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Predictive Maintenance with Machine Learning: A Comparative Analysis of Wind Turbines and PV Power Plants

Uhanto Uhanto [1], Erkata Yandri [1,2,*], Erik Hilmi [1], Rifki Saiful [1] and Nasrullah Hamja [1]

[1] Graduate School of Renewable Energy, Darma Persada University, Jl. Radin Inten 2, Pondok Kelapa, East Jakarta 13450, Indonesia; uhanto.unud@gmail.com (U.U.); erkata@gmail.com (E.Y.); erikalthaf@gmail.com (E.H.); rifkivanesa@gmail.com (R.S.); nasrullahpanasonic.nh@gmail.com (N.H.)

[2] Center of Renewable Energy Studies, School of Renewable Energy, Darma Persada University, Jl. Radin Inten 2, Pondok Kelapa, East Jakarta 13450, Indonesia

* Correspondence: erkata@gmail.com

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Abstract

The transition to renewable energy requires innovations in new renewable energy sources, such as wind turbines and photovoltaic (PV) systems. Challenges arise in ensuring efficient and reliable performance in their operation and maintenance. Predictive maintenance using machine learning (PdM-ML) is relevant for addressing these challenges by enhancing failure predictions and reducing downtime. This study examines the effectiveness of PdM-ML in wind turbine and PV systems by analyzing operational data, performing data preprocessing, and developing machine learning models for each system. The results indicate that the model for wind turbines can predict failures in critical components such as gearboxes and blades with high accuracy. In contrast, the model for PV systems is effective in predicting efficiency declines in inverters and solar panels. Regarding operational complexity, each model has advantages and disadvantages of its own, but when compared to conventional maintenance techniques, both provide lower costs with greater operational efficiency. In conclusion, machine learning-based predictive maintenance is a promising solution for enhancing the reliability and efficiency of renewable energy systems.

1. Introduction

Renewable energy has become a global priority in addressing climate change [1, 2], meeting sustainable energy needs, and reducing greenhouse gas emissions [3]. Therefore, adopting renewable energy technologies is crucial to ensuring energy sustainability and reducing carbon emissions [4, 5]. Among various renewable energy technologies, photovoltaic (PV) solar power plants and wind turbines play a crucial role in reducing dependence on fossil fuels [1, 6, 7]. While substantial research has been conducted on the operational efficiency of these technologies, few studies have provided a comparative analysis of their predictive maintenance strategies, particularly in how these approaches minimize downtime and optimize performance.

Previous studies have typically focused on a single technology, leaving a gap in cross-technology comparisons of predictive maintenance practices. This research builds on existing work by comparing these two key technologies comprehensively, highlighting the similarities and differences in their maintenance strategies. Wind turbines and PV systems are selected for their dominant roles in renewable energy production, with other technologies excluded due to their fundamentally different maintenance needs.

To optimize these renewable energy technologies, it is necessary to calculate energy consumption ratios, energy development, and performance savings using an energy management system (EMS) [8]. As the scale of renewable energy technologies and energy management systems increases, ensuring efficient and reliable operations becomes increasingly important. Energy consumption ratios refer to the proportion of energy used relative to the total generated energy, and an EMS is an application platform designed to monitor and optimize energy production and consumption. The key dimensions for evaluating and developing renewable energy systems include availability, efficiency, affordability, sustainability, and governance [9].

Availability ensures that energy resources are consistently accessible to meet demand. Efficiency focuses on the optimal use of energy by minimizing waste and maximizing output. Affordability emphasizes the importance of keeping energy costs affordable for consumers and ensuring efficient infrastructure investment. Sustainability highlights energy use's environmental and social impacts, promoting long-term, eco-friendly solutions. Finally, governance refers to proper management and regulation, ensuring energy systems are managed transparently, fairly, and by established standards. One of the key strategies to achieve these goals is predictive maintenance, which aims to predict potential failures and schedule maintenance, thus allowing for early detection of failures and reducing unplanned breakdowns. This study hypothesizes that predictive maintenance strategies will result in greater cost reductions and improved reliability for power plants. Wind turbines have more complex mechanical components with a higher risk of failure than PV systems.

Predictive maintenance is effective in maintaining the health of equipment or components across various industries, including its application in renewable energy systems such as wind power plants [10, 11] and PV solar power plants [12, 13]. PV and wind turbine systems face technical challenges and complex opportunities. Both systems operate under different environmental and technical conditions, necessitating tailored maintenance strategies. Machine learning-based predictive maintenance has become a leading solution for equipment or component maintenance [14, 15], focusing on accurate predictions and proactive management of renewable energy components. However, the comparative effectiveness of predictive maintenance for wind turbines and PV systems has not been extensively explored.

Several studies examine strategic approaches, modeling, and evaluation to achieve energy savings with PdM-ML (Predictive Maintenance-Machine Learning) in the renewable energy industry. The growing demand for sustainable energy is driving the expansion of the solar power industry. Technological advancements play a crucial role in improving the efficiency of solar panels while also reducing production costs, making solar energy more affordable and competitive in the global energy market [16]. Crucial elements of PV predictive maintenance [12] include irradiance [17–19], panel temperature [19–22], inverter performance [23–25], and power output [26, 27]. Each PV component is frequently examined to prevent early failures, implementing required repair procedures to minimize downtime and increase equipment reliability. Regular monitoring has also been used for wind turbines, whereby wind turbines are virtually inspected and wind speed and power output predictions are modeled through the integration of radio networks and cloud-based digital twins [28]. Critical data captured from wind turbines include wind speed [29–32], bearings [11, 33], gearboxes [33–35], generators [36], blades [37, 38], and power output [39, 40]. These component data are used for production energy modeling and predictive maintenance [41, 42].

According to the research review above, a comparative research study of this type already exists. Predictive maintenance models are commonly researched independently for wind turbines and photovoltaic systems. Studies on wind turbines frequently explore monitoring mechanical components, such as blades and gearboxes. For PV systems, the focus is usually on the degradation of solar panels and inverters. However, comparative analysis of predictive maintenance strategies for these two renewable energy systems remains limited. This research focuses on critical parts and PdM-ML in power plants, proposing a new comparative approach for predictive maintenance of PV and wind turbine power plants. The study aims to optimize predictive maintenance in renewable energy power plants by designing a machine learning-based framework that compares operational efficiency and maintenance effectiveness between wind turbines and PV systems.

This study aims to fill this gap by examining and comparing predictive maintenance approaches in PV systems and wind turbines. It aims to provide answers to several key questions, namely: How do predictive maintenance approaches differ between wind turbines and PV systems, and what are the key factors influencing

Table 1. Methods for collecting operational data of power generation systems.

Power Plant	Method	Description	Purpose
PV	Data collection	Irradiance, panel temperature, inverter performance, and power output	To monitor the condition and performance of the PV system
	Utilizing historical data	Further analysis to ensure data quality and consistency	Accuracy in comparing operational data of the PV system
	Data quality analysis	Validation of data quality for consistency and reliability	More accurate maintenance predictions
Wind Turbine	Data collection	Blade vibration, gearbox temperature, wind speed, and power output	To monitor the condition and performance of the wind turbine system
	Utilizing historical data	Further analysis to ensure data quality and consistency	Accuracy in comparing operational data of the Wind Turbine system
	Data quality analysis	Validation of data quality for consistency and reliability	More accurate maintenance predictions

the success of predictive maintenance in renewable energy systems? Through this comparative analysis, the research seeks to identify best practices that can enhance reliability while simultaneously reducing operational costs in these technologies.

While previous research has primarily focused on predictive maintenance models for individual technologies, wind turbines or photovoltaic systems, this study offers a novel comparative analysis of predictive maintenance strategies across both. By examining the key components of these systems and integrating machine learning-based frameworks, this research provides a unified approach to predictive maintenance that has not been extensively explored. This study identifies the most effective maintenance strategies for each technology and aims to design a machine learning framework that can optimize operational efficiency and maintenance effectiveness in both wind turbines and PV systems. The expected impact of this research is twofold. First, it will contribute to a deeper understanding of how predictive maintenance strategies can be tailored to the specific needs of different renewable energy technologies. Second, it aims to provide practical insights that can enhance the reliability and cost-effectiveness of renewable energy systems, ultimately contributing to the broader goal of sustainable energy production. By filling the gap in comparative research, this study paves the way for more integrated maintenance practices across the renewable energy sector, offering a pathway to more resilient and efficient power plants.

2. Materials and Methods

2.1. Data Operation PV and Wind Turbine

The methods for collecting operational data are outlined in Table 1. For wind turbines, data includes blade vibration, gearbox temperature, wind speed, and power output. For PV systems, data includes light intensity, panel temperature, inverter performance, and power output. Historical data ensures the quality, consistency, and accuracy of maintenance predictions, while data analysis is used for validation to enhance prediction accuracy.

2.2. Data Preprocessing

Data preprocessing involves several critical steps to ensure the quality and integrity of the dataset for machine learning models. First, data cleaning is performed through imputation and normalization to address missing or inconsistent data, ensuring the reliability of inputs for machine learning models [43]. Subsequently, feature engineering is conducted to extract relevant features for predictive maintenance. These features include trends, anomalies, and specific thresholds for PV systems and wind turbines, enhancing the model's accuracy in detecting issues. This results in data with high and precise prediction accuracy.

Data cleaning is performed through imputation and normalization to address missing or inconsistent data, ensuring the reliability of inputs for machine learning models. Imputation methods include using the mean, median, or interpolation, each of which is appropriate under different circumstances. The mean imputation is generally suitable when missing data is assumed to follow a normal distribution, as it preserves the overall data trend. The median is preferable when the data contains outliers, as it provides a more robust measure that is not skewed by extreme values. Interpolation is often used when dealing with time series data, where missing values are estimated based on nearby data points, maintaining the continuity of trends. Subsequently, feature engineering is conducted to extract relevant features for predictive maintenance. These features include trends, anomalies, and specific thresholds for PV systems and wind turbines, enhancing the model's accuracy in detecting issues. This results in data with high and precise prediction accuracy. Data cleaning and feature engineering for PdM-ML are simulated through the steps outlined in Table 2.

Table 2. Steps for data cleaning and feature engineering in PdM-ML.

Process	Procedures	Purpose
Data Cleaning	• Identify missing or inconsistent data	Find missing data or anomalies that could disrupt the analysis
	• Impute missing data (e.g., using mean, median, or interpolation)	Fill in data gaps to maintain completeness and accuracy. Mean: Suitable for data with normal distribution. Median: Best for data with outliers. Interpolation: Ideal for time series data to maintain trend continuity
	• Normalize data (e.g., rescale data)	Standardize data scales to improve consistency and quality
	• Validate and recheck data	Ensure the data is clean and ready for use in machine learning models
Feature Engineering	• Extract trends from historical data	Identify long-term patterns relevant for predictions
	• Detect anomalies (e.g., deviations from normal trends)	Identify potential issues or failures early
	• Determine specific thresholds (e.g., maximum temperature)	Set critical limits for early failure detection
	• Create additional features (e.g., ratios or trend changes)	Enhance prediction accuracy with more informative features

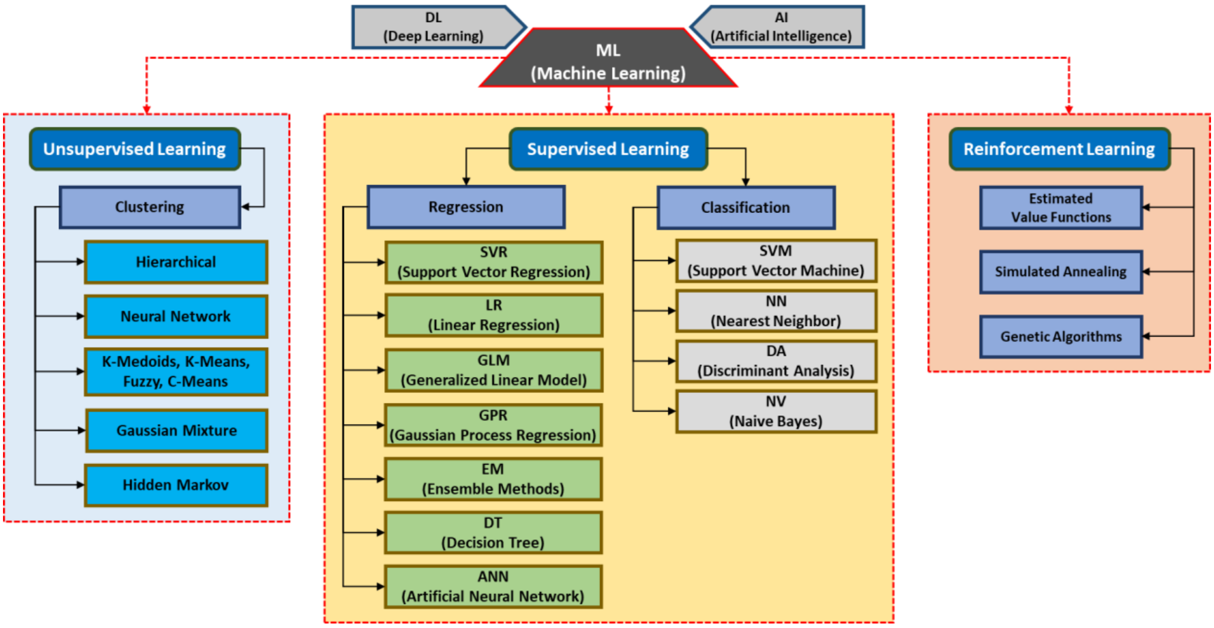

Figure 1. Classification of machine learning models and techniques.

2.3. Machine Learning Model Development

The tools used in the PdM-ML system are illustrated in Figure 1, which includes the selection of data trend analysis and data compilation models. In general, machine learning can be categorized into three types. First, unsupervised learning, where models aim to discover unknown patterns within the data [44, 45]. Second, supervised learning, where models use labeled training data with known outputs to learn the mapping from input to output. This process is often repeated until the model reaches the desired accuracy and can reliably predict outcomes [46, 47]. Finally, reinforcement learning relies on trial and error, balancing exploration and exploitation to identify actions that result in the most significant changes [14, 48]. For example, in unsupervised learning, clustering algorithms can be used to group similar equipment based on sensor data, helping to detect unusual behavior that may indicate early-stage failures. In PdM, training models can apply supervised learning to predict equipment failure based on historical data, such as temperature or vibration readings, allowing the system to trigger maintenance before a breakdown occurs. Reinforcement learning involves trial and error in exploration versus exploitation to identify actions that yield the greatest changes. For predictive maintenance, reinforcement learning could be used to optimize maintenance schedules, where the system learns from the outcome of each decision (e.g., when to perform maintenance) to minimize downtime and costs over time.

Research on PV power generation involves developing predictive maintenance models using various machine learning algorithms, including linear regression,

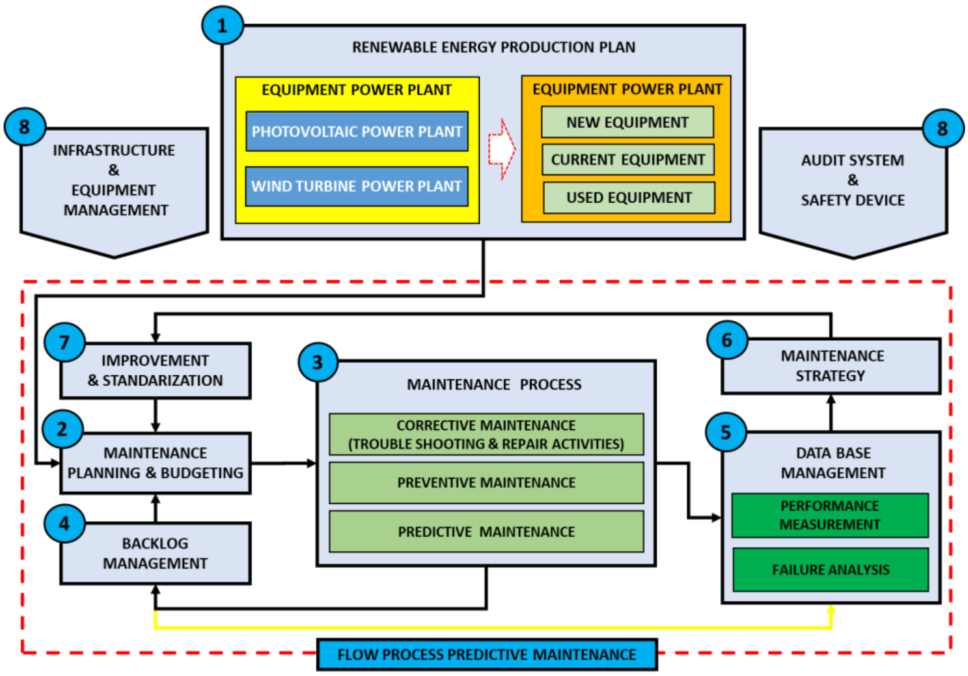

Figure 2. Predictive maintenance process flow.

polynomial regression, decision trees, support vector regression, random forest, LSTM (Long Short-Term Memory networks), and MLP (Multi-Layer Perceptron) regression [27]. LSTM is a recurrent neural network that excels at processing sequential data, making it ideal for time-series predictions in predictive maintenance, such as forecasting equipment failures based on historical trends. MLP, on the other hand, is a specific type of ANN (artificial neural network) composed of multiple layers of nodes that can learn complex relationships in data, suitable for regression and classification tasks [49]. Similarly, machine learning is employed to monitor wind turbine conditions, with SCADA (Supervisory Control and Data Acquisition) being used for condition monitoring and as a diagnostic tool for preventive maintenance analysis. Data is divided into training and testing sets, and model performance is evaluated through comparative analysis to assess the effectiveness of predictions in maintenance [36]. SCADA is a data acquisition and control system, and the classification depends on how its data is used in conjunction with machine learning algorithms.

2.4. Predictive Maintenance Framework Design

The basic concept of the maintenance process in asset management [50], or for infrastructure equipment in new renewable energy power plants, must be based on demand and production planning. The maintenance process flow is outlined in Figure 2: Step 1 involves identifying the Renewable Energy Production Plan, and Steps 2-7 cover the predictive maintenance process. Activities include inspection and data collection, followed by analysis and diagnosis to detect issues. Step 7 is the final identification for prediction and maintenance improvement. Step 8 involves maintaining system consistency through management and audits.

The effectiveness and accuracy of Step 7 in Figure 2 will be optimal by using PdM-ML methods with sensor data captured from renewable energy power plants. The first step is to understand the structure and types of data available from power plant sensing. The second step involves cleaning the data from noise and outliers during input data processing. The third step includes processing and exploring the data to identify patterns and trends. The demand of power systems includes load forecasting, anomaly detection, and demand response. This analysis provides insights into how power systems can be managed more effectively by considering various aspects of demand and response [51]. Developing machine learning models to analyze relationships between variables and predict system behavior in energy source identification, distribution, storage, and demand, as well as anomaly detection. The fourth step involves the model's analysis results providing more accurate predictions, control, and detection, which can be detailed in Figure 3.

3. Results and Discussion

Based on previous research as shown in Table 1, it is evident that the collection and analysis of operational data for PV and wind turbines are crucial for monitoring equipment performance. Historical data, quality validation, and consistency support accurate

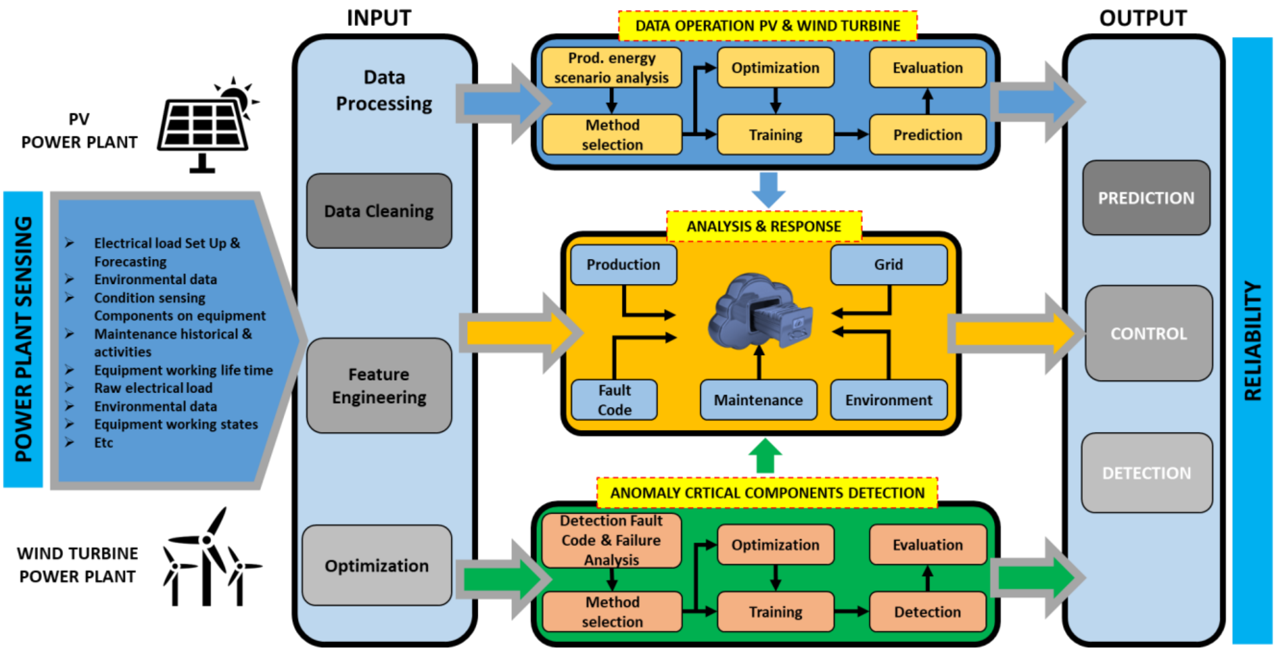

Figure 3. PdM-ML diagram with functions for detection, control, and prediction.

Table 3. Power generation systems optimized operating variables and data.

Power Plant	Parameter	Description	Optimal Value	Remarks
PV	Solar Irradiance	The intensity of solar radiation received by the solar panel (W/m²)	678.4 - 977.7	Optimal irradiance values for maximum performance are influenced by location, time of day, and season
	Panel Temperature	Solar panel's temperature (°C)	59.5 - 66.1	Lower temperatures increase panel efficiency (cooling system)
	Inverter efficiency	Inverter efficiency (%)	95 - 98	High efficiency & good power conversion
	Power Output	Power generated (kW)	Daytime 11:00 - 13:00	Optimal power output depends on capacity and operational conditions
Wind Turbine	Blade Vibration	Turbine blade vibration (mm/s)	< 2.0	Low vibration indicates good operational conditions
	Gearbox Temperature	Temperature of the wind turbine gearbox (°C)	40 - 70	Ideal temperature to prevent damage and wear
	Wind Speed	Wind speed (m/s)	12 - 15	Optimal wind speed range for maximum efficiency
	Power Output	Power generated (kW)	Based on system capacity	Optimal power output depends on turbine capacity and operational conditions

maintenance predictions, allowing for more effective maintenance and extending the lifespan and efficiency of the power generation system. Table 3 outlines the optimal values for each parameter listed in Table 1, leading to more optimal energy production and improved accuracy in predictive maintenance for PV systems and wind turbines.

For example, in PV systems, maintaining optimal solar irradiance levels (678.4–977.7 W/m²) is crucial, as deviations from this range can significantly affect energy output. Case studies, such as those conducted, have shown that implementing PdM-ML algorithms to monitor solar panel performance leads to enhanced energy production and reduced maintenance costs. These systems can identify anomalies in real-time, allowing for timely interventions. In wind turbine systems, the analysis of parameters like blade vibration and gearbox temperature is vital for ensuring reliability. A study found that machine learning models successfully predicted gearbox failures up to several weeks in advance by analyzing vibration data. This approach not only mitigated downtime but also resulted in cost savings.

Table 4 describes a comparison of PdM-ML implementation on wind turbines and PV systems based on the flow shown in Figures 1, 2, and 3. There are three comparison categories: data collection, Internet of Thing (IoT) infrastructure for machine learning, and machine learning platform.

Table 4. Comparison of PdM-ML implementation on wind turbines and PV systems.

System Architecture	Wind Turbine Power Plant	PV Power Plant
Data Collection	Blade vibration, gearbox temperature, wind speed, power output. Additional data related to turbine operational conditions based on the maintenance process framework	Irradiance, panel temperature, power output. Additional data related to environmental conditions and solar panel operation based on the maintenance process framework
	Advantages	**Advantages**
	• Comprehensive anomaly detection with various physical parameters • Real-time data improves prediction accuracy	• Environmental data provides additional insights for prediction • Simpler sensors and lower data collection costs • Real-time data improves prediction accuracy
	Disadvantages	**Disadvantages**
	• More complex and expensive sensor system • Large data requires significant storage capacity	• Limited to environmental parameters and power output • Predictions may be less accurate under extreme or unpredictable weather conditions
IoT Machine Learning Infrastructure	Sensors installed on blades, gearbox, and other critical components. Real-time data collection. Data stored and processed in the cloud	Sensors installed on solar panels, inverters, and other critical components. Real-time data collection. Data stored and processed in the cloud
	Advantages	**Advantages**
	• Continuous monitoring enables early detection • High data accessibility due to cloud-based system	• Simpler and more cost-effective infrastructure • High scalability thanks to cloud solutions
	Disadvantages	**Disadvantages**
	• Requires a stable network and sufficient bandwidth • Potential data privacy and security concerns	• Reliance on the cloud can be a risk if connection issues arise • Data processing might be limited by cloud infrastructure
Machine Learning Platform	Utilizes ML platforms for Unsupervised-learning, Supervised-learning, Reinforcement-learning, and their derivatives. Models trained with historical data for failure prediction	Utilizes ML platforms for Unsupervised-learning, Supervised-learning, Reinforcement-learning, and their derivatives. Models trained with historical data for panel performance prediction
	Advantages	**Advantages**
	• Cost-effective with the use of multiple open-source platforms • Can be customized for specific needs	• Cost-effective with the use of multiple open-source platforms • Models can be adapted to specific environmental conditions
	Disadvantages	**Disadvantages**
	• Requires technical expertise for model implementation and optimization • Performance depends on the quality and quantity of available data	• Requires expertise in model development • Models may require additional adjustments for varying environmental conditions

The evaluation of the PdM-ML model for wind turbines demonstrates that it can accurately predict the failure of critical components, such as gearboxes, blades, bearings, etc., enabling early detection and reduced downtime. On the other hand, the model for PV systems can predict efficiency degradation, particularly in inverters and solar panels, due to variability in environmental conditions. Nevertheless, both models demonstrate adequate performance, albeit with some strengths and weaknesses in handling different operational complexities.

The process of developing and implementing the PdM-ML system is detailed in Tables 1 and 2, starting from data collection through sensor interfaces to evaluating the system's effectiveness. Each stage involves specific activities aimed at ensuring data quality, model accuracy, and the positive impact of PdM-ML, measured through cost savings and improved system performance. Therefore, the focus of fault identification in critical PV components must align with the key parameters defined. The main objective is to focus on the most impactful predictions, as shown in Table 5.

Meanwhile, the identification of failures or damage to critical components of wind turbine systems, with a focus on the most impactful predictions, is presented in Table 6. This identification aims to detect potential damage early, allowing timely maintenance actions to be taken, minimizing downtime, and ensuring optimal performance of the wind turbine system.

The PdM-ML concept, as illustrated in Figure 3, theoretically enhances operational efficiency by reducing downtime (breakdowns) in both PV and wind turbine systems, thereby improving productivity and reliability.

Table 5. Critical components of PV systems.

Parameter	Failure type	Critical Component	Description & Impact
Irradiance	Decreased Energy Efficiency	Solar Panel	Insufficient sunlight can significantly reduce power output
	Dust or Dirt on the Panel	Solar Panel	Reduced sunlight due to dirty panels can lower efficiency
Panel Temperature	Overheating	Solar Panel	High temperatures can reduce energy conversion efficiency and shorten panel lifespan
	Damage to Panel Coating	Solar Panel	Damage to the coating caused by high temperatures can decrease panel performance
Inverter Performance	Decreased Conversion Efficiency	Inverter	Reduced inverter performance can result in power losses and lower system efficiency
	Inverter Failure	Inverter	Inverter failure leads to no conversion of DC to AC power, causing zero power output
Power Output	Low Power Output	Solar Panel & Inverter	Low power output may result from a combination of poor sunlight irradiance, high panel temperature, or poor inverter performance
	Cable or Connector Malfunction	Cables & Connectors	Malfunctions or damage to cables and connectors can lead to reduced power output and system efficiency

Table 6. Critical Components of wind turbine systems.

Parameter	Failure type	Critical Component	Description & Impact
Blade Vibration	Excessive Vibration	Blades	High vibration may indicate imbalance or damage to the blades, potentially causing damage to other components
	Bearing Failure	Bearings	Excessive vibration can lead to wear or damage to bearings, which may result in turbine failure
Gearbox Temperature	Overheating	Gearbox	High temperatures can cause damage to gearbox components and reduce operational lifespan
	Lubricant Damage	Lubricants	Insufficient or degraded lubricants can accelerate wear on the gearbox and related components
Wind Speed	Suboptimal Turbine Operation	Wind Turbine	Non-optimal wind speeds can cause the turbine to operate below its capacity or fail to function altogether
	Control System Damage	Control System	Unstable or extreme wind speeds can cause damage to the turbine's control system
Output Daya	Low Power Output	Wind Turbine & Inverter	Low power output may be caused by issues with various components such as blades, gearbox, or inverter
	Inverter Failure	Inverter	Inverter failure can lead to a significant decrease in power output due to inefficient power conversion

The technical application of the PdM-ML concept to wind turbine and PV systems, as detailed in Tables 5 and 6, is depicted in Figure 4. The process begins with the installation of sensors on the power generation components and their integration into an IoT platform for real-time data. This data is then monitored to ensure component health. Predictive analysis using ML forecasts failures and provides proactive alerts. Finally, automated maintenance notifications are generated for scheduling and early warning maintenance activities; operators simply need to approve notifications based on the recommended model analysis.

Existing literature provides comprehensive guidelines for the maintenance and management of renewable energy systems, particularly PV [12, 13] and wind turbine technologies [11]. However, to further enhance the efficiency of PdM and reduce costs, this study identifies three critical areas of focus that address both operational challenges and emerging technological solutions. These areas are designed to support early fault detection and optimize maintenance strategies.

First, Optimization of Predictive Maintenance through Operational Data Analysis. A key aspect of PdM is identifying and analyzing operational parameters that have the greatest impact on equipment performance and lifespan. For PV systems, important factors include sunlight irradiance, panel temperature, and electrical output, which are directly influenced by environmental conditions. For wind turbines, critical parameters such as blade vibration, gearbox temperature, and rotor speed are essential for monitoring mechanical stress and potential component wear. By continuously monitoring and analyzing these data points (Table 3), predictive maintenance strategies can be optimized to detect early signs of deterioration. This allows for timely interventions, reducing downtime and extending the

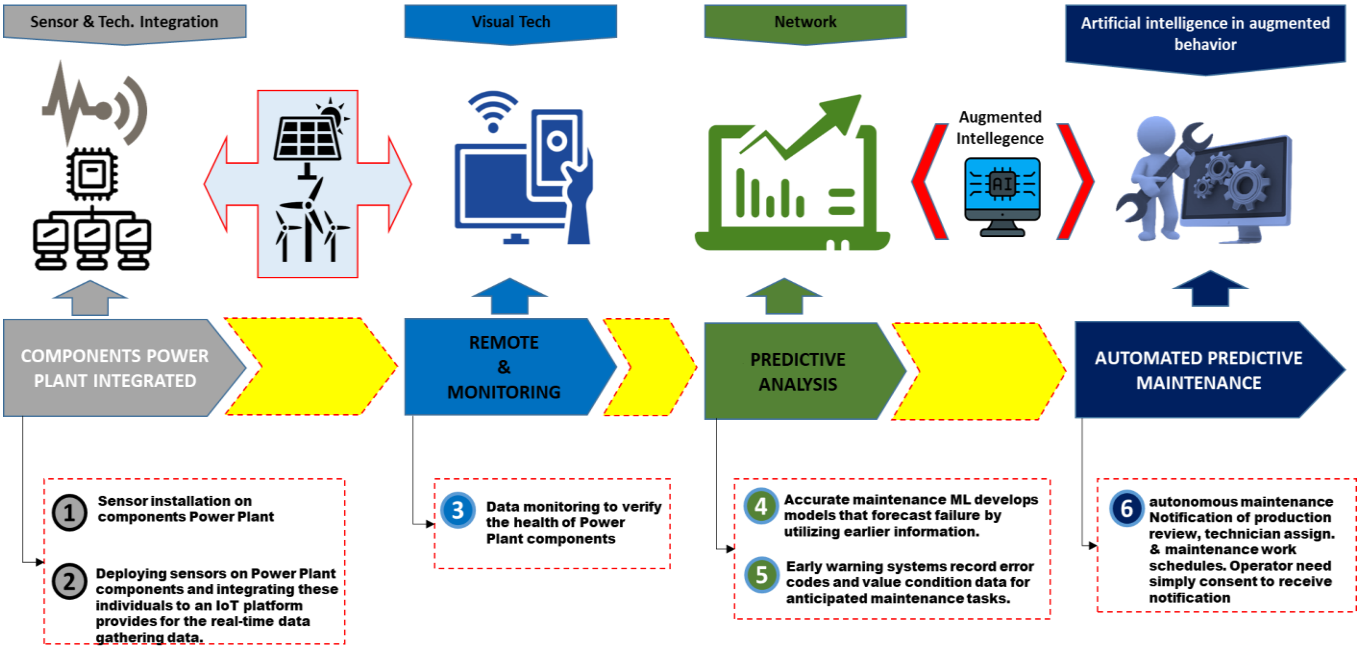

Figure 4. PdM-ML concept for efficient operations.

lifespan of the equipment. The goal here is not only to react to failures but to anticipate them based on data trends, improving overall system reliability and efficiency.

Second, comparison of PdM-ML Effectiveness for PV and Wind Turbines. The PdM-ML has shown promise in enhancing the predictive capabilities of maintenance systems. However, PV systems and wind turbines present different operational complexities that require tailored approaches. For PV systems, the relatively static nature of the equipment means that failures are often related to external factors such as weather conditions or dust accumulation on panels. In contrast, wind turbines are subject to dynamic mechanical forces, which introduce a higher risk of mechanical wear and tear. As such, the PdM-ML models for each system must be adjusted to account for these differences. The analysis provided in Table 4 compares the effectiveness of PdM-ML models for both technologies, highlighting key performance indicators such as detection accuracy, false alarm rates, and the ability to predict component failure. This comparison provides insights into how PdM-ML can be fine-tuned to meet the specific needs of each renewable energy system, ultimately enhancing predictive accuracy and reducing unnecessary maintenance costs.

Third, development of IoT and machine learning Infrastructure for Proactive Maintenance. To fully realize the potential of PdM-ML, robust IoT infrastructure is essential. IoT devices, such as sensors and smart controllers, provide the real-time data necessary for continuous monitoring of equipment health. In this study, the focus is on optimizing sensor placement and data collection methods to ensure that critical data is captured without overloading the system. The integration of ML algorithms enables the analysis of vast amounts of data in real time, allowing for proactive maintenance decisions to be made before failures occur. For example, by leveraging sensor data from both PV and wind turbine systems, machine learning models can predict potential failures with greater accuracy, thus minimizing the risk of unexpected breakdowns. Additionally, optimizing IoT infrastructure also allows for better energy production management, ensuring that both PV and wind systems operate at peak efficiency while minimizing operational costs.

This research highlights the significant benefits of applying PdM-ML in both PV systems [12, 23, 24] and wind turbines [28, 33–37, 41]. The findings demonstrate that PdM-ML not only improves operational efficiency and extends equipment lifespan but also enhances the accuracy of failure predictions for critical components. By validating the effectiveness of PdM-ML in detecting failures and estimating the remaining useful life (RUL) of key components [14, 48], this study underscores its potential to reduce maintenance costs and boost system reliability. Looking ahead, future research should focus on further developing IoT infrastructure and PdM-ML platforms [42] to address the unique operational challenges and environmental conditions inherent to renewable energy systems, thereby ensuring even greater reliability and cost-efficiency.

While using PdM-ML in PV and wind turbine systems shows great potential, there are some limitations to consider. The accuracy of PdM-ML models depends on having high-quality historical data. Often, this data can be incomplete or biased, affecting predictions. Environmental factors, like extreme weather, can also complicate model performance. Moreover, relying on IoT technologies raises concerns about data privacy and security, especially with cloud-based systems. The cost and complexity of setting up advanced sensors and machine learning platforms can be challenging for smaller operators. Future research should focus on improving data collection methods to create more comprehensive datasets. Developing more adaptable machine learning algorithms will enhance predictive accuracy under varying conditions. Additionally, exploring decentralized data processing could reduce reliance on cloud systems while maintaining data security. Investigating how new technologies, like blockchain, can improve data security in predictive maintenance is another promising area for future study.

4. Conclusions

The evaluation of the machine learning-based predictive maintenance model shows that the model for wind turbines effectively predicts failures of critical components such as gearboxes, blades, and bearings, thereby reducing downtime. On the other hand, the model for PV systems can predict efficiency losses in inverters and solar panels due to environmental variability. Although both models demonstrate adequate performance, each has its own strengths and weaknesses when addressing different operational complexities. The implementation of these models can significantly reduce costs by decreasing downtime and scheduled repairs, compared to traditional maintenance methods, which are often more expensive and less efficient. Thus, machine learning-based predictive maintenance strategies offer a more effective solution for enhancing system efficiency and reliability. To further enhance the effectiveness of PdM-ML platforms, future customization should focus on integrating advanced data analytics to better account for unique environmental conditions across different locations. Additionally, incorporating real-time adaptive learning capabilities could allow models to continuously improve based on new data, thus increasing prediction accuracy. Customization efforts might also include developing user-friendly interfaces for operators to easily interpret model outputs and adjust maintenance schedules accordingly. By implementing these enhancements, PdM-ML strategies can provide a more tailored solution, ultimately improving system efficiency, reliability, and cost-effectiveness across diverse operational challenges.

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