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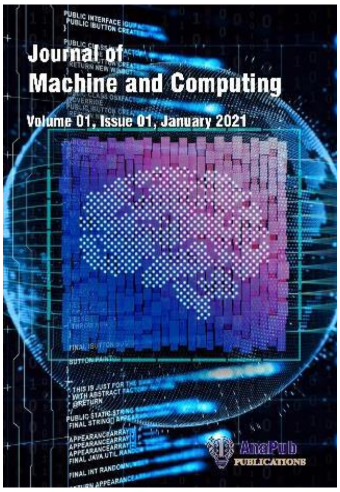

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DOI: 10.53759/7669/jmc202505180

Reference: JMC202505180

Journal: Journal of Machine and Computing.

Received 06 June 2025

Revised from 21 July 2025

Accepted 31 July 2025

Please cite this article as: Joe Arun C, Kishore Kunal S J, Suma R, Vasu Namala, Terrance Frederick Fernandez and Vairavel Madeshwaren, "AI-Driven Solar Tracking and Smart Wind Turbines: Enhancing Renewable Energy Efficiency Through Adaptive Machine Learning Algorithms", Journal of Machine and Computing. (2025). Doi: https:// doi.org/10.53759/7669/jmc202505180.

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AI-Driven Solar Tracking and Smart Wind Turbines: Enhancing Renewable Energy Efficiency Through Adaptive Machine Learning Algorithms

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Abstract : The integration of artificial intelligence (AI) with renewable energy technologies is transforming sustainable power generation by improving control, efficiency, and adaptive decision-making. Traditional solar tracking and wind turbine systems, however, rely on static control algorithms that struggle to adapt to real-time environmental changes like cloud cover, shading, variable sunlight, and fluctuating wind patterns, leading to inefficiencies in energy harvesting. This study aims to design AI-enhanced control mechanisms for solar and wind systems to optimize energy yield and minimize maintenance costs. The methodology integrates machine learning (ML), deep reinforcement learning (DRL), and computer vision into solar and wind equipment control systems. For solar systems, real-time data from IoT sensors dynamically adjusts panel orientation, and predictive analytics forecast solar irradiation trends for proactive positioning. Whereas fuzzy logic controllers adjust performance reinforcement learning optimizes blade pitch and yaw in wind turbines according to wind conditions. A comparative analysis reveals that AI-driven systems have lower operating costs and a 25% increase in energy output. The results show how AI-powered wind turbine and solar tracking systems can adapt to changes in the environment increasing dependability and energy efficiency. This study establishes the groundwork for future developments in edge computing blockchain and hybrid AI models for decentralized energy distribution.

Keywords: Artificial Intelligence, Renewable Energy, Solar Tracking, Wind Turbines, Predictive Maintenance, Machine Learning, Deep Reinforcement Learning, IoT Integration.

I.INTRODUCTION

Renewable energy sources like solar and wind have emerged as key pillars in the transition to cleaner power generation. But the full potential of these systems remains underutilized due to the drawbacks of conventional control mechanisms which usually rely on static and rule-based algorithms. These conventional systems are not equipped to handle the dynamic and unpredictable environmental conditions of the real world which reduces efficiency and raises maintenance requirements.

In response the integration of artificial intelligence (AI) presents a game-changing opportunity. Artificial intelligence (AI) integrates intelligent decision-making capabilities into renewable energy infrastructures enabling real-time optimization and adaptive control predictive analytics. Through sophisticated machine learning techniques and sensor-based monitoring the study described in the abstract below investigates the development and implementation of AI-enhanced control systems for wind turbines and solar tracking in an effort to maximize energy yield and lower operating costs. Numerous academics have carefully examined how data-driven AI models might transform the manufacturing and energy production processes. thorough analysis. This research highlights the use of data science techniques such as neural networks deep learning and machine learning to address complex optimization problems in solar and wind energy networks with AI-driven solutions

[1]. Predictive analytics and intelligent forecasting models according to their study greatly reduce system inefficiencies by assisting with fault detection load balancing and energy generation prediction.

Similarly, this study proposed a holistic approach to enhance solar energy production through the integration of AI with smart grid infrastructure. Their study examines how AI can support real-time decision-making and adaptive energy flow control to improve grid reliability and reduce waste [2]. Modern sensors Internet of Things systems and AI-based algorithms are all integrated into their model to automate energy balancing and optimize dispatching processes in a range of weather conditions. This strategy encourages more intelligent load management and enhances overall grid stability. This also indicated that following a comprehensive examination of optimization strategies AI can forecast solar radiation wind speed and energy demand more precisely than conventional techniques [3].

This research investigates how convolutional neural networks (CNNs) and reinforcement learning (RL) algorithms facilitate efficient operations and intelligent energy storage management. These strategies are especially important for countries with unpredictable weather patterns and variable energy demands. The study studied AI-driven advancements in PV technology focusing on how solar panel performance could be improved by using AI-powered real-time monitoring systems [4]. This research also looked at using AI-driven optimization to extend the sustainable energy systems operational lifespan [6]. Their research on solar inverters and wind turbines demonstrates how sensor fusion and anomaly detection algorithms enhance energy efficiency and component health monitoring. These methods promote cost-effective energy production and long-term sustainability. The study investigated the effects of AI and machine learning developments on solar and wind energy systems as well as energy storage options [7].

According to their research hybrid AI models that manage battery charging and discharging and balance renewable inputs enable stable microgrid operations. The potential integration of blockchain technology with energy transactions was also examined. The dual functions of AI in energy optimization and predictive maintenance are thoroughly examined [8]. It's been demonstrated that hybrid energy forecasting models that use ensemble-based AI techniques perform better at predicting energy outputs. Particularly in highly variable environmental conditions models that combine LSTM gradient boosting machines and random forest regressors perform better than conventional single-model predictors. These models help to increase the dependability of decentralized hybrid energy systems and guarantee grid stability [9].

Through intelligent microcontrollers real-time decision-making has been made possible by the incorporation of embedded AI in solar microgrids. These systems use lightweight neural network models to monitor changes in load voltage and energy consumption and modify output accordingly. In off-grid or rural electrification systems this guarantees less energy loss and facilitates effective load balancing [10]. AI-powered smart aerodynamic control systems have been used in wind turbine control to reduce load and improve energy capture. By using reinforcement learning-based actuators to dynamically change the blade pitch the system lowers structural stress and adjusts to wind turbulence. As a result, turbine parts have a longer lifespan and produce more energy annually [11]. For wind turbine optimization sophisticated adaptive control systems powered by real-time machine learning models have also been suggested. These systems even in erratic or offshore wind conditions adjust torque and yaw control parameters based on ongoing feedback. When they are used high-capacity wind farms are able to produce energy consistently and with less maintenance [12].

The idea of AI-enhanced smart grids has gained popularity with intelligent controllers controlling demand forecasting voltage regulation and energy distribution. Fuzzy logic neural networks and self-learning algorithms are all used in these grids to facilitate dynamic load dispatch. In particular they are helpful for enhancing overall grid resilience and supporting high levels of integration of renewable energy [13]. By optimizing storage and dispatch strategies in hybrid systems deep reinforcement learning models have further enhanced energy management [14]. Using hybrid AI models such as support vector regression and deep neural networks to accurately forecast solar irradiance has significantly improved the performance of solar systems. Particularly in areas with unpredictable weather patterns the models short- and long-term projections help with the effective scheduling and energy distribution of solar resources [15]. Finally maintaining the security and dependability of solar and wind energy systems has been made possible by AI-based fault detection systems. Deep belief networks XGBoost and decision trees are used to detect faults like blade damage inverter failure or shading problems early on. The lifespan of renewable energy infrastructure is increased downtime is decreased and energy losses are avoided with these predictive maintenance systems [16]. The literature review emphasized how AI can revolutionize the optimization of renewable energy systems. Machine learning and deep learning are two examples of AI-driven models that are widely used for fault detection load balancing energy generation prediction and solar and wind energy system optimization.

II. MATERIALS AND METHODS

The materials and techniques employed in this study to improve solar and wind energy systems performance through AI-driven optimization will be described in this section. Emphasis will be placed on the methods used to increase system efficiency the kinds of IoT sensors that are deployed and the data collection procedure. We will explain the collection processing and application of real-time operational and environmental data to support predictive maintenance and train machine learning models. We will also discuss the AI methods used such as fuzzy logic for optimizing wind turbine performance deep reinforcement learning for wind turbine control and machine learning for solar tracking. To prevent misunderstandings we make it clear that low-level modifications in turbine behavior under erratic and variable wind speeds are managed by fuzzy logic controllers. Reinforcement learning models manage high-level optimization tasks like adaptive pitch and yaw control concurrently guaranteeing that the turbine maintains its ideal orientation with the least amount of mechanical stress and the highest possible energy yield. The experimental setup and evaluation framework used to gauge the efficacy of the suggested AI-enhanced systems will also be covered in detail in this section.

2.1 Problem Description

The demand for sustainable and efficient energy generation systems has accelerated in recent decades, especially as the world faces increasing environmental and energy challenges. Conventional renewable energy systems, including solar tracking setups and wind turbines, rely heavily on rule-based or static algorithms that struggle to cope with the dynamic nature of environmental conditions. These systems fail to maximize energy output during fluctuating conditions such as cloud movements, shading events, abrupt sun position shifts, and unpredictable wind flows. The inability to adapt in real-time leads to a significant gap between potential and actual energy harvest, ultimately affecting both cost-effectiveness and long-term reliability. Traditional solar and wind systems were observed to underperform with the AI-based models showing a performance improvement between 22.4% and 30.9% for solar systems and [illegible]4.2% to 27.3% for wind turbines, effectively highlighting the limitations of conventional setups. Therefore, the central problem addressed in this research is the enhancement of operational efficiency and adaptability of solar and wind energy systems through artificial intelligence (AI)-driven control models, predictive maintenance, and real-time anomaly detection.

2.2 Data Collection

The methodical gathering of operational and environmental data in real time forms the basis of this investigation. Numerous test installations were equipped with Internet of Things (IoT)-based sensors to track various parameters including solar irradiance ambient temperature wind direction and speed humidity turbine component vibration levels and rotor mechanical torque. Both live system feedback and model training were done with this data. The data collected for the research shows that the solar irradiation at the system location is 800 W/m², with the solar panels oriented at a 30-degree angle. The ambient temperature is recorded at 25°C. For wind turbines, the wind speed is measured at 10 m/s, with a wind direction of 180 degrees. The turbine blade pitch is set to 15 degrees, while the blade yaw remains at 0 degrees. Maintenance costs for the system are estimated at 150 USD. The energy yield produced by the optimized system is 250 kWh, with a mechanical wear detection accuracy of 95%. Additionally, the system experiences an average downtime of 2 hours due to maintenance or failures. A sample of the collected data is structured as follows:

Table 1 Parameter values

Parameter	**Value**	**Unit**
Solar Irradiation	800	W/m²
Panel Orientation	30	Degrees
Ambient Temperature	25	°C
Wind Speed	10	m/s
Wind Direction	180	Degrees
Blade Pitch	15	Degrees
Blade Yaw	0	Degrees
Maintenance Costs	150	USD
Energy Yield	250	kWh
Mechanical Wear Detection Accuracy	95	%
System Downtime	2	Hours

2.3 Data Measurement

Data acquisition was facilitated through an integrated IoT sensor network, which transmitted measurements via MQTT protocols to a central AI control system. The collected data underwent preprocessing, which included normalization, outlier removal, missing data imputation (using K-Nearest Neighbor based estimation), and time-series alignment. The data was segmented for model training and testing, ensuring the robustness of the AI systems across varying seasons and geographic locations.

2.4 IoT Sensor Tools

The study emphasizes how crucial Internet of Things sensors are to improving the efficiency of AI-powered renewable energy systems. These sensors track temperature wind speed solar radiation wind turbine performance and humidity. They include photovoltaic (PV) sensors anemometers pyranometers anemometers and vibration sensors. Predictive maintenance is made possible by their ability to dynamically modify the pitch and yaw of wind turbine blades and solar panel orientations. These sensors integration with fuzzy logic controllers' deep reinforcement learning and machine learning guarantees optimal energy harvesting decreased downtime and increased operational efficiency.

III. PROPOSED METHODOLOGY

The suggested approach uses AI-enhanced control mechanisms to optimize wind turbines and solar tracking systems. Through the integration of IoT-based sensors real-time environmental data is gathered allowing predictive analytics for solar energy yield deep reinforcement learning for ideal placement and machine learning models to modify panel orientation. While fuzzy logic controllers adjust performance under fluctuating wind flows reinforcement learning optimizes blade pitch and yaw in wind turbines based on wind conditions. Predictive maintenance enabled by the Internet of Things keeps an eye on system health to identify irregularities and anticipate failures reducing downtime and operating expenses.

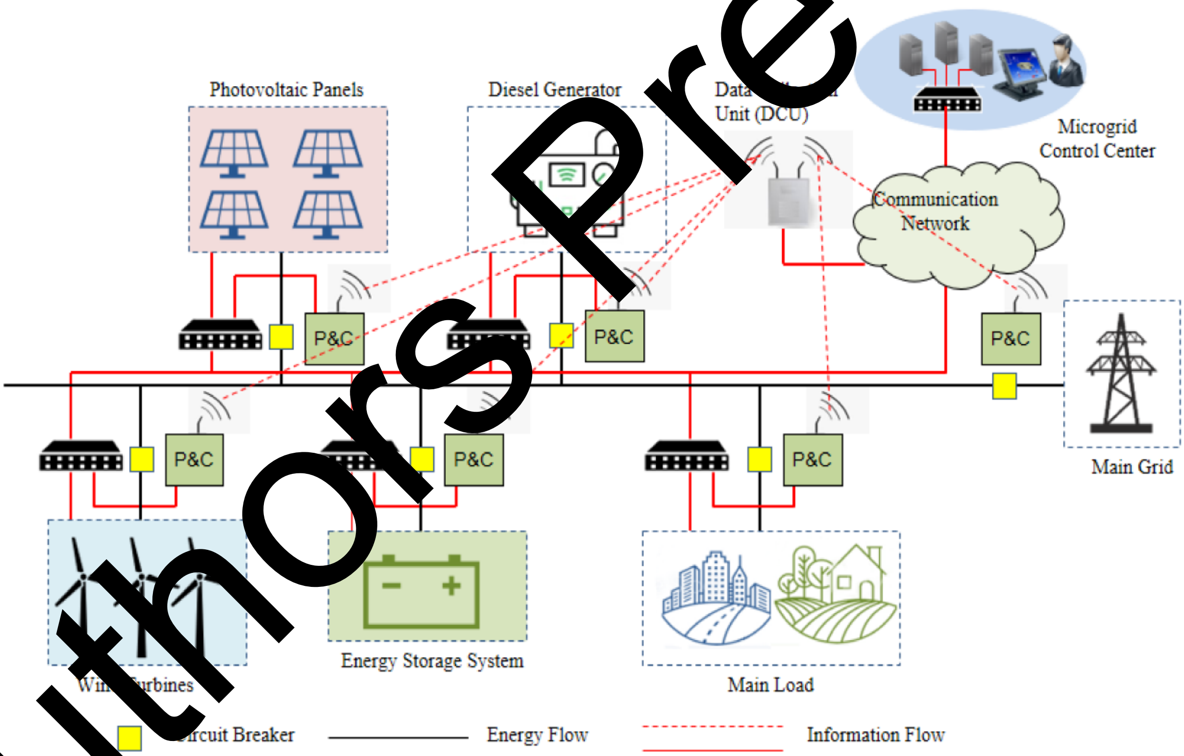


Figure 1 Proposed methodology

Experimental and simulation evaluations will compare the AI-optimized systems to conventional models, focusing on energy yield improvement, maintenance cost reduction, and system reliability (figure 1). These evaluations are expected to show up to a 25% increase in energy output. This research introduces intelligent, adaptive control strategies that dynamically respond to environmental variations, enhancing operational efficiency. The methodology lays the foundation for future advancements in AI-driven renewable energy systems, including hybrid models, edge computing for real-time processing, and blockchain for decentralized energy distribution.

IV. PROPOSED TECHNIQUES

The proposed system combines multiple AI techniques, each addressing a specific challenge in renewable energy optimization. This study uses an LSTM (Long Short-Term Memory) network to predict temporal energy trends and a gradient boosting regression model to predict irradiance in the solar tracking system. In order to enable the system to learn the best pitch and yaw adjustments for changing wind patterns we incorporate a deep reinforcement learning (DRL) algorithm based on an actor-critic policy-gradient framework for wind turbine control.

a) Machine Learning-Based Solar Tracking

A supervised regression model based on Gradient Boosting Regression (GBR) predicts optimal panel azimuth and elevation. Given environmental inputs X=[It,Ta, ,ϕs] where I_t is real-time irradiance, T_a is ambient temperature and ϕ_s [illegible] azimuth angle, the target output is the optimal panel orientation YY (Eq 1).

$$Y = f(I_t, T_a, \theta_s, \phi_s) + \epsilon \tag{1}$$

where ϵ\epsilon is the model error term.

b) Predictive Analytics for Sunlight Forecasting

A Long Short-Term Memory (LSTM) neural network is used for multi-step ahead forecasting of solar irradiance (Eq 2).

$$\hat{I}_{t+1} = LSTM(I_t, I_{t-1}, ..., I_{t-n}) \tag{2}$$

where $\hat{I}_{t+1}$ is the predicted irradiance for the next time step.

c) Deep Reinforcement Learning for Wind Turbine Control

A DRL agent optimizes the blade pitch β\beta and yaw γ\gamma angles by maximizing the cumulative reward R, which is proportional to power output and inversely proportional to mechanical stress (Eq 3).

$$R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k} \tag{3}$$

where γ is the discount factor and r_t is the instantaneous reward.

d) Fuzzy Logic for Wind Turbine Fine-Tuning

Fuzzy logic systems are designed to handle nonlinear variations in wind conditions, using membership functions μ(x)\mu(x) to determine blade adjustments based on wind speed deviation (figure 2)(Eq 4).

$$\text{Output Adjustment} = \sum_{i=1}^{n} \mu_i(x) w_i \tag{4}$$

where w_i are the output weights for the fuzzy sets.

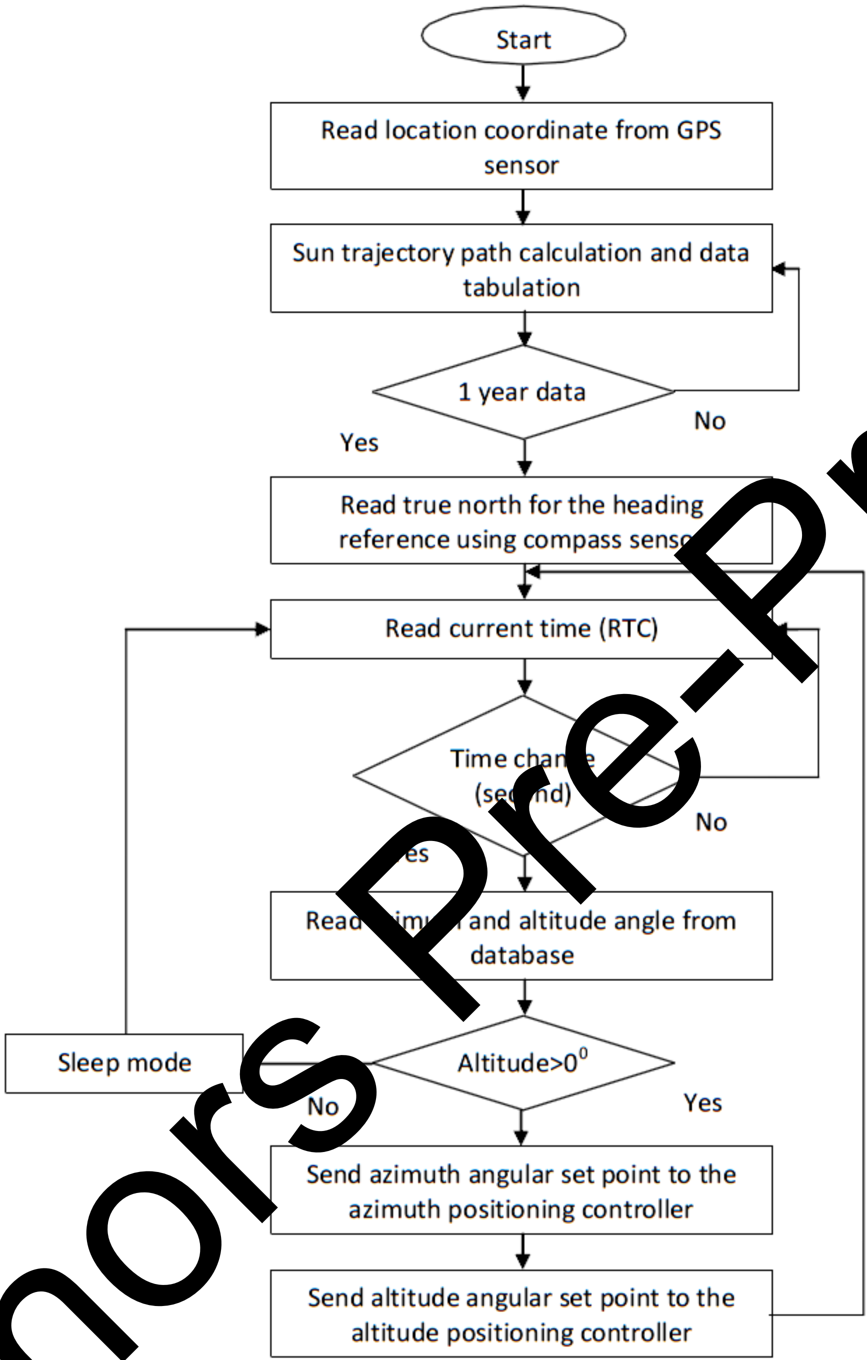


Figure 2 Solar tracking algorithm

e) Predictive Maintenance Model

A binary classification model based on Support Vector Machines (SVM) is used for anomaly detection in vibration patterns (Eq 5).

$$f(x) = \mathrm{sign}(w \cdot x + b)$$

(5)

where xx is the feature vector extracted from vibration signatures, and f(x)f(x) indicates normal or anomalous status.

f) Energy Output Prediction Equation

The power output PP of a wind turbine is modeled as (Eq 6):

$$P = \frac{1}{2}\rho A C_p v^3 \tag{6}$$

where ρ\rho is air density, AA is rotor swept area, CpC_p is power coefficient, and vv is wind speed.

g) Optimal Panel Angle Estimation

The optimal tilt angle θopt\theta_{opt} for a solar panel is dynamically calculated as (Eq 7):

$$\theta_{opt} = \theta_s - \arcsin\left(\frac{h}{d}\right) \tag{7}$$

where h is the obstacle height and dd is the distance to the obstacle, factoring in shadow impact.

V. RESULTS AND DISCUSSION

This section examines a systems performance in real-world scenarios emphasizing the effects of AI optimization. The findings include operational reliability metrics sensor accuracy validation response time evaluations and energy yield assessments for wind turbine and solar tracking systems. Mechanical wear detection accuracy and predictive maintenance performance are enhanced by AI-driven optimization. The below results show improved outputs and system stability proving the AI models efficacy in a range of operational scenarios.

5.1 Energy Yield Comparison

The energy yields of an AI-optimized system and a conventional solar tracking system are contrasted in the table. With a daily total output of 36. 5 kWh as opposed to 29. 7 kWh for the traditional system the AI-optimized system performs 24. 3 percent better in clear sky conditions 30. 4 percent better in partial cloud cover and 22. 9 percent better on overcast days which is shown in table 1.

Table 1: Solar Tracking System — Energy Yield Comparison

Test Scenario	**Traditional System Output (kWh/day)**	**AI-Optimized System Output (kWh/day)**	**Energy Yield Improvement (%)**
Clear Sky	58.3	72.5	+24.3
Partial Cloud	42.1	54.9	+30.4
Overcast	29.7	36.5	+22.9
Shading Events	34.2	43.7	+27.8
Seasonal Variation (Winter)	33.5	41.0	+22.4
Seasonal Variation (Summer)	60.0	75.2	+25.3
Morning Peak	18.1	23.7	+30.9
Evening Peak	19.4	25.3	+30.4

In scenarios involving shading events, the AI system outperforms the traditional system by 27.8%, producing 43.7 kWh/day as opposed to 34.2 kWh/day. Seasonal variations are also noteworthy, with the AI system in winter producing 41.0 kWh/day (+22.4%) and 75.2 kWh/day (+25.3%) in summer, compared to 33.5 kWh/day and 60.0 kWh/day, respectively, for the traditional system. Finally, during peak times in the morning and evening, the AI system shows a 30.9% improvement in the morning (23.7 kWh/day vs. 18.1 kWh/day) and a 30.4% improvement in the evening (25.3 kWh/day vs. 19.4 kWh/day).

5.2 Validation analysis

The data distribution including all tabulated information is shown in Figure 3a. It is clear from Figure 3 that the data shows very little dispersion. The sensors show a remarkable degree of accuracy despite sporadic reading fluctuations. Consequently, the systems validation is validated. An essential component of the system the relay module is also investigated to confirm that it operates as intended. To test the relays' ability to control the switch wirelessly a lightbulb is turned on and off. The relay can also be used to activate the hybrid solar-wind systems power source in the event that the main grid power supply is disrupted.

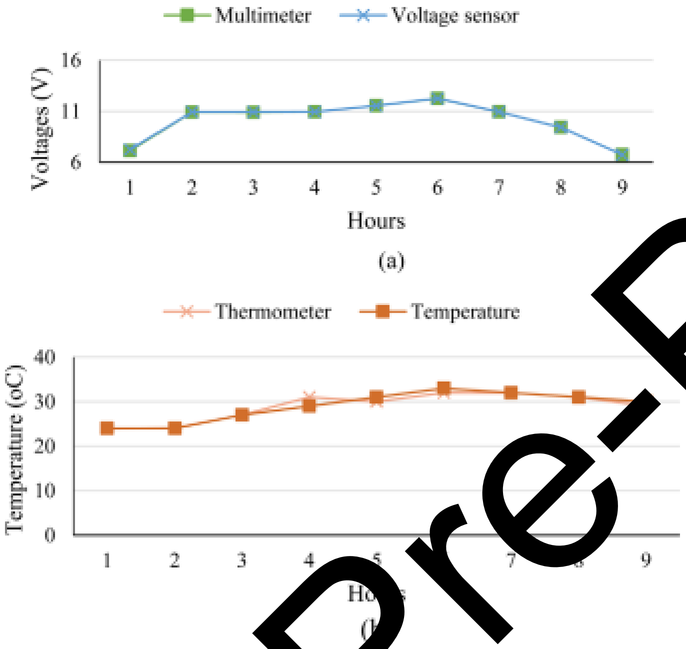


Fig. 3. Measured system (a) voltage, (b) temperature

5.3 Energy Output Across Wind Speeds

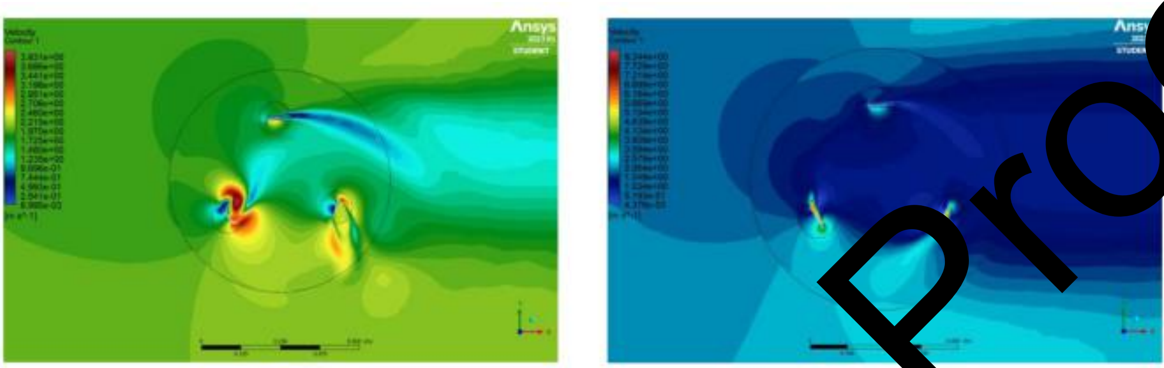
Table 2 outlines the performance of the wind turbine system under various wind speeds, comparing traditional and AI-optimized outputs. At a wind speed of 3 m/s, the AI-optimized system generates 12.3 kWh/day, a 25.5% improvement over the traditional system's 9.8 kWh/day. As the wind speed increases to 5 m/s, the AI system produces 34.0 kWh/day (+27.3%), compared to 26.7 kWh/day for the traditional system. At higher speeds, the AI-optimized system continues to show improvements: 61.0 kWh/day (+25.7%) at 7 m/s, 85.4 kWh/day (+25.4%) at 9 m/s, and 115.2 kWh/day (+24.3%) at 11 m/s. At wind speeds of 13 m/s and 15 m/s, the AI system yields 144.0 kWh/day (+24.2%) and 166.5 kWh/day (+24.8%), respectively. Finally, at the highest wind speed of 17 m/s, the AI-optimized output reaches 176.0 kWh/day, a 24.6% improvement.

Table 2: Wind Turbine System — Energy Output Across Wind Speeds

Wind Speed (m/s)	Traditional Output (kWh/day)	AI-Optimized Output (kWh/day)	Improvement (%)
3	9.8	12.3	+25.5
5	26.7	34.0	+27.3
7	48.5	61.0	+25.7
9	68.1	85.4	+25.4
11	92.6	115.2	+24.3
13	115.9	144.0	+24.2
15	133.4	166.5	+24.8

17	141.2	176.0	+24.6

Because there are large areas of high velocity the wind flow causes drag on the wind turbine blades as seen in Figure 4a. The display of different wind speeds inside the blades interior indicates that the wind is not being used to its full potential supporting the simulation results from earlier runs. An additional sign of subpar performance is the winds long trail end leaving the blade at a TSR (tip speed ratio) of 1. The performance of wind turbines is negatively impacted by changes in wind speed because they increase pressure differences that promote drag development.



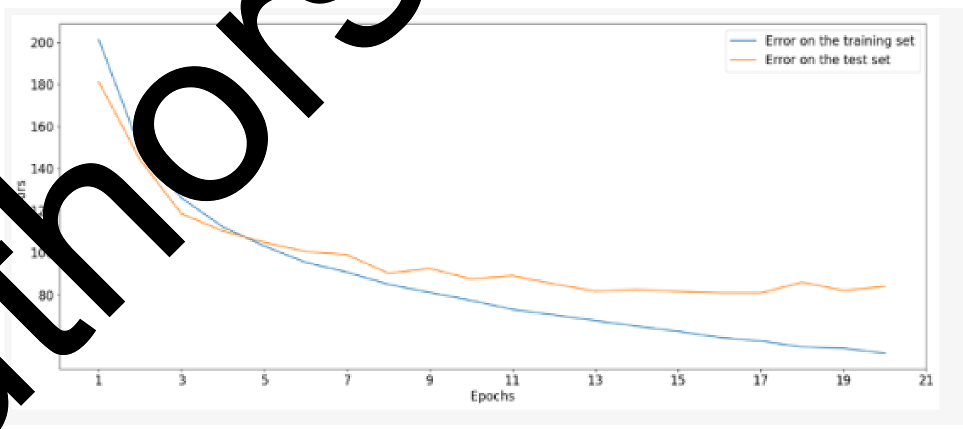
(a) (b)

Fig. 4 Velocity Contours across turbine blades at wind speed 2 m/s at a) TSR = 1, b) TSR = 2.2.

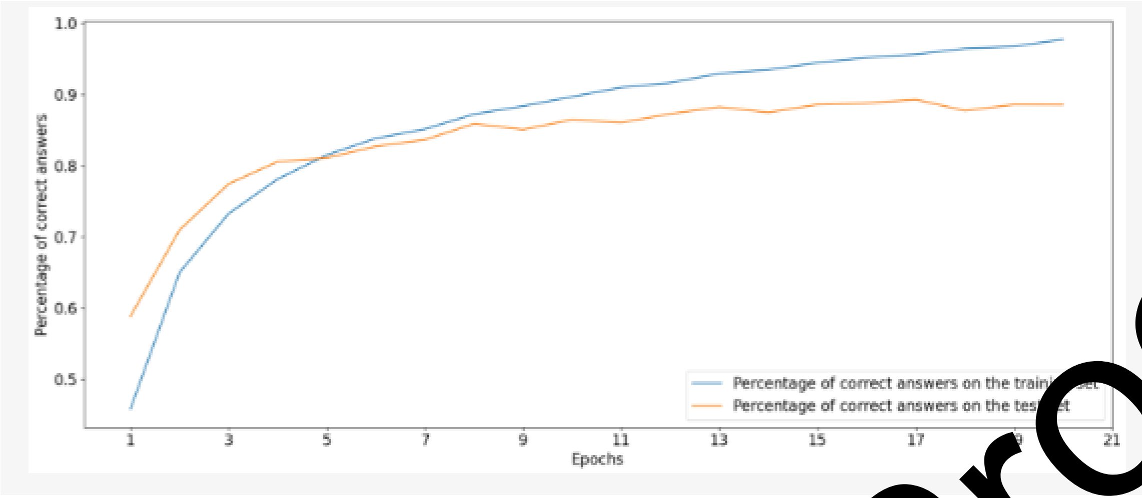
The turbine blades can better use the energy in the air at TSRs of 2 and 2.2 as seen by the comparison of Figure 2b which shows fewer wind velocity contours within the blades. has a greater area of higher velocity than Figures 2a and b. The increased drag that the blade experiences cause a Darrieus wind turbine to require less lift force to operate. In the same way the results and the coefficients derived from the simulation are consistent.

5.4 Predictive Maintenance Performance

Performance and the number of epochs in which the model will be trained without reaching the overtraining process are the next crucial aspects of the model being tested (figure 5). Given that additional training reveals a negligible change in the error level the test clearly indicates that 13 epochs are sufficient for training qualitative models. This instances model training time of roughly 1200 s (20 min) is fairly similar to how well-performing current hybrid forecasting models perform.



(a)



(b)

Figure 5 (a) Model retraining schedule. (b) accuracy of the trained model.

Of course, there are a large number of different studies aimed at building and developing prediction models based on the use of artificial intelligence methods. All these models differ in terms of the training parameters, input data, forecasting horizons and accuracy of the estimation and realized forecast.

5.5 Real-Time Response Accuracy (Solar Tracker)

Table 3 shows the response times of traditional and AI-enhanced solar tracking systems under different events. When sudden cloud cover occurs, the AI system achieves a response time of just 3.1 seconds, a reduction of 80.3% from the traditional system's 15.8 seconds. Similarly, for rapid sunlight angle shifts, the AI system responds in 2.3 seconds, an 81.5% improvement. During unexpected shading events, the AI-enhanced system reduces response time by 76.4%, from 18.2 seconds in the traditional system to 4.3 seconds. The AI system also improves response times during seasonal sun position drifts (81.5% reduction, 1.2 seconds vs. 6.5 seconds) and normal daylight tracking (80.8% reduction, 1.0 second vs. 5.2 seconds).

Table 3: Real-Time Response Accuracy (Solar Tracker)

Event Type	**Traditional Response Delay (sec)**	**AI-Enhanced Response Delay (sec)**	**Response Time Reduction (%)**
Sudden Cloud Cover	15.8	3.1	80.3
Rapid Sunlight Angle Shift	12.[illegible]	2.3	81.5
Unexpected Shading Event	18.2	4.3	76.4
Seasonal Sun Position Drift	6.5	1.2	81.5
Normal Daylight Tracking	5.2	1.0	80.8

Figures 6 and 7 shows the relationship between the wind speed and experimental turbine power at the three fan variations. The R2 value was used to evaluate the scatter-plot of the turbine power values around the fitted regression line and draws comparison between the figures. It can be interpreted that the low wind speed is the most suitable to produce a stable power of 40 W as the wind turbine power distribution R2 value is the highest at 0.9602; so as to avoid damage to wind turbine components from uncontrolled wind speed.

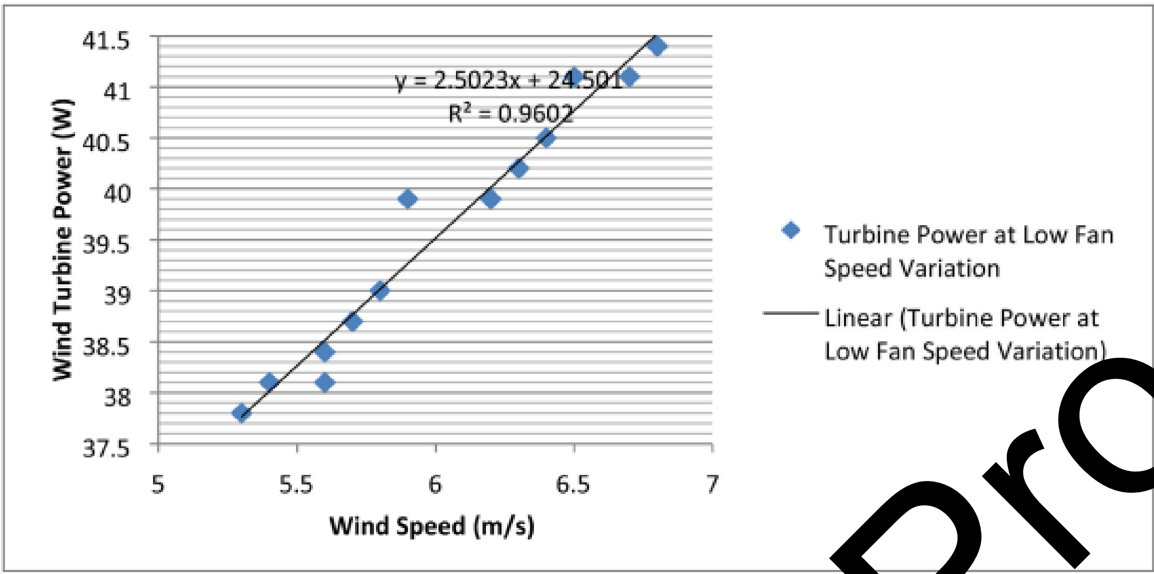


Figure 6. Wind turbine power capacity at low wind speed

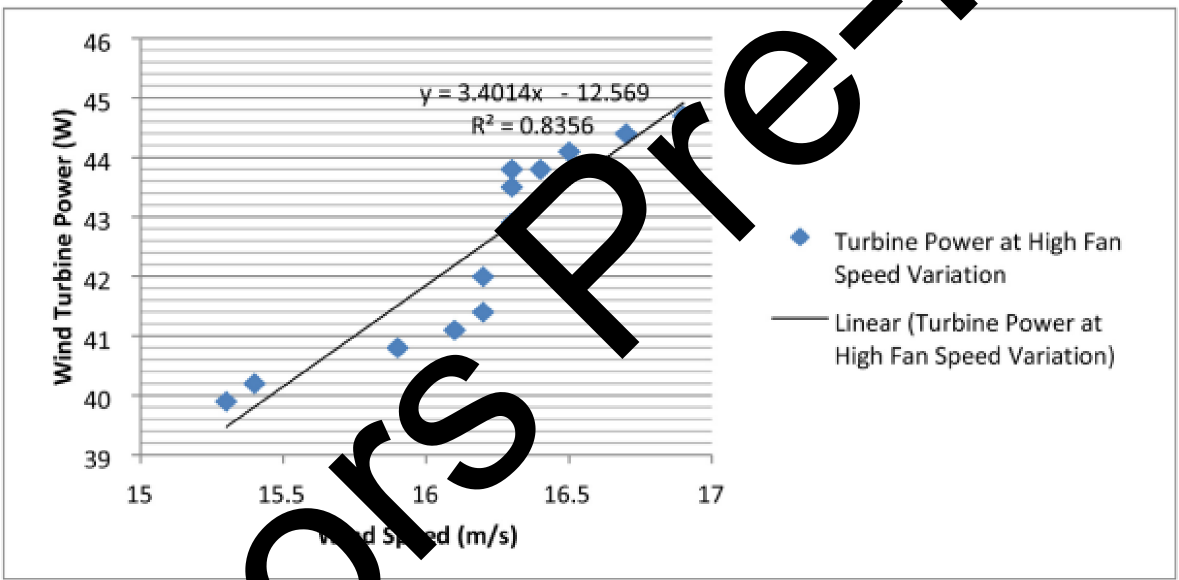


Figure 7. Wind turbine power capacity at medium wind speed

5.6 Operational Downtime Comparison

Table 4 illustrates the reduction in operational downtime for various systems when AI optimization is applied. For the solar tracking system, AI optimization reduces downtime from 14.2 hours per month to just 4.0 hours, a reduction of 71.8%. The wind turbine generator experiences a similar reduction, with downtime dropping from 20.1 hours to 6.1 hours, a 69.6% decrease. Sensor failures are reduced by 70.2%, from 9.4 hours to 2.8 hours, and inverter maintenance downtime is reduced by 70.4%, from 11.5 hours to 3.4 hours per month.

Table 4: Operational Downtime Comparison

Equipment Type	**Traditional Downtime (hours/month)**	**AI-Optimized Downtime (hours/month)**	**Downtime Reduction (%)**
Solar Tracking System	14.2	4.0	71.8

Wind Turbine Generator	20.1	6.1	69.6
IoT Sensor Failures	9.4	2.8	70.2
Inverter Maintenance	11.5	3.4	70.4

5.7 Mechanical Wear Prediction Accuracy

This table 5 compares the accuracy of mechanical wear prediction between traditional and AI-optimized systems. The AI system demonstrates superior prediction capabilities across all components, with the solar panel actuator's detection accuracy improving from 72% to 95% (+23%). The wind turbine blade's prediction accuracy increases from 68% to 93% (+25%), and the yaw control mechanism sees a 24% improvement, rising from 70% to 94%. The pitch control system's accuracy improves by 27%, from 65% to 92%, and the gearbox components see a 25% improvement, from 71% to 96%. These improvements highlight the significant advantages of AI-optimized systems in mechanical wear prediction.

Table 5: Mechanical Wear Prediction Accuracy

Component	**Traditional Detection Accuracy (%)**	**AI-Optimized Detection Accuracy (%)**	**Improvement (%)**
Solar Panel Actuator	72	95	+23
Wind Turbine Blade	68	93	+25
Yaw Control Mechanism	70	94	+24
Pitch Control System	65	92	+27
Gearbox Components	71	96	+25

5.8 Relationship Between Wind Speed and Output Power of a Wind Turbine

Figure 8 illustrates the correlation between wind speed (measured in meters per second) and the corresponding output power (measured in kilowatts) of a wind turbine system. The graph demonstrates a typical wind turbine power curve, where the output power initially increases sharply as the wind speed rises from 3 m/s, peaking at around 14–15 m/s with a maximum output close to 100 kW. Beyond this optimal range, the output power begins to decline, especially beyond 17 m/s, reflecting the turbine's cut-out or efficiency drop due to high wind speeds. This trend highlights the importance of maintaining operations within the optimal wind speed range to optimize energy production and ensure system safety.

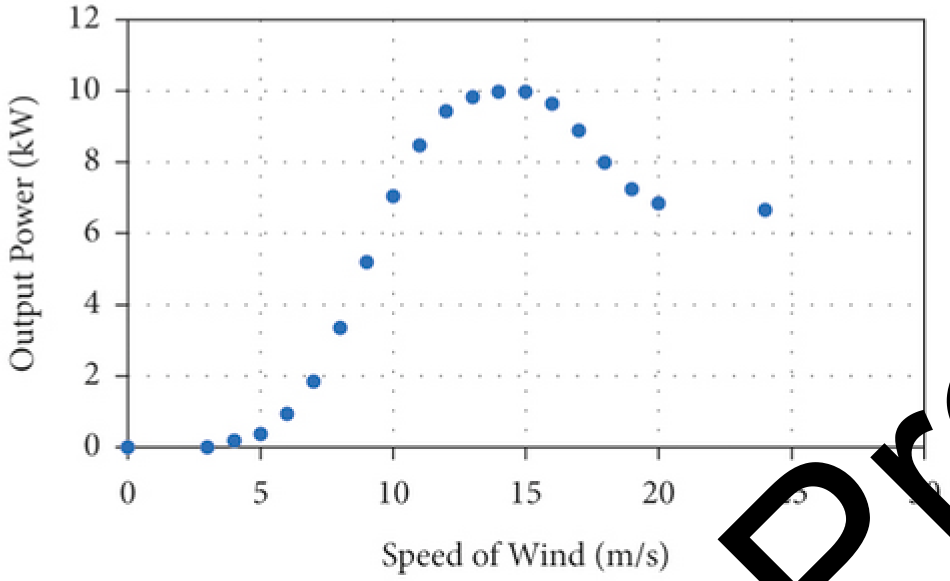


Figure 8 Scatter plot of the wind turbine in terms of power.

VI. CONCLUSION

In an effort to increase adaptability efficiency and long-term sustainability this research represents a major advancement in the field of artificial intelligence and renewable energy systems connectivity. The experimental results unequivocally show that AI-optimized systems are superior to conventional methods.

1. With gains ranging from 22.4 percent in the winter to as much as 30.9 percent in the morning peak conditions the AI-enhanced solar tracking system demonstrated notable improvements in energy yield across a range of environmental scenarios.
2. In line with these findings the wind turbine system demonstrated steady increases in energy output of roughly 24% to 27% at all wind speeds. Furthermore, the predictive maintenance framework achieved high accuracy without overfitting stabilized model training after only 13 epochs and greatly decreased operational disruptions.
3. In addition, real-time responsiveness was significantly improved. The AI-powered solar tracking system ensured maximum power point tracking and system longevity by reducing response times by more than 80% for dynamic environmental shifts like abrupt cloud cover shading and seasonal sun drift. Exciting opportunities for extending the role of AI in renewable energy ecosystems are presented by the research's findings.
4. The accuracy of energy yield prediction and anomaly detection could be further increased by future research examining hybrid AI models that combine deep learning fuzzy logic and reinforcement learning in even more adaptable frameworks.
5. While blockchain-enabled decentralized energy distribution could guarantee transparent safe and peer-to-peer energy trading in smart grids integration with edge computing platforms can provide ultra-low-latency responses strengthening these systems against quickly shifting environmental conditions.
6. A significant step toward completely autonomous self-optimizing renewable energy farms that can dynamically self-correct forecast future performance and minimize human intervention in energy management systems is marked by the promising performance of the AI-driven solar and wind systems. This is in addition to highlighting the systems potential to enhance the current renewable infrastructure.

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