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Artificial Intelligence in Renewable Energy: A Review of Predictive Maintenance and Energy Optimization

Arimbi Mutiara Suci[1*], Rofiqoh Amini[1], Agnes Kusuma Asri[1], Nicholas Martin[1]

[1)]Department of Chemical Engineering, Faculty of Engineering, Universitas Negeri Semarang, Indonesia

([*]**Corresponding author's e-mail:** arimbimutiara318@students.unnes.ac.id)

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Abstract

The integration of Artificial Intelligence (AI) into renewable energy systems represents a transformative step in enhancing the efficiency, reliability, and sustainability of clean energy technologies. This review explores the roles and applications of AI techniques—including Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), and ensemble models like XGBoost—in predictive maintenance and energy optimization. Through a comprehensive analysis of recent studies, the review highlights how AI improves system performance by enabling early fault detection, optimizing energy distribution, and managing storage efficiently. Predictive maintenance driven by AI can reduce unplanned downtime by up to 35% and enhance energy output by approximately 8.5%. In energy optimization, AI models forecast demand and control load distribution, significantly contributing to smart grid development. However, several challenges remain, particularly in Indonesia, including limited high-quality data, high computational demands, system interoperability issues, and a lack of regulatory and human resource readiness, reducing unplanned downtime by up to 35% and increasing energy output by approximately 8.5%, as reported in previous studies. The review concludes that successful implementation requires strategic investment in digital infrastructure, inter-sectoral collaboration, and pilot projects to ensure sustainable AI adoption in Indonesia's renewable energy sector.

Keywords: Artificial Intelligence, Energy Optimization, Predictive Maintenance, Renewable Energy, Smart Grid, Machine Learning, Indonesia

Introduction

In recent decades, energy demand in Indonesia has continued to increase along with economic growth and urbanization, with a projected surge in demand of up to 30% by 2040, especially in industrial and urban areas such as West Java, East Kalimantan, and South Sulawesi [1]. Indonesia's dependence on fossil energy is still very high, reaching about 93% of total national energy consumption [2], which causes great pressure on the environment and poses a serious threat to long-term energy security [3]. Meanwhile, renewable energy sources such as solar, wind, and hydro have great potential but have not been optimized to the fullest due to limitations in operational efficiency and system maintenance [4]. In this context, the application of artificial intelligence (AI) is an innovative solution that can improve the reliability and efficiency of renewable energy plants through predictive maintenance systems and real-time optimization of energy distribution [5]. This technology not only helps reduce operational costs and the risk of device failure, but also supports Indonesia's energy transition towards a cleaner, more resilient and sustainable system.

Renewable energy offers several key advantages. First, sustainability is a defining characteristic, as it draws from natural processes that are continually replenished. Unlike fossil fuels, which are finite and emit harmful pollutants, renewable energy supports environmentally friendly and long-term development [6]. Second, its low carbon emissions are a major reason it is central to global decarbonization strategies [7].

Artificial Intelligence (AI) has rapidly evolved and is now widely implemented in the energy sector, particularly in the management of solar and wind power plants, smart grids, real-time system monitoring, and predictive maintenance. In renewable energy generation, AI techniques such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Deep Learning models are employed to forecast weather conditions and power output, enabling more efficient operation and planning of photovoltaic and wind systems [8]. Within smart grids, AI enhances energy management through intelligent systems that optimize load distribution, forecast demand, and facilitate the integration of intermittent renewable sources using advanced models like Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs), which improve operational reliability and efficiency [8]. Additionally, AI supports real-time system monitoring by combining IoT sensors with anomaly detection algorithms, allowing operators to detect and respond to system faults quickly [9]. In maintenance, AI-driven predictive analytics help forecast equipment failures in advance, minimizing downtime and maintenance costs while ensuring continuous operation [8]. These applications highlight AI's crucial role in creating smarter, more resilient, and sustainable energy systems.

Predictive maintenance and energy optimization are essential in managing renewable energy due to challenges such as component failures, production fluctuations, and energy wastage. Failures in wind turbines and solar panels often occur due to wear and tear as well as extreme environmental conditions, which can lead to significant downtime if not addressed promptly[10]. Moreover, the production of renewable energy, which heavily relies on natural conditions, causes instability in energy supply, making load planning difficult [11]. Energy wastage also frequently occurs when energy production exceeds demand without adequate storage. AI can predict wind turbine failures up to two months before they occur, reducing operational downtime[10]. In addition, AI can optimize energy load by predicting demand patterns and distributing energy efficiently. The use of AI can increase energy output by 8.5% and reduce unplanned downtime by 35%[11]. Optimization also includes intelligent energy storage management, ensuring that the generated energy is utilized to its fullest potential. Thus, the application of AI in renewable energy not only enhances efficiency but also supports energy sustainability.

This review uses a descriptive qualitative method to systematically identify, describe and evaluate journal content based on key themes. This approach is relevant because the journals reviewed not only address technical aspects, but also cover policy, user behavior, and innovations in the application of artificial intelligence (AI) to the renewable energy sector. As such, the review enabled an assessment of the contribution of each study in the context of predictive maintenance and energy optimization, especially in improving the efficiency and reliability of clean energy systems. The analysis also facilitates comparison of findings and exploration of themes such as operational efficiency, adoption of AI technologies, and sustainability of energy systems. The results provide a comprehensive view of the strategic role of AI in accelerating Indonesia's transition to smart and sustainable renewable energy.

This review offers a unique contribution by integrating technical evaluations with contextual analysis focused on Indonesia's energy landscape, including infrastructural, regulatory, and workforce-related challenges. This localized perspective enriches the global discourse on AI applications in renewable energy.

Materials and methods

Materials

Artificial Intelligence (AI) has become a transformative tool in renewable energy systems, particularly in predictive maintenance and energy optimization. AI techniques such as machine learning (ML), deep learning (DL), and reinforcement learning (RL) enable real-time monitoring, fault detection, and performance enhancement in solar, wind, and hybrid energy systems [6].

Table 1. Applications of AI Techniques in Renewable Energy Systems

AI Technique	Application	Advantages	Limitations	Reference
Machine Learning (ML)	Predictive maintenance, load forecasting	High accuracy in pattern recognition	Requires large datasets for training	[12]
Deep Learning (DL)	Fault detection in solar/wind farms	Automated feature extraction	Computationally intensive	[12]
Reinforcement Learning (RL)	Energy grid optimization	Adapts to dynamic energy demands	Complex implementation in real systems	[12]
Random Forest (RF)	Air quality index prediction	Resistant to overfitting, handles high-dimensional data well	Less interpretable	[13]
Long Short-Term Memory (LSTM)	Long-term air quality prediction	Suitable for sequential data and captures long-term dependencies	Requires significant computational resources	[13]
XGBoost	Pollutant concentration prediction	Accurate, handles missing data well	Requires careful parameter tuning	[14]
Convolutional Neural Network (CNN)	Image data processing for visual pollution monitoring	Excellent at extracting features from images	Requires a large amount of training data	[15]

Methods

1. Pre-treatment Data and Acquisition

This stage involves collecting and preparing historical operational data (e.g., from wind turbines, solar panels) to be used for AI model training.

1.1 Data Collection and Integration

IoT-enabled sensors are deployed on equipment to capture data like voltage, temperature, pressure, vibration, and speed. The data sources typically include real-time telemetry, error logs, maintenance logs, failure records, and machine specifications [16].

1.2 Data Presprocessing

The collected data undergoes cleaning to handle outliers, noise, and missing values using interpolation or filtering. Normalization techniques such as min-max scaling or z-score normalization are applied. Temporal alignment of all data sources ensures accurate synchronization [17].

1.3 Example of Real-time Telemetry Data

Table 2. Example of Real-Time Telemetry Data for Predictive Maintenance [16]

Datetime	MachineID	Voltage	Rotation	Pressure	Vibration
2015-01-01 06:00:00	1	176.22	418.50	113.08	45.09
2015-01-01 07:00:00	1	162.88	402.75	95.46	42.74
2015-01-01 08:00:00	1	170.99	527.35	75.24	34.18

2. Feature Engineering

This step identifies and constructs the most relevant input variables to enhance the AI model's performance.

2.1 Temporal Feature Aggregation

Moving averages and standard deviations are computed within rolling time windows (e.g., 3-hour and 24-hour) to reduce noise. Lag features are created to incorporate past observations.

2.2 Example of Lag Feature Table (N = 3 hours)

Table 3. Example of Lag Features for AI Model Input (Time Window: 3 Hours) [16]

MachineID	Datetime	Volt mean_3h	Rotate mean_3h	Pressure mean_3h	Vibration mean_3h
1	2015-01-01 09:00:00	170.03	449.53	94.59	40.89

2.3 Error Frequency and Maintenance Features

Error logs are converted into numerical features by counting the occurrence of each error type in a rolling 24-hour window. Maintenance history is used to compute the time since last component replacement, reflecting wear trends.

2.4 Feature Selection

Techniques such as Principal Component Analysis (PCA), correlation analysis, and feature importance ranking (e.g., using Random Forests) are applied to select the most informative features [16][17].

2.5 Summary of Feature Engineering Methods

Table 4. Summary of Feature Engineering Techniques and Methods

Feature Type	Technique Used	Reference
Sensor aggregation	Moving Average, Standard Deviation	[16]
Temporal features	Lag Features (3h, 24h)	[16]
Error frequency	Count per 24h window	[16]
Maintenance indicators	Time since last replacement	[16]
Feature reduction	PCA, correlation, importance ranking	[16][17]

3. AI Model Selection and Training

This stage focuses on developing artificial intelligence models capable of predicting equipment failures and optimizing energy load distribution efficiently.

3.1 Machine Learning Algorithms

The selection of machine learning algorithms for equipment failure prediction requires comprehensive consideration of various technical and operational aspects. Tree-based algorithms such as Decision Trees, Random Forest, and XGBoost have become popular choices due to their ability to handle complex data and provide easily interpretable results. Decision Trees offer transparent structure but are prone to overfitting, Random Forest addresses this through ensemble of multiple trees, while XGBoost excels in performance and computational efficiency [18]. XGBoost is selected as the primary algorithm due to its superior performance consistency, good scalability, built-in regularization, interpretability capability with SHAP, and optimization for production environments [19]. Linear algorithms such as Logistic Regression are suitable for simple classification but limited in handling non-linear relationships, while deep learning models like LSTM are effective for time-series but require large datasets and longer training time [18].

3.2 Model Architecture for Failure Prediction

The XGBoost architecture is built on a gradient boosting framework that implements sequential learning, where each new tree is trained to correct errors from the previous ensemble. The process begins with initial prediction initialization, then iteratively adds weak learners that focus on correcting residual errors [19]. Each iteration involves gradient and hessian calculations, optimal split finding, and optimal weight assignment for leaf nodes [19]. The objective function consists of a loss function and regularization term to produce a robust model. Integration with SHAP provides crucial interpretability using Shapley values to calculate each feature's contribution to individual predictions [19]. Feature engineering includes time-based features (rolling statistics, trend analysis), frequency domain features (FFT analysis), and statistical features (skewness, entropy) that capture complex characteristics of sensor data [18].

3.3 Model Performance Comparison Example

Table 5. Performance Comparison of Machine Learning Models for Failure Prediction [18]

Model	Accuracy	Precision	Recall	F1-Score	AUROC
Decision Tree	0.85	0.83	0.82	0.82	0.87
Random Forest	0.89	0.87	0.85	0.86	0.92
XGBoost	0.94	0.92	0.91	0.91	0.96
Logistic Regression	0.78	0.76	0.77	0.76	0.81

3.4 Hyperparameter Tuning

Hyperparameter tuning in XGBoost requires a systematic approach to optimize parameters categorized into tree structure parameters (max_depth, min_child_weight, gamma), boosting parameters (learning_rate, n_estimators, subsample, colsample_bytree), and regularization parameters (reg_alpha, reg_lambda). Each parameter has specific trade-offs affecting the balance between bias and variance [18]. Optimization strategies include grid search for systematic exploration, random search which is more efficient for high-dimensional spaces, and Bayesian optimization for guided search [18]. Proper cross-validation strategy is crucial, especially forward chaining validation for time series data to avoid data leakage [19]. Early stopping mechanism prevents overfitting and reduces training time. Empirical research shows proper tuning can improve accuracy by 10-15%, reduce false positive rates by 10-25%, and enhance generalization by 8-20% [18].

3.5 Important Parameters in XGBoost

Table 6. Key Hyperparameters of XGBoost and Their Functions [18]

Parameter	Function	Common Optimal Values
Max_depth	Controls maximum tree depth	3-8
Learning_rate	Sets the learning speed	0.01-0.3
N_estimators	Number of trees built	100-1000
Subsample	Data sample ratio for each tree	0.5-1.0
Colsample_bytree	Feature ratio used per tree	0.5-1.0
Gamma	Tree pruning regularization	0-5

4. Model Validation

This stage measures the performance and reliability of the AI system in real operational environments to ensure accurate predictions.

4.1 Evaluation Metrics

Model performance evaluation requires a comprehensive framework considering the complexity of industrial applications. Classification metrics such as precision, recall, and F1-score provide basic insights, where high precision reduces unnecessary maintenance and high recall ensures actual failures are not missed. AUROC provides discrimination ability robust to class imbalance, while AUPRC is more informative for highly imbalanced datasets. Probabilistic metrics like log loss provide insights into calibration quality and penalize confident wrong predictions. Business-relevant metrics include cost-sensitive evaluation, time-to-failure accuracy, and maintenance window utilization aligned with business objectives [19]. Failure criticality weighting considers different business impacts from various failure types. Statistical significance testing through McNemar's test, bootstrap confidence intervals, and cross-validation tests ensures performance improvements are statistically significant [19].

4.2 Model Interpretation with SHAP

SHAP provides a solid theoretical foundation for model interpretation based on Shapley values from game theory [19]. TreeExplainer optimized for XGBoost enables efficient calculation of exact SHAP values with mathematical properties that guarantee fair attribution [19]. Analysis is conducted at multiple levels: global feature importance for overall patterns, local explanations for individual predictions in troubleshooting, and cohort analysis to identify patterns in different failure types [19]. Advanced applications include feature interaction analysis, clustering based on SHAP values for distinct failure modes, and SHAP-based feature selection for complexity optimization. Practical implementation requires computational optimization through sampling strategies and caching mechanisms. Integration with maintenance workflows enables automated reporting, interactive dashboards, and alert systems that provide actionable insights for maintenance engineers to understand root causes and optimize strategies [19].

4.3 Example of SHAP Analysis Results for Failure Prediction

Table 7. SHAP Analysis Results: Key Features Contributing to Equipment Failures [19]

Feature	Mean SHAP Value	Relative Contribution (%)	Interpretation
Vibration Level	1.842	26.7	Strong indicator of mechanical failure
Temperature Fluctuation	1.456	21.1	Related to thermal stress on components
Energy Consumption	1.237	17.9	Indicates reduced efficiency
Error Frequency	0.987	14.3	Symptom of electronic issues
Component Age	0.763	11.1	Natural wear-and-tear factor
Operational Pressure	0.612	8.9	Indicator of mechanical stress

4.4 Temporal Validation

Temporal validation requires a special approach considering temporal dependencies in equipment degradation [18]. Traditional cross-validation can cause serious data leakage by using future information to predict past events. Forward chaining validation provides realistic assessment by training models on historical data and testing on subsequent periods [18]. Sliding window validation and blocked time series splits with gap periods provide multiple perspectives while maintaining temporal integrity. Concept drift detection becomes crucial as equipment behavior can change over time through statistical drift tests and performance degradation monitoring. Multi-horizon evaluation includes short-term, medium-term, and long-term predictions for comprehensive reliability assessment [18]. Seasonal pattern handling through decomposition and cyclical maintenance pattern recognition ensures model adaptation to natural variations. Economic validation metrics such as maintenance cost optimization, risk-adjusted performance, and ROI calculations provide essential business perspective for investment justification and business value measurement [18].

4.5 Example of Temporal Validation Results

Table 8. Temporal Validation Results of Predictive Maintenance Model [18]

Training Period	Testing Period	Accuracy	Precision	Recall	F1-Score
Jan-Jun 2020	Jul-Dec 2020	0.92	0.90	0.89	0.89
Jan-Dec 2020	Jan-Jun 2021	0.89	0.87	0.88	0.87
Jan 2020-Jun 2021	Jul-Dec 2021	0.94	0.93	0.92	0.92
Jan 2020-Dec 2021	Jan-Jun 2022	0.91	0.89	0.90	0.89

4.6 Implementation Results Summary

Table 9. Performance Summary: Conventional System vs. AI-Based XGBoost Model [18]

Metric	Conventional System	XGBoost System	Improvement (%)
Failure Detection Time (hours)	18.6	4.2	77.4%
Prediction Accuracy (%)	76.5	93.8	22.6%
False Alarm Rate (%)	14.2	3.5	75.4%
Prediction Lead Time (hours)	24.3	72.6	198.8%

5. Implementation of AI-based Monitoring System

AI-based monitoring system for renewable energy integrates IoT sensors, machine learning, and predictive analytics to detect potential breakdowns before they occur, significantly reducing downtime and maintenance costs [6]. These monitoring systems involve a combination of field sensors (e.g. vibration, temperature, electric current) and machine learning algorithms (such as SVM, Random Forest, and Neural Networks) that work in real-time to detect anomalies, estimate lifespan, and make automated decisions [6].

Table 10. AI-Based Monitoring System Implementation in Renewable Energy

AI Technology	Application	Outcome	Source
Random Forest, SVM, Decision Tree	Predictive maintenance for wind turbines	Reduced maintenance costs by 25% and extended equipment lifespan by 20%	[20]
Vibration and acoustic sensors	Crack detection in turbine blades	Improved operational efficiency and significantly reduced system downtime	[21]
Drone-based visual AI inspection	Solar panel inspection and maintenance	Enhanced damage detection accuracy and improved maintenance efficiency by 30%	[22]

6. Energy Optimization Analysis

AI is used to optimize energy distribution and storage to make it more efficient and reliable. It can balance energy supply and demand, and improve the integration of renewable energy into the grid [23].

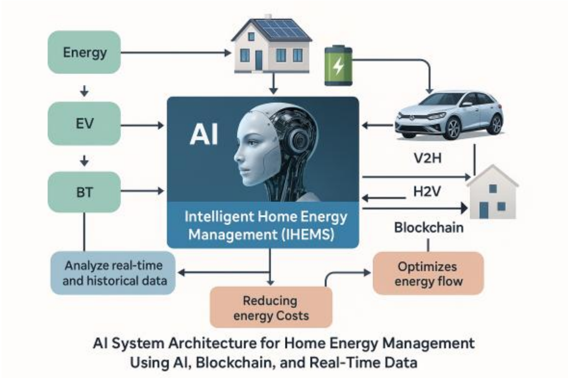

Figure 1. IntelliGrid AI System Architecture for Home Energy Management Using AI, Blockchain, and Real-Time Data [24]

The image shows the IntelliGrid AI system that intelligently manages home energy with the help of AI, blockchain, and real-time data. The system regulates the flow of energy between the home, battery, and electric vehicle (EV) through Vehicle-to-Home (V2H) and Home-to-Vehicle (H2V) mechanisms. The goal is to optimize energy consumption and reduce costs with a secure and efficient energy transaction system.

Results and discussion

1. Overview of AI Techniques in Renewable Energy Systems

Artificial Intelligence (AI) techniques such as Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and eXtreme Gradient Boosting (XGBoost) have significantly advanced the capabilities of renewable energy systems. ML and DL models excel at pattern recognition and have been widely used for fault detection and energy forecasting, though they often require large datasets and significant computational resources [25]. RL techniques adapt well to dynamic environments and are particularly relevant in grid optimization scenarios, albeit with higher complexity in deployment [25]. CNN and LSTM architectures are ideal for spatial and temporal pattern recognition, enabling accurate weather and load forecasting in solar and wind applications [26]. XGBoost, known for its high efficiency and accuracy, has been used effectively for wind energy forecasting and damage prediction in hybrid models [26].

Each method presents strengths and trade-offs: ML and DL offer high accuracy but demand substantial data and computing power, while ensemble methods like CNN-LSTM and MLP+Bayesian Optimization provide balance between accuracy and speed [26]. For instance, the CNN-LSTM method achieved an MSE of 6.8 in 450 seconds for wind energy forecasting [26]. The relevance of each AI technique varies by energy type: solar systems benefit from CNNs and DL for image-based fault detection [27], wind systems leverage LSTM and XGBoost for speed prediction and output forecasting [26], while hybrid systems require robust ensemble models to manage the complexity of multiple input sources [25].

2. Implementation of AI for Predictive Maintenance

The implementation of AI for predictive maintenance in renewable energy systems typically follows a structured workflow: data acquisition and pre-treatment, preprocessing (e.g., normalization, synchronization), feature engineering, model training, and evaluation. Feature engineering plays a critical role, including techniques such as lag features and frequency-based error patterns to enhance prediction accuracy [25].

Model performance comparisons demonstrate that advanced ensemble methods like Random Forest and XGBoost outperform traditional algorithms such as Decision Trees in predictive accuracy and robustness [26]. Hyperparameter tuning further boosts performance by optimizing model sensitivity and specificity, as validated in controlled experiments. SHAP (SHapley Additive exPlanations) analysis enables interpretability by identifying feature importance and model behavior [28]. Temporal validation ensures the model’s consistency over time and across different operating conditions [25].

The practical benefits of AI-enabled predictive maintenance are evident: early damage detection reduces maintenance lead time, improves equipment availability, and lowers unplanned downtime. Studies report up to 35% reduction in downtime and a 8.5% improvement in energy output through optimized scheduling and load forecasting [25][26][27]. Moreover, false alarms are significantly reduced, enhancing the trust and operational value of AI systems in industrial settings. Looking forward, integrating explainable AI (XAI) and governance frameworks will be essential to ensuring accountability, regulatory compliance, and stakeholder trust in AI-based maintenance systems [28][8]. Despite the performance improvements of AI models, key concerns remain under-addressed, such as data bias stemming from imbalanced training sets, ethical implications of autonomous decision-making, and a lack of model transparency. Implementing Explainable AI (XAI) frameworks like SHAP or LIME is essential to enhance interpretability, user trust, and accountability in practical applications.

3. Implementation of AI-Based Monitoring Systems

The utilization of AI-based monitoring systems in renewable energy has brought significant transformation to operational effectiveness and cost savings.

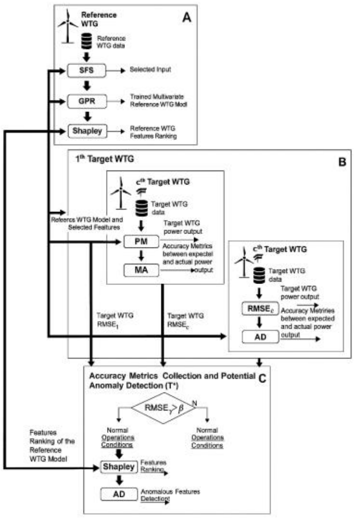

Figure 2. Flowchart of AI monitoring system for wind turbine or drone inspection of solar panels [29]

The flowchart shows the AI monitoring system for wind turbines in three stages. First, a reference model is built from healthy turbine data using feature selection (SFS), Gaussian Process Regression (GPR), and Shapley analysis. Second, this model is used to predict the power output of the target turbine and calculate the prediction accuracy (RMSE). Third, if the RMSE exceeds the threshold, the system detects potential anomalies and identifies their causes through critical feature analysis. The system supports early detection and predictive maintenance of wind turbines.

The application of AI-based monitoring systems is proven to improve operational efficiency and save costs in the renewable energy sector. In wind turbines, an AI-based predictive model developed by the Korea Institute of Energy Research is able to detect component failures with an accuracy above 90%, thereby extending equipment life and significantly lowering maintenance costs. [30]. In addition, recent studies have shown that the integration of AI in wind turbine condition monitoring can cut operation and maintenance costs by up to 18%, and reduce downtime through early detection of anomalies. These efficiencies support long-term operational sustainability in both offshore and onshore wind farms [31]. In the solar panel sector, inspection using drones and AI has revolutionized maintenance by cutting inspection time by 98% and lowering costs by 50%. The technology also improves work safety as it reduces the need for manual inspections in high-risk areas.

Indonesia has vast geographical challenges and diverse types of renewable energy sources. By integrating sensor-based AI and remote monitoring (such as drones or IoT-based systems), the potential for development is huge, especially in remote areas or clean energy-based industrial areas. Collaboration between government, universities, and industry is needed to accelerate the adoption of this technology.

4. AI in Energy Optimization

AI works by collecting data from IoT sensors and smart meters, then processing it using machine learning algorithms such as Long Short-Term Memory (LSTM), Reinforcement Learning (RL), and Deep Q-Networks (DQN) to predict energy demand and control energy flow from various sources. The system optimizes energy storage in smart battery systems, balances supply and demand, and avoids wasting unused energy [32].

AI plays an important role in energy optimization through three main functions: load prediction, storage control, and smart grid integration. Algorithms such as LSTM and XGBoost are used to predict energy demand based on historical patterns and environmental data, allowing the system to proactively respond to load fluctuations [33]. In energy storage management, AI regulates the charging and discharging of smart batteries automatically by considering electricity prices, consumption patterns, and the availability of renewable energy [34]. In addition, AI supports the integration of renewable energy into the smart grid through adaptive control systems that coordinate energy flows between households, generation, and storage in real-time, thereby improving the overall efficiency and reliability of the energy system [35].

5. Challenges and Limitations

The implementation of artificial intelligence (AI)-based systems in renewable energy development in Indonesia faces significant technical challenges. Dependence on large datasets emerges as the primary challenge, where AI systems require extensive and high-quality datasets to train models with optimal accuracy c The lack of comprehensive and representative data can cause AI models to produce unreliable or biased predictions, thus hindering appropriate decision-making in renewable energy management. Recent studies demonstrate that inconsistency, incompleteness, or inaccuracy of data actually reduces model performance despite large-scale data availability [41]. High computational requirements constitute the second substantial barrier in AI implementation for renewable energy. The training process and operation of sophisticated AI models, particularly algorithms such as deep learning and reinforcement learning, require significant computational resources, including specialized hardware such as GPUs and cloud infrastructure [36]. This condition becomes a serious challenge, especially in areas with limited access to adequate digital infrastructure. Additionally, these requirements pose significant constraints in terms of cost and availability of high-performance computing infrastructure in Indonesia [38]. Complexity of implementing Reinforcement Learning (RL) systems in real-world applications represents the third crucial technical challenge in developing intelligent energy systems. Although RL has tremendous potential for automated decision-making in energy and resource management, its field implementation faces challenges such as environmental uncertainty and high data variability [36]. Complex system dynamics and the need for real-time responses add to the difficulty level of implementation. Improper implementation can result in unstable or unsafe outcomes, particularly in the context of energy systems that require high reliability [36].

In the implementation of artificial intelligence (AI) for renewable energy in Indonesia, non-technical aspects encompass several critical dimensions that are equally important. One of the main challenges lies in the need for data standardization and system interoperability. This is due to the diversity of devices and technologies originating from various providers and institutions, which must be able to communicate effectively with one another. Without uniform data standards and interoperable systems, integrating data from multiple sources becomes extremely difficult. The absence of objective criteria for measurements such as accuracy or consistency further hampers system interoperability, for instance, in connecting small-scale renewable energy generators to the national grid. Regulation and cybersecurity become the second important concern in the era of increasingly massive energy system digitalization. The use of AI involving sensitive data and critical infrastructure requires strict regulations and protection from cyber attacks [37]. Data and control system security must be optimally maintained to avoid disrupting energy supply and protecting vital infrastructure from increasingly sophisticated cyber threats. Regulatory ambiguity can hinder innovation and increase security risks, particularly regarding data privacy and protection against cybersecurity breaches [40]. User acceptance and human resource training constitute key factors determining the success of AI implementation in the energy sector. The success of AI implementation heavily depends on the level of user acceptance and adequate workforce readiness [36]. Lack of training and understanding about AI, as well as low stakeholder understanding of the importance of quality data, can hinder the adoption of this technology at the operational level. End users and professionals need adequate training so they can understand and operate AI systems effectively [38]. A practical solution includes establishing a national open-access AI dataset repository to overcome data fragmentation and enhance model robustness. Additionally, partnerships with cloud service providers could facilitate access to subsidized computing resources for AI-driven energy startups.

6. Strategic Insights for Indonesia

Indonesia has tremendous potential to implement AI in improving the efficiency and sustainability of renewable energy. AI can significantly enhance operational efficiency through various strategic applications, including reinforcement learning-based energy distribution optimization and energy demand prediction using machine learning models [38]. Additionally, real-time monitoring of renewable energy infrastructure conditions can be conducted more effectively. Microgrid management, renewable energy production prediction, and energy consumption efficiency in village communities are concrete examples of AI implementation potential in Indonesia's renewable energy sector [39]. Based on in-depth analysis of existing challenges and potential, several strategic recommendations can be implemented to support AI adoption in Indonesia's renewable energy sector. Strengthening collaboration between academia, industry, and government becomes the key to overcoming complex technical and non-technical challenges [38]. This tri-party collaboration enables academia to develop innovative AI models, industry to provide necessary data and infrastructure. Meanwhile, the government can establish comprehensive and sustainable supporting policies [39].

Investment in digital infrastructure and workforce training represents an urgent strategic priority that must be realized. Recent research findings prove that improving workforce capacity in data literacy and preprocessing techniques is the main foundation before implementing large-scale AI [41]. The government needs to seriously invest in high-performance computing infrastructure and training programs to enhance human resource capacity in AI and renewable energy fields. This includes specialized training for PLN technicians or solar power plant managers regarding data management to reduce bias in energy predictions. Pilot testing of AI systems at microgrid or energy-independent village scale becomes a highly recommended strategic step as proof of concept before national implementation [38]. Small-scale implementation allows Indonesia to assess AI implementation effectiveness and challenges directly, while building competent technology and human resource capacity. This gradual approach also enables technology adjustment according to local needs and minimizes failure risks [39]. However, the success of these pilot tests heavily depends on input data quality, making ensuring standardized data availability a more urgent initial step [41]. This implementation strategy is expected to support sustainable technological innovation, enhance national energy security, and accelerate Indonesia's transition toward a more efficient and environmentally friendly energy system. As emphasized in the literature, "high-quality data is the bedrock of proficient machine learning performance" [41]. Therefore, priority focus should be directed toward data infrastructure preparation and technical competency enhancement of energy sector practitioners before jumping to experimental projects. A phased implementation strategy is recommended: (1) deploy AI systems in microgrid settings within rural communities, (2) evaluate performance and gather stakeholder feedback, and (3) expand adoption through regional collaboration. This approach ensures technical preparedness while accommodating local adaptability.

In addition to the use of Artificial Intelligence (AI) in predictive maintenance and energy optimization, an integrative approach to locally-based renewable energy is also a significant complementary strategy. [42] examined the use of corn cob waste as a feedstock for bioethanol, highlighting the potential of agroindustrial biomass in supporting sustainable energy resilience in rural areas. [43] added a perspective from the marine sector by proposing Eucheuma cottonii seaweed as a source of bioethanol, which is highly suitable for application in Indonesia's coastal regions. Furthermore, [44] evaluated Combined Heat and Power (CHP) technology in the efficient conversion of livestock waste into electrical energy. When combined with AI systems that support monitoring and automated decision-making, the integration of this technology can accelerate the adoption of renewable energy based on local potential.

Conclusions

Artificial Intelligence (AI) is rapidly transforming the renewable energy sector, offering breakthroughs in predictive maintenance, real-time monitoring, and energy optimization. Through various AI techniques such as machine learning (ML), deep learning (DL), reinforcement learning (RL), and ensemble models like XGBoost renewable energy systems are becoming more efficient, resilient, and adaptive. These advancements contribute to tangible improvements, including reduced unplanned downtime, increased energy output, enhanced equipment lifespan, and optimized load balancing, especially when integrated with smart grid infrastructures. Beyond technical performance, this review highlights the strategic role of AI in enabling data-driven energy governance, particularly in emerging economies like Indonesia. The findings are not only relevant to Indonesia’s national energy goals but also generalizable to other developing nations with similar infrastructure limitations and energy transition challenges. By demonstrating the potential of AI for distributed energy management, the review extends its implications to decentralized electrification models, energy equity, and climate adaptation strategies. However, realizing this potential requires more than algorithmic excellence. Major systemic barriers such as (poor data quality, limited computing infrastructure, lack of interoperability standards, and regulatory uncertainty must be addressed holistically). The successful adoption of AI in renewable energy hinges on strategic investments in digital infrastructure, capacity building, and strong collaboration between academia, industry, and government. Pilot-scale projects in microgrids and remote communities are essential as scalable testbeds to validate both the technology and its social acceptability. In conclusion, the integration of AI into renewable energy systems represents more than a technological evolution it is a catalyst for rethinking energy resilience, equity, and sustainability. Future innovations should emphasize the development of interpretable and resource-efficient AI models, while simultaneously aligning with local needs, policies, and capacities. As such, AI holds transformative potential not only to optimize renewable energy performance but to reshape energy systems for a just and inclusive low-carbon future.

References

[1] International Energy Agency, “World Energy Outlook 2023 | Enhanced Reader,” pp. 23-28, 2023.

[2] S. P. Hadi, B. Prabawani, and H. Purnaweni, "Environmental and social issues on energy policy in Indonesia," *E3S Web Conf.*, vol. 73, pp. 4–6, 2018, doi: 10.1051/e3sconf/20187302002.

[3] Z. A. S. Bahlawan *et al.*, "Immobilization of Saccharomyces cerevisiae in Jackfruit (Artocarpus heterophyllus) Seed Fiber for Bioethanol Production," *ASEAN J. Chem. Eng.*, vol. 22, no. 1, pp. 156–167, 2022, doi: 10.22146/ajche.69781.

[4] F. Martins, C. Felgueiras, M. Smitkova, and N. Caetano, "Analysis of fossil fuel energy consumption and environmental impacts in European countries," *Energies*, vol. 12, no. 6, pp. 1–11, 2019, doi: 10.3390/en12060964.

[5] Z. Liu *et al.*, "Artificial intelligence powered large-scale renewable integrations in multi-energy systems for carbon neutrality transition: Challenges and future perspectives," *Energy AI*, vol. 10, no. July, p. 100195, 2022, doi: 10.1016/j.egyai.2022.100195.

[6] Shedrack Onwusinkwue *et al.*, "Artificial intelligence (AI) in renewable energy: A review of predictive maintenance and energy optimization," *World J. Adv. Res. Rev.*, vol. 21, no. 1, pp. 2487–2799, 2024, doi: 10.30574/wjarr.2024.21.1.0347.

[7] G. Kyriakarakos, "Artificial Intelligence and the Energy Transition," *Sustain.*, vol. 17, no. 3, 2025, doi: 10.3390/su17031140.

[8] T. Ahmad *et al.*, "Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities," *J. Clean. Prod.*, vol. 289, p. 125834, 2021, doi: 10.1016/j.jclepro.2021.125834.

[9] M. M. Alam, M. J. Hossain, M. A. Habib, M. Y. Arafat, and M. A. Hannan, "Artificial intelligence integrated grid systems: Technologies, potential frameworks, challenges, and research directions," *Renew. Sustain. Energy Rev.*, vol. 211, no. November 2024, p. 115251, 2025, doi: 10.1016/j.rser.2024.115251.

[10] L. Gigoni and A. Betti, "A Scalable Predictive Maintenance Model for Detecting Wind Turbine Component Failures Based on SCADA Data".

[11] S. F. Bello, I. U. Wada, O. B. Ige, and E. C. Chianumba, "AI-driven predictive maintenance and optimization of renewable energy systems for enhanced operational efficiency and longevity," 2024.

[12] V. Sebestyén, "Renewable and Sustainable Energy Reviews: Environmental impact networks of renewable energy power plants," *Renew. Sustain. Energy Rev.*, vol. 151, no. September, p. 111626, 2021, doi: 10.1016/j.rser.2021.111626.

[13] S. Sankarananth, M. Karthiga, E. Suganya, and S. Sountharrajan, "AI-enabled metaheuristic optimization for predictive management of renewable energy production in smart grids," *Energy Reports*, vol. 10, pp. 1299–1312, 2023, doi: 10.1016/j.egyr.2023.08.005.

[14] Y. Ledmaoui, A. El Maghraoui, and M. El Aroussi, "Review of Recent Advances in Predictive Maintenance and Cybersecurity for Solar Plants," pp. 1–23, 2025.

[15] L. A. Yousef, H. Yousef, and L. Rocha-Menese, "Artificial Intelligence for Management of Variable Renewable Energy Systems : A Review of Current Status and," 2023.

[16] D. Cardoso and L. Ferreira, "Application of predictive maintenance concepts using artificial intelligence tools," *Appl. Sci.*, vol. 11, no. 1, pp. 1–18, 2021, doi: 10.3390/app11010018.

[17] R. B. Kamgba, "Development of Predictive Maintenance Technologies for Critical Industrial Systems Using AI and IoT," vol. 1, no. 2, pp. 1–9, 2024, [Online]. Available: https://doi.org/10.22541/au.172172848.85394455/v1

[18] T. Chen and C. Guestrin, "XGBoost : A Scalable Tree Boosting System," pp. 785–794, 2016, doi: 10.1145/2939672.2939785.

[19] S. M. Lundberg and S. Lee, "Predictions," no. Section 2, pp. 1–10, 2017.

[20] M. Ahsan, A. B. Mohammed, and A. Sadaqat, "AI-Driven Predictive Maintenance for Energy Storage Systems: Enhancing Reliability and Lifespan.," vol. 48, no. 3, pp. 686–701, 2024.

[21] V. S. D. Tejaswi, "IoT-Based Predictive Maintenance for Solar and Wind Energy Systems Using Machine Learning Models," vol. 5, no. 2, pp. 6–10, 2025.

[22] W. Shin, J. Han, and W. Rhee, "AI-assistance for predictive maintenance of renewable energy systems," *Energy*, vol. 221, p. 119775, 2021, doi: 10.1016/j.energy.2021.119775.

[23] D. J. B. Harrold, J. Cao, and Z. Fan, "Renewable energy integration and microgrid energy trading using multi-agent deep reinforcement learning," *Appl. Energy*, vol. 318, 2022, doi: 10.1016/j.apenergy.2022.119151.

[24] S. Binyamin and S. Ben Slama, "IntelliGrid AI: A Blockchain and Deep-Learning Framework for Optimized Home Energy Management with V2H and H2V Integration," *AI*, vol. 6, no. 2,

2025, doi: 10.3390/ai6020034.

[25] Z. Allal, H. N. Noura, O. Salman, and K. Chahine, "Machine learning solutions for renewable energy systems: Applications, challenges, limitations, and future directions," *J. Environ. Manage.*, vol. 354, no. December 2023, 2024, doi: 10.1016/j.jenvman.2024.120392.

[26] S. M. Malakouti, F. Karimi, H. Abdollahi, M. B. Menhaj, A. A. Suratgar, and M. H. Moradi, "Advanced techniques for wind energy production forecasting: Leveraging multi-layer Perceptron + Bayesian optimization, ensemble learning, and CNN-LSTM models," *Case Stud. Chem. Environ. Eng.*, vol. 10, no. June, p. 100881, 2024, doi: 10.1016/j.cscee.2024.100881.

[27] D. Dwivedi, K. V. S. M. Babu, P. K. Yemula, P. Chakraborty, and M. Pal, "Identification of surface defects on solar PV panels and wind turbine blades using attention based deep learning model," *Eng. Appl. Artif. Intell.*, vol. 131, no. January, 2024, doi: 10.1016/j.engappai.2023.107836.

[28] R. Alsaigh, R. Mehmood, and I. Katib, "AI explainability and governance in smart energy systems: A review," *Front. Energy Res.*, vol. 11, pp. 1–20, 2023, doi: 10.3389/fenrg.2023.1071291.

[29] D. Astolfi, F. De Caro, and A. Vaccaro, "Condition Monitoring of Wind Turbine Systems by Explainable Artificial Intelligence Techniques," *Sensors*, vol. 23, no. 12, pp. 1–24, 2023, doi: 10.3390/s23125376.

[30] U. Lützen and S. Beji, "Predictive maintenance for offshore wind turbines through deep learning and online clustering of unsupervised subsystems: a real-world implementation," *J. Ocean Eng. Mar. Energy*, vol. 10, no. 3, pp. 627–640, 2024, doi: 10.1007/s40722-024-00335-z.

[31] A. Turnbull and J. Carroll, "Cost benefit of implementing advanced monitoring and predictive maintenance strategies for offshore wind farms," *Energies*, vol. 14, no. 16, 2021, doi: 10.3390/en14164922.

[32] M. R. A T *et al.*, "Intelligent Energy Management across Smart Grids Deploying 6G IoT, AI, and Blockchain in Sustainable Smart Cities," *IoT*, vol. 5, no. 3, pp. 560–591, 2024, doi: 10.3390/iot5030025.

[33] L. Semmelmann, S. Henni, and C. Weinhardt, "Load forecasting for energy communities: a novel LSTM-XGBoost hybrid model based on smart meter data," *Energy Informatics*, vol. 5, no. 1, pp. 1–21, 2022, doi: 10.1186/s42162-022-00212-9.

[34] M. Krishna Pasupuleti, "AI-Enhanced Renewable Energy: Intelligent Systems for Sustainable Power Management," *AI Renew. Energy Manag. Tools Optim. Sustain. Power Syst.*, no. August, pp. 56–85, 2024, doi: 10.62311/nesx/905728.

[35] J. Venkatesh, "Renewable Energy Integration in Smart Grids – Smart Grid Seminar," no. January 2022, 2025.

[36] A. Shufian et al., "Perspectives and pathways to a Carbon-free Advanced Power Network (CAPN) in Bangladesh for sustainable development," *Clean. Energy Syst.*, vol. 10, no. January, p. 100172, 2025, doi: 10.1016/j.cles.2025.100172.

[37] R. Ridlo and A. Hakim, "Model Energi Indonesia, Tinjauan Potensi Energi Terbarukan Untuk Ketahanan Energi Di Indonesia: Sebuah Ulasan Model Energi Indonesia, Tinjauan Potensi Energi Terbarukan Untuk Ketahanan Energi Di Indonesia: Sebuah Ulasan," no. April 2020, 2021.

[38] Q. Wang, "Does Artificial Intelligence (AI) enhance green economy efficiency? The role of green finance, trade openness, and R&D investment," 2025, doi: 10.1057/s41599-024-04319-0.

[39] L. Judijanto and I. Suryahani, *Green Economy (Teori, Konsep, Gagasan Penerapan Perekonomian Hijau Berbagai Bidang Di Masa Depan)*, no. January. 2024.

[40] R. Kaur, "Artificial intelligence for cybersecurity: Literature review and future research directions," vol. 97, no. April, 2023, doi: 10.1016/j.inffus.2023.101804.

[41] R. Kaushik, "Evaluating the Impact of Data Quality on Machine Learning Model Performance," no. February, 2024, doi: 10.36893/JNAO.2023.V14I1.0013-0018.

[42] H. G. Pratama, W. Sari, K. Wijayanti, A. Devi, and O. R. Permatasari, “Bioethanol Production from Corn Cob Trough Utilization of Agro- biomass Waste in East Java as Renewable Energy : a Review,” 2024.

[43] R. Ijas, N. Rasyid, M. F. Dzikri, H. Laudza, and E. A. Davina, “Bioethanol Production as Renewable Energy from Macroalgae Eucheuma cottonii : A Mini Review,” 2024.

[44] W. I. Kholiq, A. S. Pramanta, J. Rumi, and D. Harahap, “Comparison of the Effectiveness of Electrical Energy Production from Livestock Manure by Optimization using Combined Heat and Power (CHP) Method : A Literature Review,” 2024.