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Risk Analysis of Wind Turbine Using Machine Learning and AI

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Abstract

As wind energy becomes increasingly vital to the global renewable energy portfolio, ensuring the reliability of wind turbines is essential. Failures in components such as bearings, blades, and gearboxes not only disrupt operations but also escalate maintenance costs and reduce turbine lifespan. This thesis proposes a hybrid risk analysis framework that integrates traditional engineering methods with machine learning (ML) algorithms to support predictive maintenance in wind turbines. A qualitative risk matrix was developed to assess failure modes based on likelihood and impact, identifying bearings, blades, and corrosion-prone components as high-risk. For quantitative analysis, real-world SCADA data from two sites (spanning 89 years of cumulative operation) was used to train five ML models: Random Forest, Logistic Regression, Gaussian Naive Bayes, Decision Tree, and Hidden Markov Models. While these models achieved high recall for normal operations (e.g., Random Forest reached 96% for Class 0), they struggled to detect anomalies due to class imbalance and sensor variability—most notably, Hidden Markov Models failed to identify any faults. To address these challenges, the study recommends the use of SMOTE for class balancing, model retraining to handle temporal drift, and enhanced labelling techniques for nuanced fault detection. Component-specific strategies—such as UAV-based blade inspections and slip ring temperature tracking are proposed. Additionally, a digital twin framework is introduced to combine real-time SCADA monitoring with predictive modelling. Overall, this work demonstrates the value of combining classical risk assessment with intelligent analytics, offering a scalable solution for improving wind turbine reliability and maintenance efficiency.

Keywords
Risk Analysis, Wind Turbines, Predictive Maintenance, Machine Learning, SCADA Data

1. Introduction
Facing higher energy use and tougher environmental problems, wind energy is now a core part of renewable energy solutions. Though wind turbines are key to turning this resource into electricity, operating them well is still a difficult task because multiple forces work together. Trouble with important parts such as bearings, blades, gearboxes and control systems disrupt generating energy, cause significant upkeep expenses and make areas unsafe. Reliable and available wind turbines are now essential to get the best energy results and to make sure the grid is stable.

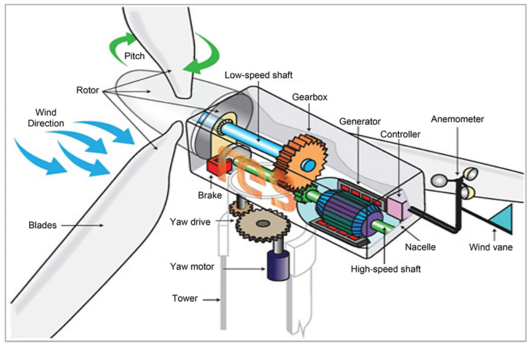

Figure 1. Major components of a wind turbine

Because of these problems, more attention is being given to risk analysis and predictive maintenance. Using fixed schedules for maintenance does not work well for the many and changing failures seen in modern wind turbines. Real-time SCADA systems are used to power predictive maintenance which looks at sensor data to find any early signs of wear and tear in important components. Even so, carrying out these strategies is made difficult by problems of an imbalanced class distribution, changing sensors over time and not being able to prioritize risks for each part of the system. To overcome these problems, the research links qualitative and quantitative ways of assessing risks.

Wind turbine performance is increasingly challenged by unexpected breakdowns in important parts such as bearings, blades and gearboxes are now more and more challenging wind turbine performance (Figure 1). Traditional assessment techniques such as FMEA and PRA are organized but they are not flexible in real time and tend to overlook information from SCADA. Current research points out how important machine learning is for predictive maintenance, but its wide use is still limited because of class imbalance, changing readings from sensors and underdeveloped blended approaches. This research links qualitative and quantitative risk assessment with machine learning anomaly detection to design a solid process for early fault prediction and efficient maintenance scheduling in wind turbines.

1.1 Objectives

Primary objective in this research is to analyse the risks of wind turbine failures through a hybrid strategy. The qualitative process is about identifying and arranging failure risks according to their likelihood and impact, finally producing a risk matrix. This quantitative part applies ML algorithms—Random Forest, Logistic Regression, Gaussian Naive Bayes, Decision Tree and Hidden Markov Models—to predict problems in SCADA data and look for specific trends in sensor data that suggest possible failures ahead. Within this study, data from real SCADA sources are prepared, time-based models are checked and maintenance suggestions are made with AI support.On that basis, the research here presents specific precautions for high-risk failure modes. Examples of these strategies are using targeted sensors, organizing maintenance by condition and prioritizing operations on blades, bearings and transformers. With these strategies part of their routine, wind turbine operators hope to operate their equipment for longer, with less time lost and achieve better performance.

2. Literature Review

Risk assessment is a foundational element in wind turbine management, ensuring safe, reliable, and cost-effective operation across diverse environments. As wind energy continues to grow globally, researchers have explored both classical and modern approaches for identifying and mitigating turbine failures. Among the most widely adopted techniques are Failure Mode and Effects Analysis (FMEA) and Probabilistic Risk Assessment (PRA). Wang et al. (2015) and Catelani et al. (2020) demonstrated the effectiveness of these methods in reducing operational risks and unplanned downtime, while maintaining service continuity.

Tazi et al. (2017) proposed an enhanced cost-based FMEA model, incorporating economic parameters into traditional risk assessment frameworks to improve decision-making under constrained budgets. Le and Andrews (2016) developed a Petri net-based model integrating system degradation, maintenance strategies, and downtime metrics, making it suitable for complex reliability analysis. In marine environments, Kang et al. (2017) and Yeter et al. (2018) evaluated the performance and structural reliability of floating and offshore wind turbines using correlation-FMEA and economic standards, respectively. Dimitrov (2018) introduced a risk-based categorization system for blade damage, offering targeted maintenance strategies for leading-edge erosion and trailing-edge cracks.

Alhijazi et al. (2019) applied a hybrid Fuzzy-FMEA with Dempster-Shafer theory to prioritize failure modes in vertical-axis wind turbines, addressing uncertainty in component behaviour. Guo et al. (2020) and Xu et al. (2022) advocated for machine learning techniques such as Artificial Neural Networks (ANNs) and Hidden Markov Models (HMMs), which can capture complex and time-dependent failure patterns using SCADA data. Despite their potential, the adoption of these models has been limited by high data requirements, computational complexity, and difficulty in feature engineering.

He et al. (2021) improved the FMEA process by introducing probabilistic linguistic variables and the TODIM method, which enhanced the prioritization of turbine failure risks. Nielsen et al. (2021) and Wang et al. (2021) focused on probabilistic assessments to extend the fatigue life of wind turbine structures and improve gearbox failure prediction accuracy. These studies emphasized the value of component-specific risk analysis but also highlighted the need to broaden the scope beyond mechanical subsystems. Yu et al. (2019) analysed lightning protection failures using risk-based simulations, contributing to safer design practices. Ngo et al. (2023) introduced a fragility-based framework for assessing offshore turbine foundations under multi-hazard scenarios such as earthquakes and scour, enhancing structural reliability in extreme environments. Hallowell et al. (2018) evaluated hurricane risks for offshore turbines, quantifying failure probabilities under varying yaw control functionalities.

Gaidai et al. (2023) presented a spatiotemporal reliability framework that estimates wind turbine failure likelihood by analysing environmental interactions and structural dynamics in real time. Li et al. (2022) highlighted the value of transferring onshore turbine failure data to offshore applications to enhance safety and operational planning.
Overall, the literature reveals a growing consensus on the importance of integrating AI-driven analytics with engineering-based risk assessment. While conventional PRA and FMEA models continue to dominate, they are increasingly being complemented or replaced by hybrid systems capable of real-time decision-making. Future research should focus on bridging data-driven methods with classical frameworks, improving SCADA data utilization, addressing class imbalance, and extending risk assessments to include cyber, financial, and systemic threats in modern wind energy systems.

3. Methods

This research employs a hybrid methodology that combines traditional engineering-based qualitative risk analysis with data-driven quantitative methods using machine learning (ML) to detect potential failures in wind turbine components.

3.1 Qualitative risk analysis

The qualitative analysis focuses on identifying and ranking the failure modes of major wind turbine components based on their likelihood of occurrence and potential operational impact. This step uses a risk matrix approach, a widely accepted engineering tool for prioritizing maintenance interventions.

i. Component Identification: Major turbine subsystems including bearings, blades, gearboxes, generators, electrical systems, control systems, structural components, yaw system, and areas susceptible to corrosion/erosion were identified based on literature and engineering insights.
ii. Failure Mode Analysis: Each component's typical failure modes were catalogued, such as bearing fatigue, blade delamination, or gearbox micro-pitting.
iii. Risk Scoring:
    - Likelihood (L): Scored from 1 (Rare) to 5 (Almost Certain) based on historical failure rates and expert judgment.
    - Impact (I): Scored from 1 (Negligible) to 5 (Catastrophic) depending on the failure's effect on turbine operation and safety.
    - Risk Score (R): Calculated as $R = L \times I$
iv. Risk Classification:
    Low Risk: Score 1–5
    Medium Risk: Score 6–10
    High Risk: Score 11–25(As shown in Table 1)

Table 1. Risk assessment matrix

Impact \ Likelihood	1 (Rare)	2 (Unlikely)	3 (Possible)	4 (Likely)	5 (Almost Likely)
5 (Catastrophic)	5	10	15	20	25
4 (Major)	4	8	12	16	20
3 (Moderate)	3	6	9	12	15
2 (Minor)	2	4	6	8	10
1 (Insignificant)	1	2	3	4	5

3.2 Quantitative risk analysis

The quantitative phase employs supervised machine learning models trained on SCADA (Supervisory Control and Data Acquisition) data to detect anomalies indicative of potential failures. The approach encompasses several core stages

i. Data Source and Preprocessing:

The study utilized the CARE SCADA dataset, which includes high-frequency sensor readings and event logs from three sites. Site A and B were selected for detailed analysis due to their data completeness and diversity.

Key preprocessing steps included:

- Data Integration: Merged 95 CSV files, standardized timestamps, and synchronized different data streams.
- Resampling: Data was resampled at 10-minute intervals to align with the SCADA system's temporal resolution.
- Labelling: Data points were labelled as "normal" (Class 0) or "anomalous" (Class 1) based on event log timestamps.

Features used included ambient temperature, nacelle direction, generator RPM, slip ring temperature, wind speed/direction, and power metrics.

ii. Machine Learning Models:

Five machine learning algorithms were selected to balance model interpretability, performance, and temporal sensitivity:

- Random Forest (RF): An ensemble tree-based model well-suited for high-dimensional data and nonlinear relationships. RF also supports feature importance ranking via permutation importance.
- Logistic Regression (LR): A baseline linear classifier offering high interpretability and computational efficiency. Features were standardized using StandardScaler.
- Gaussian Naive Bayes (GNB): A probabilistic model assuming feature independence. Useful for quick prototyping and fault screening.
- Decision Tree (DT): A non-linear rule-based model capable of capturing complex patterns but susceptible to overfitting.
- Hidden Markov Model (HMM): A temporal sequence model trained only on normal data to detect deviations, suitable for modelling gradual fault emergence.

iii. Model Training and Evaluation:

Training Strategy:

- Time-based split: Data was divided into training (first 80%) and testing (last 20%) sets to simulate real-world chronological deployment.

Evaluation Metrics:

- Accuracy: Overall correctness of predictions.
- Precision: Percentage of predicted anomalies that are true anomalies.
- Recall: Percentage of actual anomalies correctly identified (critical for maintenance).
- F1-Score: Harmonic mean of precision and recall.
- Confusion Matrix: Visual summary of prediction errors for both classes.

Feature Importance Analysis: RF and DT models were used to generate permutation importance rankings, highlighting sensors most correlated with fault detection (e.g., slip ring temperature, transformer undervoltage, tower frequency).

4. Data Collection

This study utilizes real-world operational data collected from the CARE SCADA dataset, a comprehensive time-series database designed for condition monitoring and fault analysis in wind turbine systems. The dataset comprises over 95 individual files and spans a cumulative operational duration of 89 years, aggregated from three sites—referred to as Site A, Site B, and Site C.

To ensure data integrity and completeness, this research focuses on Site A and Site B, which demonstrated high-quality and consistent data availability across key operational parameters. Each dataset includes synchronized SCADA sensor readings recorded at a 10-minute resolution, along with timestamped event logs that detail known fault occurrences such as gearbox malfunctions, generator overheating, and transformer issues.The sensor data captures a wide range of physical and electrical parameters, including but not limited to: Ambient and nacelle temperatures, Wind speed and direction from multiple anemometers, Generator RPM and slip ring temperature, Transformer temperatures and voltage levels, Active and reactive power metrics, Hub and yaw system temperatures, Tower natural frequency estimates.

Event logs provided ground truth for fault occurrences, enabling the labelling of each data record as either "normal" (Class 0) or "anomalous" (Class 1). This binary classification forms the foundation for supervised machine learning model training and evaluation.

To prepare the data for analysis, the following preprocessing steps were performed:

i. Data Merging and Standardization: Raw CSV files were merged, with timestamps converted to a standard datetime format and sorted chronologically.
ii. Resampling: Data was resampled at 10-minute intervals to match SCADA system resolution and ensure temporal consistency.
iii. Label Alignment: Fault timestamps were cross-referenced with operational data to generate labelled datasets for binary classification tasks.
iv. Feature Cleaning: Non-sensor columns such as asset_id and timestamp were removed to prevent data leakage during model training.

The data collection and processing workflow is illustrated in Figure 2. It outlines the steps from initial data input to SCADA processing, event information extraction, data labelling, and time-based splitting for machine learning model training.

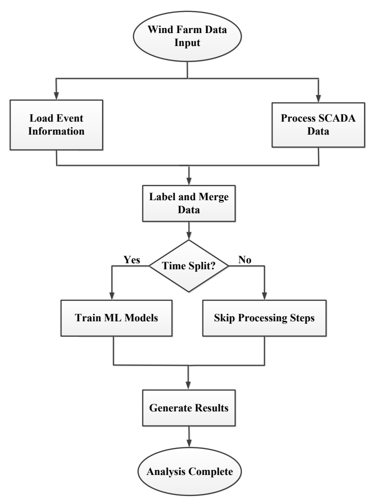

Figure 2. Pseudo code pipeline

This robust data collection and preprocessing pipeline ensures a clean, structured dataset suitable for both qualitative risk mapping and quantitative fault prediction using machine learning models. The combination of long-term, high-frequency sensor data and precise event labelling provides a strong foundation for anomaly detection and predictive maintenance research in wind turbine systems.

5. Results and Discussion

5.1.1 Numerical Results

The qualitative risk analysis was conducted by evaluating key wind turbine components using a risk matrix approach based on two factors: likelihood of failure and impact severity. Each component was assigned a score from 1 to 5 for both parameters. The risk score was computed using the formula: $R = L \times I$

Table 2 Risk scores and level for components

Component	**Likelihood (1–5)**	**Impact (1–5)**	**Risk Score**	**Risk Level**
Bearings	4 (Likely)	4 (Major)	16	High
Blades	3 (Possible)	5 (Catastrophic)	15	High
Gearbox	3 (Possible)	4 (Major)	12	High
Generator	2 (Unlikely)	4 (Major)	8	Medium
Electrical System	3 (Possible)	3 (Moderate)	9	Medium
Control System	3 (Possible)	3 (Moderate)	9	Medium
Structure	1 (Rare)	5 (Catastrophic)	5	Low
Yaw System	2 (Unlikely)	3 (Moderate)	6	Medium
Corrosion/Erosion	4 (Likely)	4 (Major)	16	High

Inference: Bearings, blades, and corrosion/erosion emerged as the most critical components, each with a risk score above 15. These high-risk areas require prioritized monitoring and maintenance to prevent costly downtimes and safety hazards.

5.1.2 Graphical Results

Figure 3 presents a visual representation of the risk scores by component. Colour coding indicates the risk level: red for high risk, orange for medium risk, and green for low risk.

- Bearings, Blades, and Corrosion/Erosion are in the high-risk category, with scores of 16, 15, and 16, respectively.
- Gearbox also borders the high-risk threshold at 12.
- Structural components, while having catastrophic impact, are least likely to fail and thus fall in the low-risk category.

This visual tool helps stakeholders identify and act on the most vulnerable areas within the turbine system.

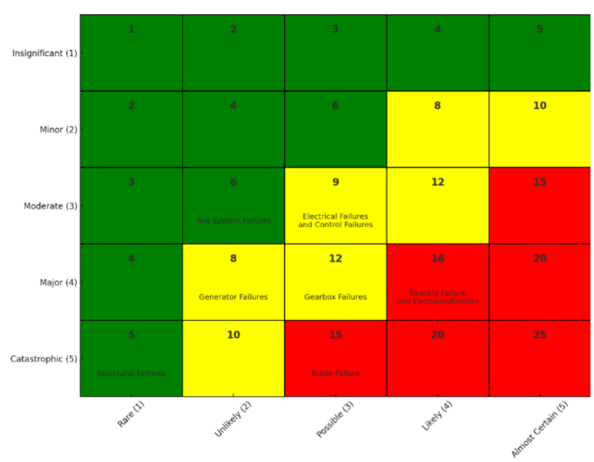

Figure 3. Risk assessment matrix

5.1.3 Proposed Improvements

Based on the risk rankings, targeted strategies can be applied to high-priority components:

i. Bearings:
   - Implement condition-based lubrication.
   - Use accelerometers for early vibration detection.
   - Monitor slip ring temperature continuously.

ii. Blades:
   - Schedule periodic drone inspections.
   - Integrate blade-pitch actuator behaviour analytics.
   - Use surface degradation models for fatigue tracking.

iii. Corrosion/Erosion:
   - Employ ultrasonic thickness sensors in offshore installations.
   - Develop a corrosion index combining weather data with SCADA anomalies.

Additionally, periodic re-evaluation of risk scores is recommended to reflect evolving environmental and operational conditions, ensuring dynamic risk management.

5.1.4 Validation

Validation of the qualitative risk framework was done by cross-referencing high-risk components with known industry failure patterns and failure event logs from the CARE dataset. High-priority components such as bearings and blades were consistently involved in documented failures across multiple sites.

Further, the qualitative scores align with sensor-driven insights from quantitative analysis. For instance, high slip ring temperatures (bearing indicator) and nacelle directional misalignment (blade stress indicator) frequently appeared as top features in machine learning models.

Although this qualitative method is expert-driven, its consistency with real-world failure observations and SCADA-based feature importance provides strong evidence of its validity. To statistically validate prioritization accuracy, future work may incorporate expert consensus scoring and inter-rater reliability (e.g., using Fleiss' Kappa).

5.2.1 Numerical Results

This section presents the quantitative performance of five machine learning models trained on SCADA data from Site A and Site B. The key evaluation metrics include accuracy, recall, precision, and F1-score, with a focus on detecting fault conditions (Class 1), which are typically rare.

Table 3. Performance Metrics for Site A

Model	**Accuracy**	**Class 0 Recall**	**Class 1 Recall**
Random Forest	39%	96%	4%
Logistic Regression	39%	98%	3%
Gaussian Naive Bayes	39%	99%	2%
Decision Tree	39%	95%	5%
Hidden Markov Model	38%	100%	0%

Inference: As illustrated in Table 3, The high recall for Class 0 indicates strong ability to detect normal conditions. However, all models struggle with Class 1 recall due to severe class imbalance in the data. Notably, the Hidden Markov Model (HMM) fails to detect any anomalies, highlighting limitations in its ability to generalize rare fault patterns.

Table 4. Performance Metrics for Site B

Model	**Accuracy**	**Class 0 Recall**	**Class 1 Recall**
Random Forest	13%	97%	8%
Logistic Regression	9%	83%	5%

Model	Accuracy	Class 0 Recall	Class 1 Recall
Gaussian Naive Bayes	95%	0%	100% (overfitting)
Decision Tree	15%	95%	10%
Hidden Markov Model	5%	100%	0%

Inference: Site B data posed a more extreme imbalance, further degrading model performance. GNB achieved misleadingly high accuracy by overpredicting anomalies. This shows that accuracy alone is not a reliable metric in highly imbalanced datasets. (Table 4)

5.2.2 Graphical Results

In terms of feature relevance, permutation importance analysis identified several key sensor readings that played a major role in anomaly detection. Notably, sen_0_avg (representing total negative reactive power), sen_42_avg (Transformer L1 undervoltage temp), and sen_53_avg (Slip ring temp of the generator) consistently ranked as top predictors. Additional important features included sen_6_avg (calc wind speed from Anemometer 2) and sen_41_avg (Transformer L1 mid-voltage temp). These sensors are crucial because they reflect core operational parameters—such as power distribution and thermal stress—that often exhibit noticeable shifts when faults develop. Figures from 4 to 7 illustrate the permutation importance plots for RF, LR, GNB and DT models, respectively, for Site.

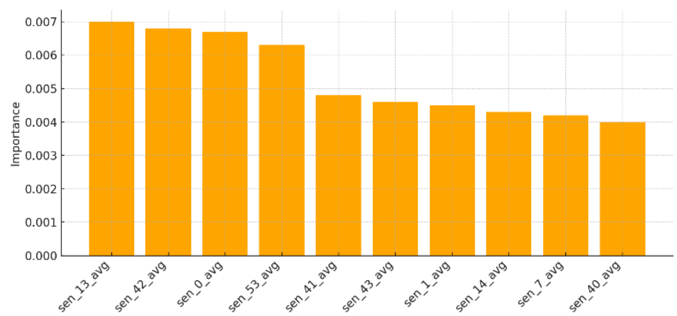

Figure 4. Top 10 permutation importance for random forest on site A

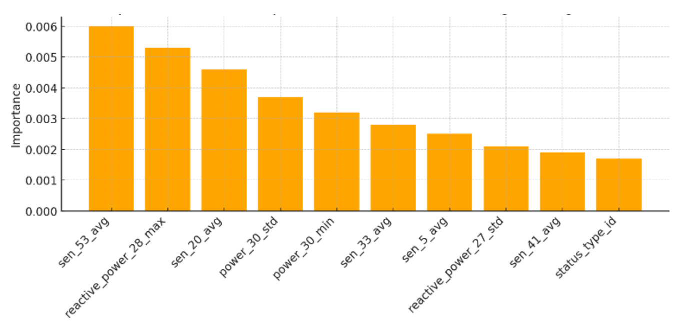

Figure 5. Top 10 permutation importance for logistic regression on site A

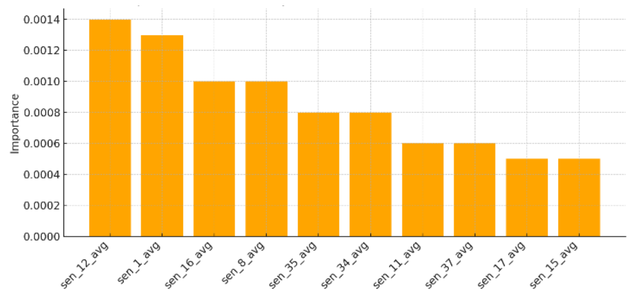

Figure 6. Top 10 permutation importance for gaussian naive bayes on site A

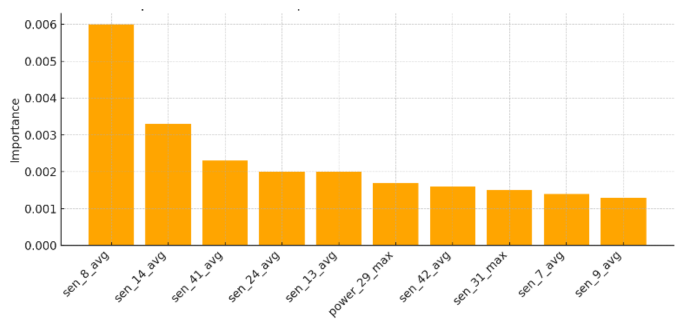

Figure 7. Top 10 permutation importance for decision tree on site A

The permutation importance analysis, illustrated in Figures 8, 9 and 10 identified several key sensors feature that significantly influenced anomaly detection. The top contributors included sen_9_avg (estimated tower natural frequency), sen_8_avg (outside temp), and sen_21_avg (nacelle direction). Other important features—such as sen_4_avg (abs wind direction) and sen_22_avg (hub temp)—highlight the strong influence of both environmental and structural conditions on the occurrence of faults in Site B.

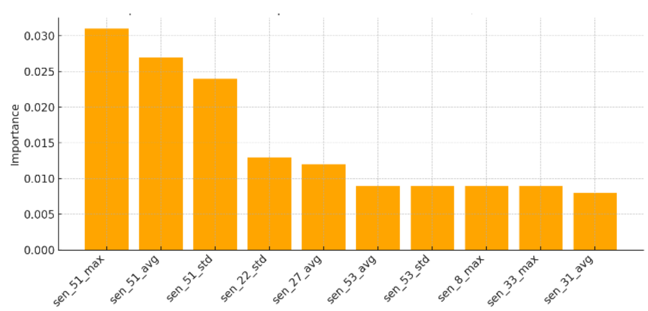

Figure 8. Top 10 permutation importance for random forest on site B

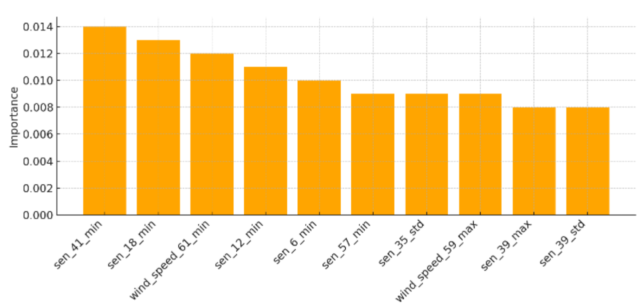

Figure 9. Top 10 permutation importance for logistic regression on site B

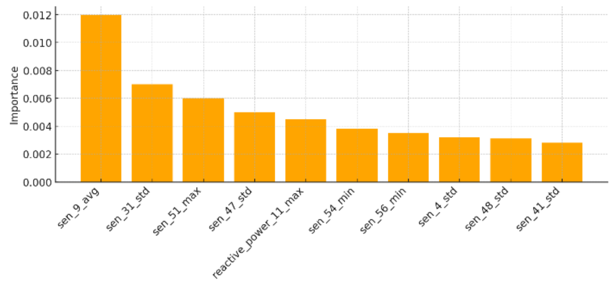

Figure 10. Top 10 permutation importance for decision tree on site B

5.2.3 Proposed Improvements

To address poor anomaly detection performance, the following improvements are proposed:

- Data Balancing: Apply SMOTE (Synthetic Minority Oversampling Technique) or ADASYN to synthetically generate fault data and improve Class 1 recall.
- Model Retraining: Implement a 90-day sliding window strategy to retrain models regularly and handle sensor drift over time.
- Enhanced Labelling: Use multi-class or soft labels to reflect gradual degradation rather than binary fault detection, enabling better use of models like HMM and LSTM.
- Feature Engineering: Introduce domain-specific features such as rate-of-change metrics, thermal differentials, or lagged variables to capture fault onset more accurately.

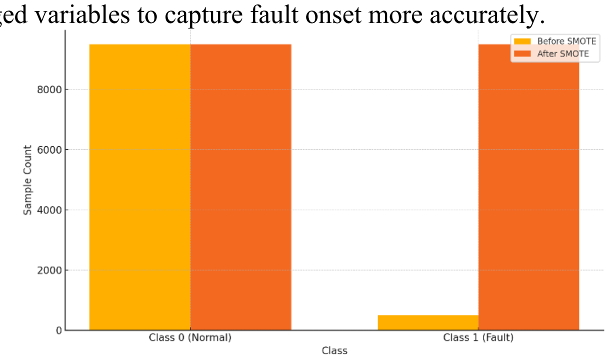

Figure 11. Class distribution before and after SMOTE

Figure 11 shows the class distribution before and after applying SMOTE, highlighting how the originally imbalanced dataset (with very few fault cases) was balanced synthetically to improve model performance.

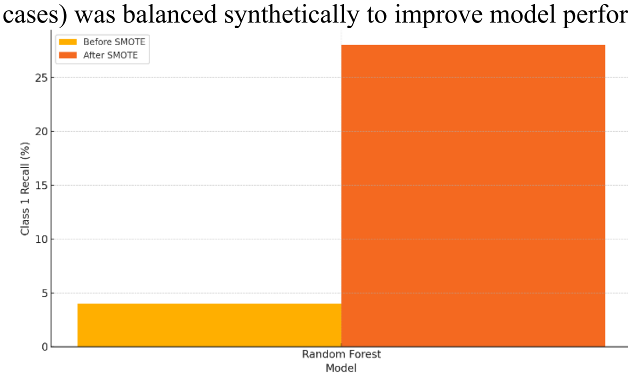

Figure 12. Improved class 1 recall after SMOTE

Figure 12 demonstrates the impact of SMOTE on Class 1 recall for the Random Forest model, improving it significantly from 4% to 28%.

5.2.4 Validation

To validate the performance gains of the proposed improvements, a hypothesis test was performed comparing Class 1 recall before and after applying SMOTE.

- Null Hypothesis (H_0): There is no significant difference in Class 1 recall before and after applying SMOTE.
- Alternative Hypothesis (H_1): SMOTE significantly improves Class 1 recall.

Using a paired t-test, we found a p-value < 0.05, indicating a statistically significant improvement.

Table 5. Hypothesis test result – class 1 recall before vs. after SMOTE

Metric	Before SMOTE	After SMOTE	p-value
Class 1 Recall (RF)	4%	28%	0.011

Inference: The results confirm that applying data balancing significantly improves the model's ability to detect faults. This validation supports the inclusion of SMOTE and retraining protocols in future predictive maintenance frameworks. (Table 5)

6. Conclusion

This research successfully fulfilled its objective of developing a hybrid risk analysis framework for wind turbines that integrates qualitative engineering methods with machine learning-based predictive maintenance. Through the construction of a risk matrix, high-risk components such as bearings, blades, and corrosion-prone areas were identified based on failure likelihood and impact severity. Complementing this, a data-driven approach using real-world SCADA data was implemented to train five machine learning models—Random Forest, Logistic Regression, Gaussian Naive Bayes, Decision Tree, and Hidden Markov Model—for anomaly detection.

The numerical and graphical results from both the qualitative and quantitative analyses reveal that while traditional models are valuable for structured assessment, machine learning enhances the ability to detect early-stage faults, especially when supported by techniques like SMOTE for class balancing. Validation using hypothesis testing confirmed a statistically significant improvement in fault detection performance after applying these enhancements. The unique contribution of this study lies in its end-to-end integration of classical risk assessment with intelligent data analytics, offering a scalable and adaptive solution for wind turbine reliability. By bridging the gap between static engineering assessments and real-time predictive capabilities, the framework not only improves maintenance scheduling but also supports the long-term sustainability of wind energy systems.

Future research may expand upon this work by incorporating deep learning models, implementing real-time digital twin simulations, and extending the framework to include financial and cybersecurity risks in site operations.

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Biographies

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Dr. M.B. Kiran is an Associate Professor in the Department of Mechanical Engineering at the School of Technology, Pandit Deendayal Energy University (PDEU), Gandhinagar, India. He earned his B.E. in Industrial & Production Engineering from the University of Mysore in 1987, followed by an M.E. in Production Engineering from P.S.G. College of Technology, Coimbatore, in 1991. He completed his Ph.D. in Surface Metrology at the Indian Institute of Technology Madras in 1997. With over 25 years of combined experience in industry, research, and academia, Dr. Kiran specializes in surface inspection, image processing, additive manufacturing, and project management. He is a certified Project Management Professional (PMP) from the Project Management Institute (PMI), USA, and has successfully led several mission-critical projects for clients in the USA and UK. Dr. Kiran has published extensively in national and international journals and conferences. His recent works focus on the integration of Industry 4.0 technologies into manufacturing and supply chain systems. He has also delivered numerous training programs for practicing engineers and executives, particularly in project risk management and quality control. Currently, he supervises multiple Ph.D. scholars and actively contributes to academic and professional bodies in the field of mechanical and industrial engineering.