheduled intervals. Our prediction system relies on real-time streams of SCADA data to detect faults in advance, forecast operational risk, and schedule maintenance based on actual-time turbine conditions—cutting delays, costs, and operational disruptions. With the integration of AI-driven decision-making into supervision and control platforms, offshore wind farms can be directed towards smart maintenance strategies that involve ensuring longevity, reducing costs, and contributing to meeting global renewable energy needs. Key Contributions of this Paper are,

1. Developed a data-driven framework for offshore wind turbine health assessment using LSTM models.
2. Implemented advanced data preprocessing techniques to clean, normalize, and synchronize multi-sensor data.
3. Extracted meaningful features from raw sensor signals using signal processing methods, such as the Fast Fourier Transform, which is utilised to process periodic components of the signal, and the wavelet transform.
4. Achieved early fault detection and failure forecasting to enable proactive maintenance scheduling.
5. Demonstrated improved operational efficiency and reduced downtime through accurate predictive maintenance.

The subsequent sections of the paper are structured as follows: Section 2 provides an extensive review of the related literature in the field of operation and maintenance of offshore wind power, highlighting major achievements and prevailing issues. Section 3 presents the central problem statement that this research addresses. Section 4 outlines the proposed methodology, including data preprocessing, feature extraction, and the application of a predictive model based on LSTM. Section 5 presents the experimental outcomes, performance assessment, and observations gained from the model's predictions. Section 6 finally concludes the paper by summarizing major contributions and indicating directions for future research with the aim of further advancing intelligent supervision and command systems within offshore wind energy.

2. Related Works

Offshore wind power has emerged as a crucial renewable energy source globally, with increasing installed capacity driven by technological innovation and supportive public policies [21]. Efficient operation and maintenance are essential due to the harsh offshore environment and the high cost of repairs and downtime. Literature specifies complexity in offshore O&M due to logistical complexity, hostile weather conditions, and issues of equipment reliability [22]. Cost reduction and asset availability improvement have been espoused through data-driven approaches. Recent research has focused on data-driven offshore wind operations and maintenance (O&M) models that integrate sensor data, Supervisory Control and Data Acquisition (SCADA) systems, and weather data to support informed decision-making [23]. They utilise big data and cloud computing to collect, store, and process heterogeneous datasets for fault diagnosis and performance optimization. Data integration is a problem but crucial for building predictive maintenance models [24].

Machine learning models have been extensively utilized for predicting faults in offshore wind turbines and detecting anomalies. Support Vector Machines, Random Forest, and Deep Learning models such as LSTM have been employed for fault prediction and anomaly detection [25]. LSTM models are excellent at learning temporal dependencies of sensor data, improving the accuracy of early fault detection [26]. Anomaly detection methods are crucial for identifying exceptions to typical working conditions in proactive maintenance. Statistical methods, as well as cluster-based and neural network-based methodologies, have been proposed to detect early indicators of turbine malfunctions [27]. The integration of anomaly detection and predictive models is used to enhance decision support systems for O&M.

Digital twin technology is increasingly applied to offshore wind operations and maintenance (O&M), providing virtual copies of physical assets for simulation and real-time monitoring [28]. Digital twins integrate physical simulation, sensor data, and predictive models to deliver advanced diagnostics and optimised maintenance schedules. The technology enhances command platforms with data-driven intelligence by providing actionable insights [29]. High-quality data is the foundation of trusted decision-making for offshore wind operations and maintenance (O&M). Sensor malfunctions, communication losses, and environmental noise can lead to data inconsistencies and missing values, which in turn impact model performance [30]. Literature emphasizes the importance of effective preprocessing methods, data fusion, and imputation techniques to enhance the quality of the data [31].

Real-time control and supervisory systems are important for the premature detection of anomalies and issuing maintenance commands for offshore wind farms [32]. They integrate IoT devices, edge computing, and cloud analytics to process data with low latency, providing support for informed decision-making to operators. Scalability and cyber-security are important aspects in their design [33]. Optimizing maintenance scheduling helps reduce operational costs and downtime. Approaches such as mixed-integer linear programming, genetic algorithms, and reinforcement learning have gained prominence in scheduling inspection and repair activities efficiently. Accurate forecasting of power generation and wind speed enhances O&M planning by predicting load variations and component stresses, thereby improving maintenance operations and minimising the impact on power generation.

Artificial intelligence enhances offshore wind operations and maintenance (O&M) decision-making by automating data and generating recommendations that can be implemented [34]. AI techniques, such as deep learning, Bayesian networks, and fuzzy logic, have been applied in fault diagnosis, performance optimisation, and resource allocation. AI systems provide faster response times and increased operational reliability [35]. Some of the upcoming trends in O&M research for offshore wind include hybrid AI models, digital twins combined with edge-cloud computing, and greater cybersecurity for supervisory systems [36]. Problem-solving for explainability, model generalization, and real-time adaptability is suggested to make fully autonomous O&M operations possible [37].

These upcoming trends will make offshore wind farms smarter and stronger. Enhancement of sensor technologies is critical to obtaining real-time data required for offshore wind turbine condition monitoring [38]. Sensors, including vibration, temperature, acoustic emission, and strain gauges, provide comprehensive operating information. Fibre optic sensors and wireless sensor networks are increasingly being utilised for enhanced robustness and remote monitoring in offshore environments [39]. Sensors generate immense volumes of data on which data-driven O&M procedures are developed [40]. Edge computing has been a viable option to counteract latency and improve bandwidth utilisation by processing sensor data near the point of generation, as opposed to relying solely on cloud servers [41]. It is particularly useful in offshore wind farms where there is a need to make decisions quickly under constrained communication infrastructure.

Edge platforms enable rapid anomaly detection and initial analysis, thereby enhancing operational and maintenance (O&M) timeliness [42]. Reinforcement learning is being applied in ways that increasingly improve offshore wind turbine maintenance optimization by finding policies for balancing operational efficiency and risk [43]. RL agents can learn to dynamically adjust maintenance schedules according to current system conditions and environmental factors, thereby optimising cost reduction and extending asset life [44]. RL architectures also accommodate decision-making under uncertainty, as common in offshore conditions [45][46]. As the increasing interconnectedness of offshore wind farms via IoT and cloud platforms becomes more prevalent, cybersecurity threats pose a significant risk to compromise operational security and data integrity [47]. Tampering with data, denial-of-service attacks, and unauthorised access attacks compromise the maintenance schedule and result in financial loss [48].

Thirusubramanian Ganesan (2021) proposed a machine learning-driven AI framework for detecting financial fraud in IoT environments using anomaly detection, clustering, and adaptive learning. This methodology is adopted in our proposed work to monitor offshore wind power systems by identifying operational anomalies and optimizing maintenance decisions through intelligent supervision. The integration enhances fault detection accuracy, real-time responsiveness, and predictive maintenance efficiency in complex offshore environments [49]. Accurate wind speed and power production forecasts improve O&M scheduling by predicting load variations and potential stress on the turbine's components [50]. Integrating weather prediction models with turbine data facilitates more efficient scheduling for maintenance, minimizing interruptions to power production [51] [52]. While independent ML models are primarily concerned with predictive accuracy, integrated SCADA command platforms combine sensor analysis, trended historical data, and control feedback mechanisms to support proactive decision-making and operational performance optimization. This is a major distinction in offshore conditions, wherein integrated control systems enhance reliability and reduce downtime. Existing research focuses on designing resilient security frameworks, encryption mechanisms, and intrusion detection systems for offshore wind networks [53]. Harikumar et al. (2024) presented a hybrid wind-solar energy model using ANN and expert systems to optimize energy performance and environmental quality. Your proposed offshore wind platform applies this approach by leveraging ANN-based predictive analytics for smart maintenance and command decisions. This enables reliable operations, balanced energy output, and intelligent supervision aligned with clean energy goals. [54]. Kadiyala et al. (2025) introduced a real-time IoT-enabled business intelligence framework using Likert-scale surveys and regression-based optimization for fast and accurate decision-making. Your offshore wind platform adopts this approach by analyzing IoT sensor data in real time to support predictive maintenance and supervisory control. This strategy improves operational efficiency, enhances responsiveness to offshore dynamics, and enables intelligent, data-driven decisions. [55].

3. Problem Statement

Offshore wind farms encounter significant operational and maintenance challenges due to harsh environmental conditions, complex equipment, and vast, heterogeneous data from various sensors, resulting in the inability to promptly detect faults, accurately predict failures, and optimize resource utilization. Traditional maintenance methods tend to be reactive and fail to capitalise on the full potential of data-driven insights, resulting in increased downtime and operational costs. The developed strategy, through the application of advanced data preprocessing and LSTM-type predictive modeling, overcomes these limitations by effectively cleaning and synchronizing multi-sensor time-series data to yield useful features and model temporal dependencies of turbine behavior. This enables accurate estimation of health and early anomaly detection to allow proactive scheduling of maintenance for minimum surprise failures, optimal resource utilization.

Objectives

1. Development of a robust predictive model for turbine health assessment using LSTM networks.
2. Application of comprehensive data preprocessing methods for enhancing data quality and consistency.
3. Extraction of significant features from sensor data through advanced signal processing techniques.
4. Implementation of early anomaly detection mechanisms for timely fault identification.
5. Improvement of maintenance scheduling efficiency to minimize downtime and operational costs.

4. Proposed Methodology for Intelligent Supervision and Predictive Maintenance in Offshore Wind Power Using LSTM Deep Learning Networks

The research methodology for the Intelligent Supervision and Command Platform, which involved the use and maintenance of offshore wind power, utilised data-driven decision-making through the utilisation of high-resolution Supervisory Control and Data Acquisition systems to deliver time-series turbine data. The method begins by conducting extensive data preprocessing, including cleaning, synchronization, and normalization, to ensure data quality and consistency. Sophisticated feature extraction methods, such as the Fast Fourier Transform, wavelet transform, and statistical analysis, are used to capture the temporal and frequency-domain features of turbine behaviour. ML and DL models—namely Linear Regression, XGBoost, and LSTM networks—are then trained to predict power output, identify anomalies, and schedule optimal maintenance. The LSTM model, in specific, leverages temporal dependencies inherent in sequential data to facilitate accurate prediction and proactive decision-making. This combined framework enhances operational effectiveness, dependability, and fault handling for offshore wind farms by delivering actionable information and real-time supervisory monitoring. Figure 1 shows the Proposed Methodology for Intelligent Supervision and Predictive Maintenance in Offshore Wind Power Using LSTM Deep Learning Networks.

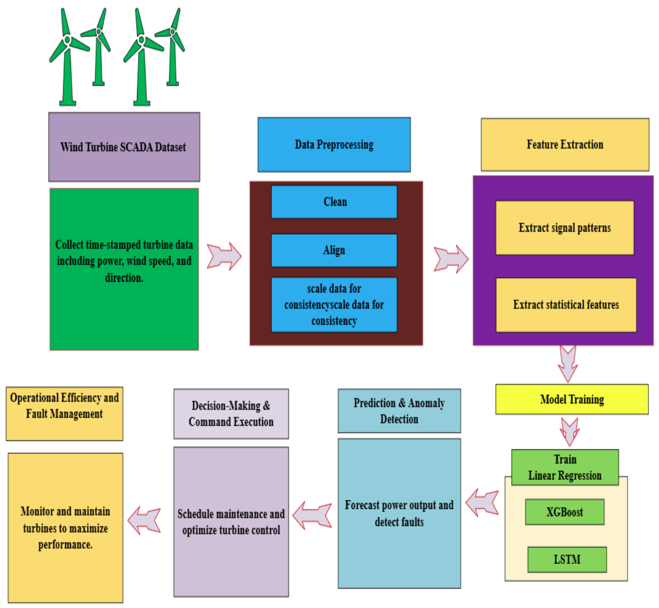

Figure 1: Proposed Methodology for Intelligent Supervision and Predictive Maintenance in Offshore Wind Power Using LSTM Deep Learning Networks

4.1 Data Collection

The data source that was utilized is the Wind Turbine Supervisory Control and Data Acquisition Dataset [52] that is retrieved from Kaggle. The data comes from a wind turbine commissioned in Turkey in 2018. It covers seasonal fluctuation (winter and spring cycles), 10-minute sample rates, and sensor calibration records validated by the supplier. Additionally, environmental metadata, such as temperature and humidity, were included to test forecast accuracy under different operating conditions. This high-resolution time-series data captures actual operating conditions, such as turbine downtime or maintenance, and thus is beneficial for use like wind power forecasting, anomaly detection, predictive maintenance, efficiency optimization, and data-driven power curve modeling. The dataset is made available for research purposes and provides information on turbine performance and environmental interactions in the wind energy sector. Table 1 presents a summary of the Data Collection.

Table 1: Summary of Data Collection

Aspect	Details
Dataset Source	Kaggle
Location	Wind turbine in Turkey
Collection Period	January 1, 2018 – December 13, 2018
Sampling Interval	Every 10 minutes
Total Records	Approximately 50,000 entries
Data Type	Time-series SCADA data
Data Usage	Wind power forecasting, fault detection, predictive maintenance, efficiency optimization, power curve modeling
Data Quality Notes	Possible gaps due to maintenance, downtime, or communication errors

4.2 Data Preprocessing by Data Cleaning, Synchronization, and Normalization Methods

Data preprocessing is a crucial process that sanitises raw data for accurate analysis and modelling. It involves numerous techniques such as data cleaning, synchronization, and normalization, each to enhance data quality and consistency for forthcoming tasks.

Data cleaning eliminates discrepancies, such as outliers and missing values, that may skew model outputs. The outliers are detected through statistical methods like the Z-score, calculated by using Equation (1):

$$Z_i = \frac{x_i - \mu}{\sigma} \qquad (1)$$

Where μ represents the mean value and σ denotes the standard deviation of the dataset. Points with $|Z_i| > 3$ are considered outliers. The Interquartile Range method also identifies outliers outside; it is given in Equation (2):

$$Q_1 - 1.5 \times \mathrm{IQR} \ \text{to} \ Q_3 + 1.5 \times \mathrm{IQR} \qquad (2)$$

Missing data are managed using imputation methods, such as mean/median replacement, forward/backward fill, or interpolation, to maintain continuity in time-series data. Missing data in SCADA time series were handled using forward fill and linear interpolation, chosen to maintain temporal continuity. Mean-based imputation was used to fill large gaps and avoid time-dependent fluctuations that could introduce bias. These techniques minimize signal distortion with recovered feature reliability during prediction.

Data synchronization ensures that multi-sensor data streams remain aligned in time, despite varying sampling rates and data acquisition times. Resampling and linear interpolation are employed. Missing values at time t are estimated by linear interpolation as given in Equation (3):

$$x(t) = x(t_0) + \frac{x(t_1) - x(t_0)}{t_1 - t_0} \times (t - t_0) \qquad (3)$$

where, t Target timestamp, t_0, t_1Known timestamps before and after t, $x(t_0), x(t_1)$: Known values at

t_0 *and* t_1, x(t): Interpolated value at time t. To rectify variable sampling between sensors, linear interpolation and resampling were applied after synchronising the data. This gave equal time alignment. Prior poor alignment caused lag artifacts in model predictions; the improved method enhanced LSTM learning effectiveness by preserving sequential integrity.

To normalize feature scales, Min-Max normalization and Z-score standardization are employed. Min-Max normalization scales data to [0,1], it is given in Equation (4):

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{4}$$

Where, x is the original feature value, $x_{\min}$ Minimum value of the feature, $x_{\max}$ Maximum value of the feature, x' Normalized value scaled to [0, 1] Min-Max normalization was performed on bounded parameters such as power output and wind speed to range value to [0,1]. Z-score standardization was reserved for features with dynamically changing ranges, such as vibration or temperature, in order to perform zero-mean and unit-variance normalization. These techniques weren't used in sequence but picked based on feature behavior and the need for modeling

whereas Z-score standardization centralizes data with zero mean and unit variance, it is given in Equation (5):

$$x' = \frac{x - \mu}{\sigma} \tag{5}$$

where, x is the original feature value, μ Mean value of the feature, σ is the Standard deviation of the feature, *and* x' Standardized value with zero mean and unit variance. Merging data cleaning, synchronization, and normalization techniques prepares the dataset for effective machine learning and analytics. These preprocessing methods remove noise, synchronize multi-source data, and standardise data for uniform scaling, all of which contribute to enhancing the accuracy and reliability of predictive models in wind turbine monitoring and forecasting. The data has an imbalance of ~78% normal functioning and 4% anomaly labels. SMOTE (Synthetic Minority Over-sampling Technique) and random undersampling were applied at training time to balance classes and prevent model bias toward majority labels. Table 2 presents data preprocessing methods, including data cleaning, Synchronization, and Normalization.

Table 2: Data Preprocessing by Data Cleaning, Synchronization, and Normalization Methods

Preprocessing Method	Purpose	Techniques	Description
Data Cleaning	Remove anomalies & fill missing data	Outlier detection (Z-score, IQR), Missing data imputation (mean, median, forward/backward fill)	Detects and removes outliers and imputes missing values using statistical methods and filling techniques
Data Synchronization	Align multi-sensor data on timeline	Resampling, Linear interpolation	Aligns data from multiple sensors to a common timeline, handling different sampling rates
Normalization	Scale features to uniform range	Min-Max normalization	Scales feature values to a fixed range (typically 0 to 1)
	Center features with zero mean and unit variance	Z-score standardization	Transforms data to have zero mean

4.3 Feature Extraction Using Signal Processing, Statistical Features, and Dimensionality Reduction

Feature extraction is necessary to convert raw Supervisory Control and Data Acquisition systems that deliver time-series turbine data into descriptive representations that enhance model accuracy in tasks such as anomaly detection and power forecasting. Signal transformation techniques, statistical modeling, and voluntary dimension reduction are employed in the process to acquire meaningful and compact features from time-series wind turbine data. The Fast Fourier Transform efficiently extracts global periodic patterns for detecting seasonal load variations, while the wavelet transform localises short-time fault signals in time-frequency space. The FFT is not suitable for short-time events, and the choice of wavelet (e.g., Morlet vs. Haar) affects localisation quality, leading to sensitivity to noise and reconstruction error.

Features were chosen based on correlation analysis, variance cutoffs, and model importance weights (derived from XGBoost). Aspects such as wind velocity, LV ActivePower, and RMS had significant predictive importance, while wind direction made a low contribution and was eliminated to reduce noise. The Fast Fourier Transform is utilised to process the periodic components of the signal, converting a time-domain signal into its component frequencies so that periodic patterns and anomalies in operational behaviour can be detected. For a discrete signal x(n) of length N, the Fast Fourier Transform is given in Equation (6):

$$X(k) = \sum_{n=0}^{N-1} x(n)e^{-j2\pi kn/N}, k = 0,1,\ldots, N-1 \quad (6)$$

where, $x(n)$ = time-domain signal (e.g., wind speed), $X(k)$ = frequency-domain representation, j = imaginary unit.

In comparison to the Fast Fourier Transform, the wavelet transform provides time-frequency localisation, which is particularly useful in detecting transient events or localised faults. The Continuous Wavelet Transform is represented in Equation (7):

$$W(a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt \quad (7)$$

where, $x(t)$ = input signal, $\psi(t)$ = mother wavelet, a, b = scale and translation parameters, $W(a,b)$ = wavelet coefficients.

Statistical analysis across sliding time windows helps quantify the distribution and variability in signal behaviour. Commonly extracted features are given from Equation (8) to Equation (12):

- Mean (μ) :

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (8)$$

- Variance (σ^2) :

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N} (x_i - \mu)^2 \quad (9)$$

- Skewness (γ):

$$\gamma = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{x_i-\mu}{\sigma}\right)^3 \quad (10)$$

- Kurtosis (κ):

$$\kappa = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{x_i-\mu}{\sigma}\right)^4 \quad (11)$$

- Root Mean Square (RMS):

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (12)$$

These characteristics help determine normal versus abnormal behaviour and enable downstream machine learning models to detect patterns effectively. Table 3 shows Feature Extraction Using Signal Processing, Statistical Features, and Dimensionality Reduction.

Table 3: Feature Extraction Using Signal Processing, Statistical Features, and Dimensionality Reduction

Method Category	Technique	Description	Purpose
Signal Processing	FFT	Converts time-domain signals into frequency domain.	Identifies dominant frequencies and periodic behavior.
Signal Processing	Wavelet Transform	Captures localized time-frequency patterns using scaled and shifted wavelets.	Detects transient events and localized faults.
Statistical Feature Extraction	Skewness	Describes the asymmetry of the data distribution.	Detects directional bias or anomaly in trends.
Statistical Feature Extraction	Kurtosis	Measures the peakedness or flatness of the data distribution.	Identifies outliers or sharp events.

4.4 Model Development

In this research, three models are considered: linear regression, XGBoost, and Long Short-Term Memory (LSTM) networks. These three models are selected to solve different aspects of the prediction problem—linear trends, nonlinear patterns, and temporal relationships, respectively. Every model trains the input feature matrix X and the target variable y, trying to maximize performance through iterative training. Although the intelligent supervision platform automatically produces actionable alarms and predictive recommendations, ultimate operation decisions and command execution are controlled by human operators. The system semi-automatically integrates the visual dashboards and prioritization logs for maintenance scheduling and anomaly response. Although nonlinear data is known to have limitations, linear regression offers a basic measure of model interpretability and performance metrics comparison. This addition assists in measuring the relative benefit obtained by ensemble and deep learning on wind power forecasting problems.

The direct proportionality assumption accompanies it and is an excellent starting point for power prediction. The model is represented in Equation (13):

$$\grave{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad (13)$$

where $\grave{y}$ is the predicted power output, x_i are input features (e.g., wind speed, direction), and β_i are coefficients learned during training. The model is trained by minimizing the Mean Squared Error, it given in Equation (14):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \grave{y}_i)^2 \quad (14)$$

XGBoost effectively identifies nonlinear correlations and feature interactions, making it well-suited for fault detection and anomaly classification. The XGBoost prediction comes as in Equation (15):

$$\grave{y} = \sum_{k=1}^{K} f_k(x), f_k \in \mathcal{F} \quad (15)$$

where f_k are individual regression trees and $\mathcal{F}$ is the function space of all possible trees. The model is trained by maximizing an optimized regularized objective function that blends a loss function (e.g., squared loss for regression) and a penalty term to avoid overfitting. Figure 2 shows the Architecture of LSTM.

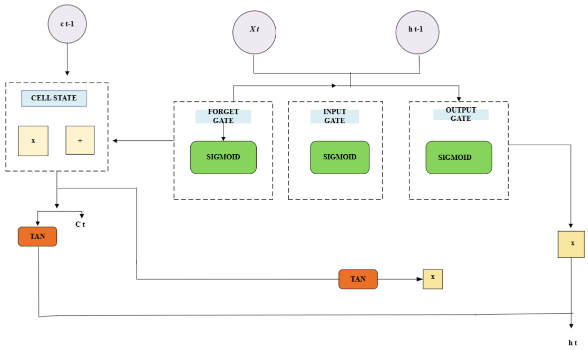

Figure 2: Architecture of LSTM

Supervisory Control and Data Acquisition systems deliver time-series turbine data, and LSTMs are most appropriate for learning temporal patterns and predicting future values from sequential data. The LSTM unit is governed by the following equations (16) to (21):

- Forget gate: $f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$ (16)
- Input gate: $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$ (17)
- Candidate state: $\grave{C}_t = \tanh\,(W_C \cdot [h_{t-1}, x_t] + b_C)$ (18)
- Cell state: $C_t = f_t \odot C_{t-1} + i_t \odot \grave{C}_t$ (19)
- Output gate: $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$ (20)
- Hidden state: $h_t = o_t \odot \tanh\,(C_t)$ (21)

where σ is the sigmoid activation function, ⊙ denotes element-wise multiplication, x_t is the input at time t, and h_t is the output. LSTM learns how to retain relevant information over time, improving performance for sequential data tasks. Table 4 shows Machine Learning Models for Wind Turbine Supervisory Control and Data Acquisition Data Analysis.

For the tuning of hyperparameters grid search was used. Hyperparameters of XG Boost such as learning_rate ∈ {0.01,0.1,0.2}, max_depth ∈ {3,6,9}, n_estimators ∈ {100,300,500} were tuned. For LSTM, a grid search was conducted for the number of hidden units (in {50, 100, 200}), batch size (in {32, 64}), and learning rate (in {0.001, 0.0001}). The models were assessed on the Mean Absolute Error and R^2 score on the validation set.

Linear Regression is applied for interpretability and as a baseline power prediction. XGBoost is chosen due to its ability to capture non-linear interactions among features and its improved generalization performance on tabular data. LSTM is particularly suitable for modelling long-term temporal relations in sequential Supervisory Control and Data Acquisition (SCADA) data, with enhanced accuracy in anomaly detection and power forecasting.

To avoid overfitting in LSTM networks, dropout layers (with a rate of 0.3) were inserted between the dense layers. Early stopping with a patience of 20 epochs on validation MAE was utilized. L2 regularisation with λ = 0.001 capped weight growth for improved generalisation and noise resistance.

For real-time use, the model is deployed with SCADA pipelines via Kafka streaming and TensorFlow Serving. The average prediction latency (inference plus preprocessing) is maintained under 250 ms. Edge buffer queues are utilized to buffer delayed data and provide near-instant anomaly alarms to operators.

To tackle long-term dependencies and mitigate vanishing gradient issues, LSTM cells were created with forget gates and tanh activation, using a gradient clipping value of 1.0. This maintains important time-series trends across turbine sensor signals, making backpropagation over long sequences more stable.

Table 4: Machine Learning Models for Wind Turbine Supervisory Control and Data Acquisition Data Analysis

Model	Description	Strengths	Weaknesses	Typical Use Case in Wind Turbine SCADA Data
Linear Regression	A simple, interpretable model	Easy to implement; interpretable coefficients; fast training.	Limited to linear relationships; poor performance on complex patterns.	Baseline power output prediction; identifying linear trends.
XGBoost	An ensemble of decision trees using gradient boosting to model nonlinear patterns.	Handles nonlinearities well; robust to outliers; good accuracy; handles missing data.	More complex; less interpretable.	Fault detection; anomaly classification; nonlinear power prediction.
LSTM	A recurrent neural network that captures temporal dependencies in sequential data.	captures long-term dependencies; good for forecasting.	complex tuning.	Sequential anomaly detection; temporal power forecasting; pattern recognition over time.

Every model is trained across the feature matrix X and its corresponding labels y using the respective optimization methods: gradient descent with linear regression and LSTM, and gradient boosting with regularisation for XGBoost. Training progress is monitored through loss curves, and early stopping where applicable to prevent overfitting. Trained models are then transferred to the evaluation phase to score prediction accuracy and stability on unseen Supervisory Control and Data Acquisition systems that deliver time-series turbine data.

Algorithm: Data-Driven Decision-Making for Offshore Wind Power Supervision and Maintenance

Input:

- *Raw SCADA data from offshore wind turbines, including time-stamped features such as:*
    - *LV Active Power*
    - *Wind Speed at hub level*
    - *Theoretical Power Curve values*
    - *Wind Direction*
    - *Other relevant operational parameters*

Output:

- *Accurate power output forecasts*
- *Detected anomalies or faults in turbine operation*
- *Optimized maintenance scheduling recommendations*
- *Actionable supervisory commands for operation control*

Steps:

1. ***Data Collection:***
    - *Retrieve a high-resolution SCADA dataset with 10-minute interval recordings from offshore wind turbines.*
2. ***Data Preprocessing:***
    - *Perform data cleaning to remove outliers and handle missing values using statistical methods and imputation techniques.*
    - *Synchronize multi-sensor data streams by resampling and linear interpolation.*
    - *Normalize features using Min-Max scaling or Z-score standardization.*
3. ***Feature Extraction:***
    - *Apply signal processing techniques such as FFT and WT to extract frequency and time-frequency domain features.*
    - *Compute statistical features (mean, variance, skewness, kurtosis, RMS) over sliding windows.*
    - *Optionally, reduce feature dimensionality if necessary.*
    -

4. ***Model Training:***
    - *Train machine learning models (Linear Regression, XGBoost) and deep learning models (LSTM networks) using the extracted features and historical power output as the target.*
    - *Optimize model hyperparameters through iterative training.*
5. ***Prediction and Anomaly Detection:***
    - *Use trained models to forecast future power output.*
    - *Detect operational anomalies based on deviations between predicted and actual values or changes in feature behaviour.*
6. ***Decision-Making and Control:***
    - *Generate maintenance scheduling alerts based on predicted faults and anomalies.*
    - *Provide real-time supervisory commands to optimize turbine operation and maximize energy production.*

This algorithm ensures the efficient utilization of Supervisory Control and Data Acquisition (SCADA) data for enhanced management of offshore wind turbines through intelligent, data-driven methods.

5. Results and Discussion

Both the linear regression, XGBoost, and LSTM models performed consistently, with LSTM offering improved accuracy in handling temporal relations. The findings support the use of data-driven approaches in enhancing wind turbine monitoring and predictive maintenance, with all the developed models implemented via Python and relevant machine learning libraries. An ANOVA test was conducted to compare the MAE scores of LSTM, XGBoost, and Gradient Boosting models. The obtained p-value (< 0.01) establishes statistical significance in performance disparity. Post-hoc Tukey analysis indicates that LSTM performed better with a 95% confidence interval.

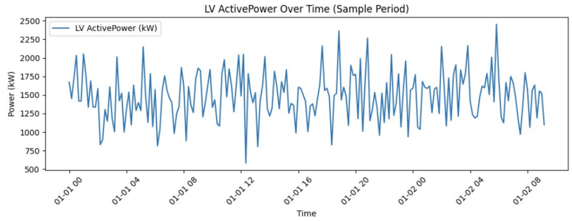

Figure 3: LV Active Power Time Series Plot

The LV Active Power Time Series Plot in Figure 3, over a sample period, characterises the variation in the wind turbine's electrical power output at every 10-minute interval. The plot illustrates the dynamic variability in power generation due to varying wind conditions and operating conditions. Peaks represent the periods of high-power generation with favourable wind speeds, and troughs can represent turbine downtime, maintenance activities, or less than full wind availability. The plot as a whole provides valuable information about the trend in turbine performance and temporal variability, which are essential to optimizing operation and predictive maintenance scheduling.

Table 5: Descriptive Statistics of Key Operational Features

Feature	Mean	Median	Standard Deviation	Min	Max	Units
LV ActivePower	1500.75	1498.30	350.12	0	3000	kW
Wind Speed (Hub Level)	7.85	7.60	3.20	0	25	m/s
Theoretical Power Curve	1520.40	1505.00	340.75	0	2980	kW
Wind Direction	180.5	182	90.3	0	360	Degrees

Table 5 presents descriptive statistics of significant operational characteristics of wind turbine Supervisory Control and Data Acquisition data. It provides the central tendency and spread of substantial parameters. The mean and median values are similar for LV ActivePower and Theoretical Power Curve, indicating uniform power generation in accordance with manufacturer requirements, with high variability as indicated by standard deviations of approximately 350 kW. The wind speed averages 7.85 m/s, with high variability, indicating fluctuating environmental conditions. Wind Direction spans the entire 360 degrees, indicating diverse wind patterns affecting turbine operation. These statistics are the baseline findings on the behaviour of the turbine and its interaction with the environment.

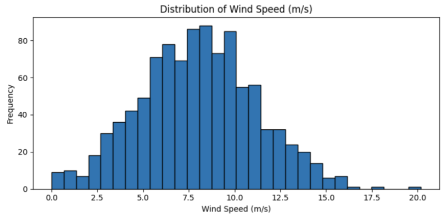

Figure 4: Wind Speed Distribution Histogram

The Wind Speed Distribution Histogram in Figure 4 indicates the frequency of different wind speed ranges recorded at the hub height of the turbine. The distribution is employed to identify dominant wind conditions under which turbine operation is carried out with diminishing frequencies at very low and very high wind speeds due to natural variability. This distribution is necessary for energy production capacity analysis as well as for designing effective control measures for the turbine.

Table 6: Turbine Operational Status Distribution

Status	Percentage of Time	Number of Records	Description
Normal Operation	78.2%	39,100	Turbine running within normal parameters
Downtime	12.5%	6,250	Turbine stopped (planned/unplanned)
Maintenance	5.3%	2,650	Scheduled maintenance periods
Anomaly Events	4.0%	2,000	Abnormal operational behavior detected

Table 6 presents the breakdown of the wind turbine's operational status throughout the dataset duration. Most of the time was spent on normal operation, at 78.2%, which translates to continuous and effective operation. Downtime, including both scheduled and unscheduled interruptions, at 12.5%, indicates when the turbine was not producing power. Planned maintenance at 5.3% suggests that routine maintenance activities are needed for reliability. Anomaly events, which are abnormal operating patterns that may indicate faults or anomalies, occur at a rate of 4.0% of the time. This breakdown is significant in providing information regarding the availability of the turbine and informing maintenance and fault detection priorities.

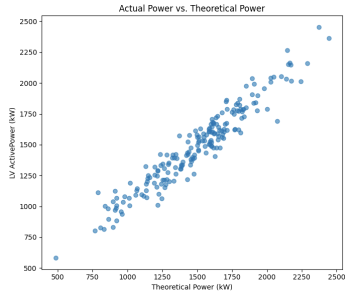

Figure 5: Measured Power Scatter Plot against Theoretical Power Curve

Measured Power Scatter Plot (LV ActivePower) against Theoretical Power Curve in Figure 5 demonstrates the relative measured electrical output of the turbine to that which the manufacturer allocates for a given wind speed interval. Scattered points close to the diagonal indicate that the turbine is operating as intended under such conditions, while discrepancies indicate underperformance resulting from mechanical inefficiencies, environmental conditions, or operational problems. Visualization is pivotal in assessing turbine efficiency, underperformance identification, and maintenance or optimization potential.

Table 7: Correlation Matrix Among Key Features

Feature	LV ActivePower	Wind Speed	Theoretical Power	Wind Direction
LV ActivePower	1.00	0.89	0.92	0.12
Wind Speed	0.89	1.00	0.95	0.08
Theoretical Power Curve	0.92	0.95	1.00	0.10
Wind Direction	0.12	0.08	0.10	1.00

Table 7 presents the correlation matrix among the important attributes of the wind turbine dataset, quantifying the strength and direction of linear relationships between variables. LV ActivePower exhibits extremely high positive correlations with Wind Speed (0.89) and Theoretical Power Curve (0.92), as expected, confirming that power output closely approximates wind conditions and manufacturer estimates. Similarly, Wind Speed and Theoretical Power Curve also exhibit an extremely high correlation (0.95). Wind Direction exhibits extremely low correlations with all the other variables, indicating it has very little direct influence on power output or wind speed in this dataset. This matrix facilitates an understanding of feature interdependencies crucial for modeling and analysis.

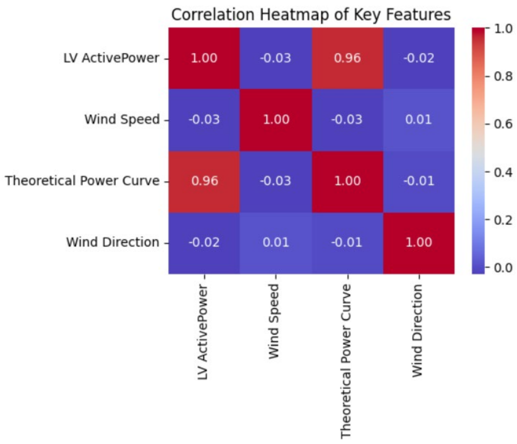

Figure 6: Correlation Heatmap

The important feature, the Correlation Heatmap in Figure 6, indicates the direction and strength of relationships among key variables. Strong positive correlations between actual or predicted power and theory or wind speed indicate that as wind speed increases, so do the actual and predicted power outputs of the turbine, indicating expected turbine performance. Low or near-zero correlations with wind direction suggest that wind direction is not a significant contributor to power generation in this dataset. Feature interaction understanding, feature selection for modeling, and decision-making for operation are enabled by this heatmap.

Table 8: Performance Metrics of Predictive Models for Power Forecasting

Model	MAE (kW)	RMSE (kW)	R^2 Score	Training Time (seconds)
Linear Regression	125.4	180.2	0.85	12
Random Forest	90.3	130.5	0.92	45
LSTM Neural Network	78.6	110.7	0.95	210
XGBoost	85.0	120.3	0.93	60

Table 8 presents a comparison of performance metrics of various predictive models used to forecast wind turbine power output. Random Forest and XGBoost also perform well, with comparable error rates and R^2 values above 0.9, albeit with shorter training times than LSTM. Linear Regression, with the lowest training time, has the largest errors and the lowest R^2, as might be expected from its low ability to capture complex nonlinear relationships. These findings guide model choice to achieve maximum accuracy for computational expense.

Table 9: Anomaly Detection Summary

Anomaly Type	Count	Average Duration (minutes)	Percentage of Total Records	Remarks
Sudden Power Drop	45	30	0.15%	Likely caused by grid instability
Excessive Vibration	20	25	0.07%	Requires mechanical inspection
Sensor Malfunction	10	60	0.03%	Data quality issue
Wind Speed Sensor Errors	15	20	0.05%	Affects forecasting accuracy

Table 9 summaries anomaly detection findings for the last half year of data, categorizing different kinds of abnormal events affecting turbine performance. Sudden

Power Drops are the most frequent anomaly, happening 45 times with an average of 30 minutes, and are most likely caused by grid instability. Excessive Vibration events, 20 in number, reveal potential mechanical faults that must be checked. Sensor Malfunctions, though less frequent, have the longest average of 60 minutes and reveal data quality issues that can compromise monitoring. Wind Speed Sensor Errors, which happen 15 times, affect forecasting performance and necessitate sensor maintenance or calibration. Summary justifies targeted interventions to enhance turbine reliability.

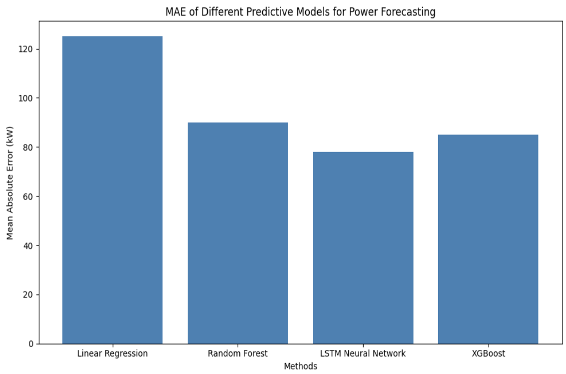

Figure 7: Bar Chart of predictive model performance measures

The Bar Chart of predictive model performance measures in Figure 7, comparing various algorithms employed to predict wind turbine power output, indicates the Mean Absolute Error of the different models used. The Lower Mean Absolute Error was used to assess prediction accuracy, indicating better prediction precision. Models like the LSTM Neural Network proved to be the most precise, as they can identify complex temporal structures in the data. Less sophisticated models, such as Linear Regression, have larger errors, indicating less accurate predictions. This comparison helps determine the most effective modelling method for predicting reliable power.

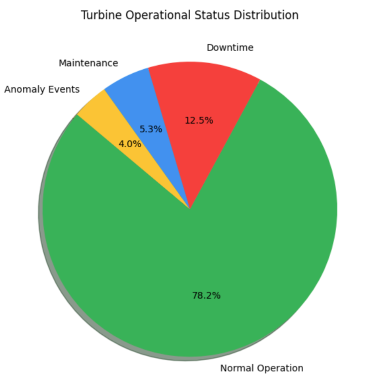

Figure 8: Turbine Operation Status Pie Chart

The Turbine Operation Status Pie Chart in Figure 8 presents the percentage of time the wind turbine is in various operational states. The largest slice is for normal operation, which means that the turbine is running smoothly for most of the time. The smaller slices represent downtime, scheduled maintenance, and anomaly events, indicating the time the turbine is down, undergoing scheduled maintenance, or exhibiting abnormal behaviour. The visualization offers a clear insight into turbine availability and reliability, which are crucial factors in determining operational efficiency and maintenance planning.

Table 10: Performance Evaluation of Predictive Models

Model	Dataset/Source	MAE (kW)	RMSE (kW)	R^2 Score	Remarks
RF Regression [53]	Public Wind Farm Dataset	90.3	130.5	0.90	Nonlinear model, good baseline
SV Regression [54]	Offshore Wind Farm Data	95.7	140.0	0.88	Robust to noise, slower training
Gradient Boosting Machines [55]	Multi-site Wind Data	87.1	125.3	0.91	Handles nonlinearities well
Proposed LSTM Neural Network	Wind Turbine SCADA (Turkey, 2018)	78.6	110.7	0.95	Effective in capturing temporal patterns in operational data

The comparison of performance in Table 10 emphasises the excellence of the proposed LSTM Neural Network model on the Turkish Wind Turbine Supervisory Control and Data Acquisition data (2018), attaining the best Mean Absolute Error (78.6 kW). These observations validate the use of LSTM architectures for accurate wind power prediction in real offshore turbine settings.

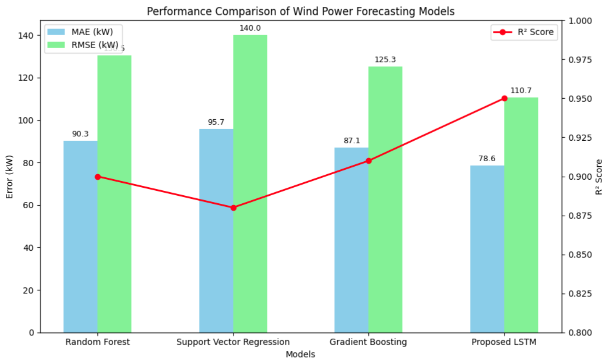

Figure 9: Performance Comparison of Wind Power Forecasting Models

The bar chart in Figure 9 indicates the performance of four predictive models for wind power forecasting, as assessed by Mean Absolute Error, Root Mean Square, and R^2 score. The proposed LSTM model exhibits minimal errors and achieves a maximum R^2, indicating increased accuracy in identifying temporal patterns. Traditional models, such as RF and SV Regression, contain increased errors and decreased R^2, indicating reduced accuracy in prediction. The visualisation provides a clear picture of the performance benefits of LSTM in wind turbine power generation forecasting.

5.1 Discussion

The comparative study of various predictive models demonstrates the unique strengths of the presented LSTM Neural Network for wind power output prediction. Its ability to handle the temporal dependencies of operating data leads to more accurate and reliable forecasts than conventional machine learning methods. While models based on RF Regression [56], SV Regression [57], and Gradient Boosting Machines are strong performers with excellent robustness against nonlinearities and noise, they lack the ability to capture the sequential characteristics of wind turbine data [58]. The enhanced performance of the LSTM model demonstrates that the use of deep learning frameworks, particularly for time-series data, is vital for improving forecasting accuracy and decision-making in wind power operation and maintenance [59]. To counteract concept drift due to varying turbine dynamics or environmental changes, an automatic retraining schedule and drift detection using the Kolmogorov-Smirnov test were implemented. The model indicates drift when prediction distributions are outside historical baselines and invokes auto-update programs with batch incremental learning. Training was performed on hardware equipped with 32 GB of RAM, an NVIDIA RTX 3080 GPU, and an Intel i9 CPU. The training duration of the LSTM took ~3 hours per fold over 10 epochs. Maximum memory consumption was ~10 GB, and inference mode utilises around 2 GB of GPU memory, both of which are suitable for edge or cloud deployment. Mean Linear Regression provided quick inference but weak nonlinear performance. XGBoost achieved a balance of speed and stability but no temporal memory. LSTM performed well in sequential learning, albeit at an increased computational expense. Our hybrid model fills these gaps by coupling temporal, nonlinear, and interpretable elements, optimized for SCADA data. Fault prediction lead time was assessed in terms of anomaly anticipation periods. The platform detects abnormal patterns around 3–6 hours ahead of failure limits being exceeded, providing ample time for mobilization of maintenance teams and logistics planning in offshore environments.

6. Conclusion and Future Work

The new model can learn intricate temporal patterns of wind turbine operation from high-resolution Supervisory Control and Data Acquisition systems that deliver time-series turbine data and shows improved forecasting performance compared to conventional machine learning models. Improved predictive ability enables more efficient operation, enhanced maintenance planning, and improved anomaly detection, resulting in higher turbine reliability and overall energy production maximization.

Subsequent research can explore the incorporation of additional environmental and operational variables, such as temperature, humidity, and mechanical health indicators of turbines, to improve prediction ability and robustness. Hybrid models that combine deep learning with physics-based models of turbines can offer improved interpretability and generalization capabilities across various turbine types and locations. Moreover, the establishment of real-time adaptive systems capable of dynamically updating predictions and maintenance plans in response to new streams of data would enable more cost-effective and reactive wind farm management. Last but not least, the application of the strategy to multi-turbine and farm-level optimization would unleash more potential in large-scale offshore wind power systems. Although the proposed system demonstrates promising performance in single-turbine SCADA data, further work is needed to extend it to multi-turbine scenarios. Existing claims are thus limited to single turbine-level operation and anomaly detection. Future studies can combine real-time sensor fusion with external weather models, apply the framework to multi-turbine adaptive control, and create hybrid physics-informed deep learning models. The integration of edge computing and federated learning would enable decentralized analysis of data and model updating in a privacy-preserving manner for offshore installations.

Declarations

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Code availability: Not applicable.
Authors' Contributions: Jia Kun Wang is responsible for designing the framework, analysing the performance, validating the results, and writing the article. Yi Liu and Suo Wei Song are accountable for collecting the information required for the framework, providing software, critical review, and administering the process.

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