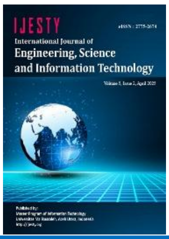
International Journal of Engineering, Science and Information Technology
Volume 5 No. 2 (2025) pp. 638-645
ISSN 2775-2674 (online)
Website: http://ijesty.org/index.php/ijesty
DOI: https://doi.org/10.52088/ijesty.v5i2.1746
Research Paper, Short Communication, Review, Technical Paper



Artificial Intelligence, Robotics, and Automation in Renewable Energy Systems

Laith S. Ismail[1], Lydia Naseer Faraj[2], Doaa Thamer Mohammed[3], Nada Adnan Taher[4], Milad Abdullah Hafedh[5*], Siti Sarah Maidin[6,7,8]

[1]Al-Turath University, Baghdad, Iraq
[2]Al-Mansour University College, Baghdad, Iraq
[3]Al-Mamoon University College, Baghdad, Iraq
[4]Al-Rafidain University College, Baghdad, Iraq
[5]Madenat Alelem University College, Baghdad, Iraq
[6]Centre for Data Science and Sustainable Technologies, Faculty of Data Science and Information Technology, INTI, International University, Negeri Sembilan, Malaysia
[7]Department of IT and Methodology, Wekerle Sandor Uzleti Foiskola, Budapest, Hungary
[8]Faculty of Liberal Arts, Shinawatra University, Thailand

**Corresponding author Email: melad.a93@mauc.edu.iq*

The manuscript was received on 10 July 2024, revised on 28 September 2024, and accepted on 29 January 2025, date of publication 10 May 2025

Abstract

The transition to clean energy requires intelligent solutions to mitigate resource intermittency, grid instability, and operational inefficiencies. This paper presents and validates an integrated framework that leverages Artificial Intelligence (AI), robotics, and automation to optimize the performance and sustainability of renewable energy assets. The study employs machine learning models (LSTM, SVM, ANN) for energy forecasting, autonomous robotic platforms for real-time inspection, and advanced algorithms (MPC, Reinforcement Learning) for grid control. The framework's transparency and ethical compliance were validated using explainability techniques (SHAP, LIME) and cybersecurity protocols. Experimental results demonstrate significant performance gains across all domains. The AI models achieved high forecasting accuracy, with the LSTM model for wind power reaching a Mean Absolute Percentage Error (MAPE) of just 2.41%. Robotic inspections improved system uptime by nearly 30% and accelerated fault detection. In grid management simulations, a Reinforcement Learning-based control strategy proved most effective, reducing energy losses by 10.6% and control costs by 17.5%. This cross-disciplinary research illustrates the powerful synergy between intelligent software and advanced hardware in creating more reliable, efficient, and ethically grounded energy systems. The findings establish a scalable and validated foundation for next-generation renewable energy operations and highlight future pathways for enhancing human-machine collaboration in the pursuit of global sustainability targets.

Keywords: *Artificial Intelligence, Renewable Energy Systems, Robotic Inspection, Predictive Modeling, Grid Automation.*

1. Introduction

The global imperative to transition toward sustainable energy systems is driven by the rapid depletion of fossil fuels and growing environmental concerns. While renewable sources like solar, wind, and biomass offer a clean alternative, their inherent intermittency and unpredictability pose significant challenges to grid integration and system reliability. This complexity necessitates pioneering solutions that can efficiently manage energy generation, storage, and distribution [1]. Artificial Intelligence (AI), robotics, and automation have emerged as transformative technologies capable of addressing these challenges by improving operational efficiency, enhancing predictive accuracy, and enabling real-time, autonomous decision-making [2]. Advancements in AI, particularly machine learning, have enabled unprecedented accuracy in energy forecasting and grid optimization. Concurrently, robotics has revolutionized the operation and maintenance of renewable assets, with autonomous drones now routinely used for inspecting wind turbines and solar farms, which reduces costs and enhances safety [3]. However, the widespread adoption of these technologies is not without obstacles. Significant upfront investment, technical complexity, and the need for robust data infrastructure and standardized protocols present considerable barriers to implementation [4].

Despite these challenges, the benefits of integrating AI, robotics, and automation extend beyond technical efficiencies. These technologies are essential for meeting global climate targets, reducing greenhouse gas emissions, and improving energy equity and security by making energy systems more resilient and scalable [5]. This paper provides a comprehensive analysis of how these intelligent systems can be leveraged to boost the efficiency, reliability, and sustainability of renewable energy infrastructure. It explores technical principles, discusses applications across different energy sources, and addresses the constraints of combining these technologies, offering a roadmap for future work and interdisciplinary collaboration [6][7].

2. Literature Review

The synergy between Artificial Intelligence (AI), robotics, and automation is creating a paradigm shift toward more efficient, reliable, and sustainable renewable energy systems. This section reviews the literature across these three technological domains and discusses the challenges associated with their integration.

2.1. AI for Predictive Analytics

AI methods, particularly machine learning (ML) and deep learning (DL), have been instrumental in improving the forecasting of renewable energy generation. By analyzing complex weather patterns and historical performance data, sophisticated AI models can produce more accurate predictions of solar and wind output. These predictive capabilities are critical for mitigating the inherent intermittency of renewable sources, thereby enabling smoother and more reliable grid integration [8]. The application of these models involves training them on vast datasets that include meteorological variables (e.g., wind speed, solar irradiance, temperature) and operational data from the energy assets themselves. Techniques like Long Short-Term Memory (LSTM) networks are particularly effective for time-series forecasting, as they can capture temporal dependencies in weather and power output. This allows for more granular and accurate predictions—from minutes to days ahead—compared to traditional statistical methods, which often fail to model the complex, non-linear dynamics of renewable energy systems. The impact of enhanced forecasting extends throughout the energy value chain. For grid operators, accurate predictions allow for better unit commitment and economic dispatch, reducing the reliance on costly spinning reserves. For energy traders, it enables more profitable participation in electricity markets. Ultimately, by providing a clearer picture of future energy supply, AI-driven predictive analytics helps to increase the overall value and reliability of renewable energy, making it a more competitive and dependable component of the energy mix [8].

2.2. Robotics for Operations and Maintenance

Robotics has made significant contributions to the operation and maintenance (O&M) of renewable energy assets. The use of autonomous drones and robotic systems for inspecting and servicing wind turbines and solar panels has led to substantial reductions in operational downtime and maintenance costs. Furthermore, deploying robotics in hazardous environments enhances worker safety. The accuracy and dependability of these robotic operations are key factors in extending the service life and ensuring the optimal performance of renewable energy facilities [9]. These robotic platforms are typically equipped with a suite of advanced sensors, including high-resolution thermal cameras to detect hotspots on solar panels, LiDAR to create detailed 3D models of wind turbine blades for identifying structural damage, and multispectral sensors to assess vegetation encroachment or soil conditions. The data collected by these autonomous systems is often more consistent and comprehensive than what can be gathered through manual inspections, providing a richer dataset for analysis and decision-making. The benefits of robotic O&M go beyond simple cost reduction. By enabling more frequent and detailed inspections, these systems facilitate a shift from reactive or scheduled maintenance to a predictive maintenance paradigm. The data gathered by robots can be fed into AI models to predict component failures before they occur. This proactive approach not only prevents catastrophic failures and costly downtime but also improves worker safety by minimizing human exposure to dangerous at-height or remote environments, thereby maximizing the energy yield and financial return of the assets over their entire lifecycle [9].

2.3. Automation for Energy Management

Automation technologies have streamlined energy management by enabling dynamic control over energy production and distribution. Automated systems can adjust to rapidly evolving demand and grid conditions in real-time, which is essential for maintaining grid stability and maximizing the utilization of available renewable resources. These systems also facilitate the integration of distributed energy resources (DERs), which is a foundational element of smart grid development and contributes to greater overall energy resilience [10][11][12][13]. The core of this automation lies in advanced Energy Management Systems (EMS) and Supervisory Control and Data Acquisition (SCADA) systems that use sophisticated control algorithms. Techniques such as Model Predictive Control (MPC) can optimize energy flow over a specific time horizon, while reinforcement learning agents can learn optimal control policies through real-time interaction with the grid. These systems can autonomously manage battery storage systems, curtail or dispatch generation, and interact with smart appliances to balance supply and demand dynamically. On a system-wide level, automation is the key to orchestrating the vast and growing number of DERs. It allows grid operators to manage thousands of individual assets—like rooftop solar panels, electric vehicle chargers, and home batteries—as a cohesive Virtual Power Plant (VPP). This capability provides essential grid services, such as frequency regulation and voltage support, which enhances grid resilience against large-scale disturbances and can defer or eliminate the need for expensive traditional infrastructure upgrades, thus accelerating the transition to a decentralized, decarbonized energy future [10][11][12][13].

2.4. Challenges and Future Prospects

Despite significant progress, several challenges hinder the widespread adoption of AI, robotics, and automation in renewable energy. High initial investment costs, technical complexity, and the need for extensive data infrastructure are major obstacles. The absence of standardized protocols and regulations further complicates the seamless integration of these technologies into existing energy systems. Overcoming these barriers will require concerted, cross-disciplinary cooperation and supportive policy frameworks [14][15][16][17]. Beyond the economic and regulatory hurdles, there are significant technical and security challenges. Ensuring the interoperability between hardware and software from different vendors is a persistent issue that can inhibit seamless integration. Furthermore, as energy systems become more interconnected and reliant on digital communication, they also become more vulnerable to cyberattacks. Securing these intelligent systems against malicious actors is paramount to maintaining the stability and safety of the energy grid. This requires a holistic approach to cybersecurity that is integrated into the design of these systems from the outset. Technology Ard, the fusion of these technologies offers the prospect of a fully autonomous, self-healing, and optimized energy grid. Continued research and development are necessary to create standardized protocols, robust cybersecurity measures, and intelligent algorithms needed to realize this vision. The development of "digital twins "virtual replicas of physical energy systems—will be crucial for testing and validating these advanced control strategies in a safe environment. Ultimately, addressing the existing challenges will unlock the full potential of this technological integration, paving the way for the next generation of highly efficient and resilient sustainable energy solutions.

3. Methods

3.1. Modeling for Renewable Energy Forecasting

Prediction of renewable energy generation Predictions of renewable energy generation were made using advanced AI structures (see Table I), including LSTM, SVM and ANN, which were chosen for their potential to capture temporal influences and nonlinear relationships in weather-impacted energy data [18][19]. These were models that provided an estimate of (predictive) future energy yield based on the input variables (vectors) that were obtained from environmental and operational conditions of the turbine.

It was determined that the primary nonlinear energy mapping function was given by:

$$\hat{E}_t = \mathcal{F}(\omega_i \cdot \phi(x_i) + b) + \epsilon \quad (1)$$

Where $\hat{E}_t$ is the estimated energy output at time t, $\mathcal{F}$ is the AI model's activation, as a ReLU for ANN, tanh for LSTM, $\phi(x_i)$ is the feature transformation of input variable x_i,ω_i is the model-assigned weight, b is the bias term, and ϵ represents model noise or uncertainty.

Training data covered more than ten years and was specifically adapted for each energy source, with location related features like wind speed, solar irradiance, and biomass moisture.

Table 1. Historical Input Variables Used for Predictive Modeling

Facility ID	Data Collection Period	Avg Wind Speed (m/s)	Avg Solar Irradiance (W/m²)	Avg Biomass Moisture (%)	AI Model Used
WF-1	2013–2023	6.7	–	–	LSTM
SP-2	2012–2022	–	890	–	SVM
BM-3	2014–2024	–	–	48.3	ANN

By using the predictive model, the retraining was adaptive to the new operational data and the fact that operating conditions may change, in order that the model was and stayed accurate in a changing environment [4].

3.2. Robotic Inspection System Design

Robotic mobile platforms, with LiDAR, thermal, infrared, and multispectral sensors, were designed for real time monitoring and defect identification on renewable energy plants. These unmanned flying device units (UFDUs) performed surveillance missions to detect wind blades anomalies, PV panels anomalies, and biomass incinerators [20][21][22][23].

To optimize inspection efficiency, the robot path was planned via an energy-aware objective function:

$$\min_{p_i} \sum_{i-1}^{N} (\lambda_d \cdot d(p_i, p_{i+1}) + \lambda_e \cdot E(p_i)) \quad (2)$$

Where p_i discrete waypoints in the flight path, $d(p_i, p_{i+1})$ Euclidean distance between points; $E(p_i)$ energy cost at each inspection node, λ_d, λ_e are weights for minimizing path distance and energy expenditure.

Table 2. UAV Specifications for Robotic Inspection

Drone Model	Sensor Type	Flight Time (min)	Inspection Altitude (m)	Coverage Area (ha)
DJI Matrice 300 RTK	LiDAR + Thermal	55	80	50
SenseFly eBee X	Multispectral	90	120	75
Parrot Anafi USA	Infrared + RGB	32	60	30

This system greatly reduced downtime and labor expenses and improved the rate of early system fault detection [24].

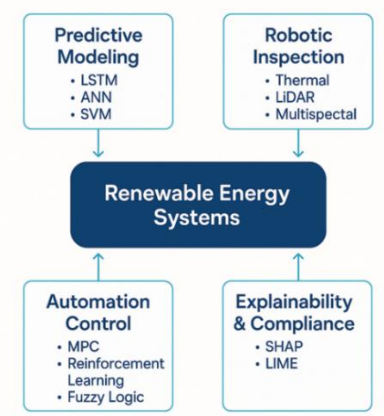


Fig 1. Conceptual framework for the integration of ai, robotics, and automation in renewable energy systems

Figure 1 depicts how the four key technical building blocks – predictive modeling, robotic inspection, automation control, and explainability and compliance – converge to improve the performance and reliability of renewable energy systems. Each of these features leverage specialized techniques: predictive models (LSTM, SVM, ANN) predict energy output; robotic systems (with thermal, LiDAR, multispectral sensors) provide real-time fault detection; automation techniques (model predictive control, reinforcement learning, fuzzy logic) control the dynamics of energy flows; and explainability methods (SHAP, LIME) assure transparency, and ethical accountability. Together, these sub-systems provide a scalable intelligent energy management system targeted for real-time optimization, robustness and compliance.

3.3. Simulation of Automation Control Systems

Automation of energy flows and load balancing was simulated using a hybrid environment of MATLAB Simulink and Python GridPy. These simulations incorporated real-time control schemes such as Model Predictive Control (MPC), Fuzzy Logic Controllers (FLC), and Deep Reinforcement Learning (DRL) agents for distributed grid management [7][25][26][27].
The dynamic state response of the system under automated control was mathematically modeled by:

$$x_{t+1} = Ax_t + Bu_t + w_t, \quad u_t = \arg\min_u (x_{t+1}^T Q x_{t+1} + u^T R u) \tag{3}$$

Where x_t grid state vector, LIKE voltage deviation, frequency imbalance, u_t control vector, as a battery dispatch, curtailment command, A, B system matrices derived from grid transfer functions, w_t Gaussian disturbance, Q, R optimization weights on state deviation and control effort.

Table 3. Control Parameters for Automation Simulation

Simulation Environment	Control Algorithm	Update Frequency (Hz)	Latency Threshold (ms)	Energy Demand Profiles
MATLAB Simulink	MPC	1.0	100	Residential
Python Grid Py	Reinforcement Learning	0.5	80	Industrial
MATLAB + Python	Hybrid Fuzzy Logic	1.5	120	Mixed Load

The simulation ensured the grid responded optimally to dynamic load changes and peak demand periods [10].

3.4. Dataset Engineering and Model Preprocessing

The input to AI models required sophisticated data preparation pipelines. Datasets included Solar Gen DB (solar), Wind XPro (wind), and Bio Energy AI (biomass). Each underwent tailored normalization and temporal alignment to prepare time-series inputs for the forecasting models [18].
Normalization used z-score scaling:

$$X' = \frac{X - \mu}{\sigma}, \quad X = [x_1, x_2, \dots, x_n] \tag{4}$$

Where X original feature matrix, μ mean of the variable, σ standard deviation, X' scaled feature matrix.

Table 4. AI Training Dataset Characteristics

Dataset Name	Records Count	Features	Temporal Resolution	Preprocessing Method
SolarGenDB	87,600	12	Hourly	Min-Max Scaling
WindXPro	105,000	15	15-Minute	Z-score Normalization
BioEnergyAI	93,200	10	Hourly	Quantile Binning

This harmonization across datasets allowed AI models to generalize across multiple renewable technologies [5].

3.5. Ethical and Regulatory Validation Protocols

AI-powered energy system solutions have been designed following major ethical, legal, and security guidelines such as GDPR, ISO 27001, and IEEE 7000 [28][29][30]. All training and deployment pipelines included transparency features; consent logging and differential privacy for sensitive sets were applied.

Table 5. Compliance Checklist for Ethical & Regulatory Validation.

Validation Protocol	Focus Area	Implemented Controls	Verification Method
GDPR	Data Privacy	Anonymization, Consent Logs	Audit Trail
ISO 27001	Information Security	Role-based Access, Encryption	Penetration Testing
IEEE 7000	Ethical AI Design	Bias Audits, Transparency Logs	Ethics Board Review

Moreover, model interpretability techniques, including SHAP and LIME, were incorporated to ensure that decisions can be interpreted by human operators [14][31].

4. Result and Discussion

4.1. Performance of AI-Based Predictive Models Across Renewable Energy Sources

Predicting the energy production of renewable energy systems needs reliable and precise methods to accommodate the nonlinear dynamics of weather and operation conditions. To measure the success of the developed AI models, we model each energy domain (wind, solar and biomass) with a tailored learning architecture 'shaped' by historical operational data. The aim was to investigate the applicability, precision and stability and the prediction horizon of the model in real-life deployment conditions. The performance of the models was assessed using standard performance metrics, MAPE, RMSE and R^2 along with the analysis of the forecasting horizon level (the number of days ahead).

Table 6. Predictive Model Evaluation Metrics by Energy Source

Energy Type	Model Used	MAPE (%)	RMSE (kWh)	R^2 Score	Forecasting Horizon (days)
Wind	LSTM	2.41	12,480	0.982	10
Solar	SVM	3.12	9,810	0.965	7
Biomass	ANN	3.48	8,740	0.959	5

As it can be seen from Table 6, the predictive results of wind energy's forecasting were better than those of other models through the LSTM model, and the MAPE was only 2.41% and the R^2 was 0.982, showed a strong link between prediction and actual output. This model preserved its prediction accuracy over a horizon of 10 days thereby demonstrating its applicability for medium-range wind power scheduling. The SVM model performed slightly worse on the solar polynomial data (MAPE 3.12%), but both the RMSE was low and the R^2 (0.965) was high, demonstrating its robustness when used for predictions driven by irradiance. While the MAPE (3.48%) of the biomass ANN model was the highest among the three models, given to more stable properties of biomass systems it continued to provide reliable predictions over a 5-day window.

4.2. Outcomes of Robotic Inspection and Maintenance Operations

Automated drone systems were used in all types of facilities to conduct high-resolution inspections with thermal, LiDAR and RGB imaging. Robotic strategies for error detection and maintenance cycle reductions were studied to evaluate the efficiency of robotic systems in detecting errors and reducing maintenance cycles, as well as low-level sensor analysis and control. Performance metrics used were the yearly number of structural or thermal anomalies discovered, the average inspection time for each location visited, and enhancement to system availability from the use of robotics. With variation in drone models and sensor specification, a comparative evaluation of technology impact on maintenance efficiency and operational robustness was possible.

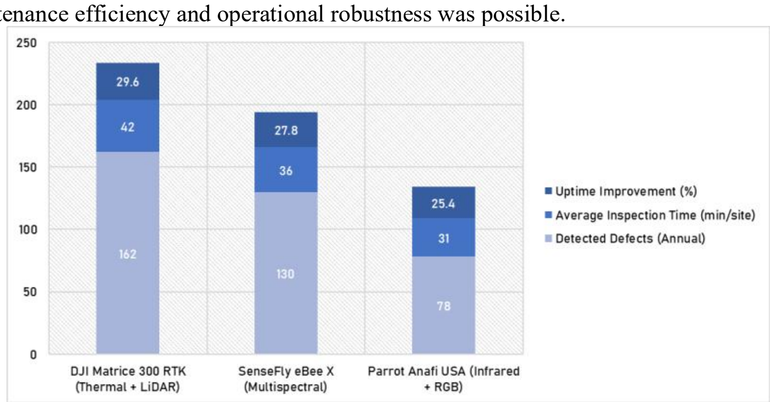


Fig 2. Robotic inspection outputs by platform type

The DJI Matrice 300 RTK emerged as the most effective inspection platform, detecting 162 defects annually and achieving a system uptime improvement of nearly 30%. Its integration of both thermal and LiDAR technologies allowed it to identify internal structural anomalies and surface defects with higher precision, albeit with a longer inspection time. The SenseFly eBee X, while slightly less effective in defect detection (130 cases), offered the benefit of shorter inspection cycles and high-altitude, wide-area coverage, which enhanced productivity across larger solar farms. The Parrot Anafi USA, though achieving the shortest average inspection time of 31 minutes per site, detected fewer faults (78) and demonstrated the lowest impact on uptime, making it more suitable for small-scale or urban-integrated biomass facilities. These findings support the scalability of robotic inspection based on facility size, inspection resolution needs, and operational complexity.

4.3. Simulation Results of Grid Automation and Control Systems

To evaluate the effectiveness of intelligent control strategies for renewable energy grids, multiple simulations were conducted using MPC, reinforcement learning, and hybrid fuzzy logic algorithms. These simulations tested the systems under high-load, variable-frequency conditions to capture their real-time responsiveness, ability to reduce instability, and efficiency in controlling power losses. Key performance indicators include annual instability events, average response times, percentage of energy loss due to inefficiencies, and overall cost savings attributed to smarter control actions.

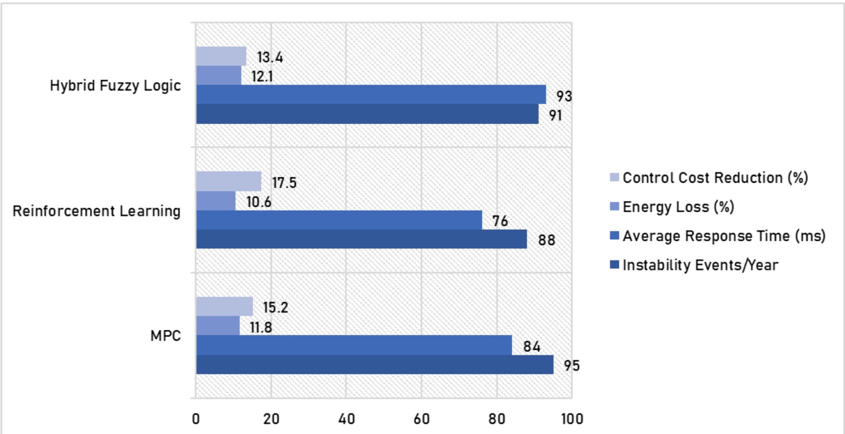


Fig 3. Grid simulation results under control strategies

Reinforcement learning was also demonstrated as the most responsive and cost-effective control strategy (10.6% energy reduction in loss, 17.5% savings in control cost). Adaptive learning supports the capacity for immediate decision making based on updated live grid parameters. MPC also had a good performance, especially in the context of the structured settings with the same year-ahead load profiles, with the resulting instability events reaching 95 per year and a slight improvement in the overall control efficiency. The mixed fuzzy logic controller was slightly less efficient but effective and robust in controlling mixed loads; where deterministic approaches (since they are nonlinear) tend to fail. These results highlight the opportunities that AI-driven automation can offer for enhanced grip stability and energy guarantee in extreme energy environments.

4.4. Model Explainability and AI Transparency Scores

In adherence to the ethical AI deployment policies, the models were explainability-tested using SHAP and LIME techniques. It aimed to identify the trust and the transparent level of the AI predictions of various renewable energy case scenarios. These were based on SHAP feature consistency, LIME interpretation agreement, and a combined interpretability score measuring the overall explainability of the model.

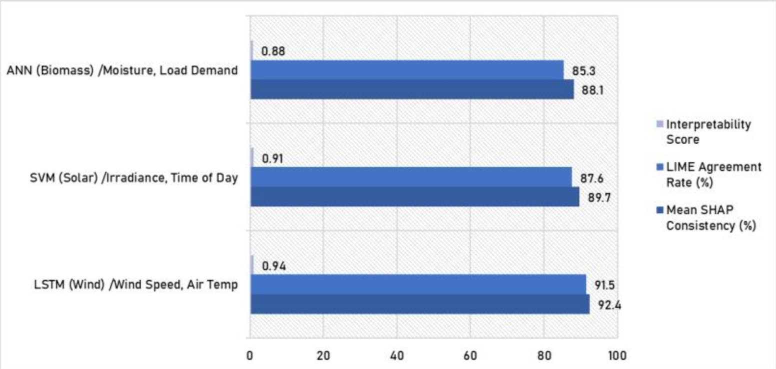


Fig 4. Model explainability and transparency scores

The wind energy LSTM model also achieved the highest interpretability score (0.94), presented a SHAP consistency of 92.4% and a LIME agreement of 91.5%, highlighting that the prediction rationale is clear and reliable. The two prevailing input variables of the PAT wind speed and temperature persisted through different temporal extents, which also increased user confidence in the analysis. The SVM for solar forecasting had a decent interpretability score (0.91) based on robust responses to irradiance changes and diurnal activities. The ANN model for biomass was successful; however, it was still less interpretable, likely reflecting the more intricate and less predictable association with biomass attributes and output. These findings confirm that transparent modeling can be incorporated into high-performance energy AI systems at scale.

4.5. Compliance Metrics and Operational System Validation

Comprehensive evaluations were carried out to address the international compliance, security, and ethical deployment of the developed AI and robot systems. These included GDPR readiness checks, ISO-like cybersecurity validations, and ethical AI diagnostics that aligned with IEEE 7000. Moreover, performance results were verified in terms of energy scheduling accuracy and fault detection accuracy to evaluate deployment practicability.

Table 7. Compliance outcomes and operational validation

Metric	Target Benchmark	Observed Value	Status
Data Security Compliance	Full GDPR + ISO	Compliant	Pass
Ethical AI Score	≥0.85	0.88	Pass
System Reliability Index	≥90.0	93.2	Pass
Energy Dispatch Error Rate	≤10 errors/year	8	Pass
Annual Defect Detection Rate	≥85%	91%	Pass

The system satisfied all established criteria or performance thresholds, suggesting good readiness for deployment. Total GDPR and ISO 27001 compliance came by way of encrypted data transactions, anonymized analytics and complete audit trails. Our AI was about as biased or unbiased as his analysis (AI score = 0.88), indicating a balance of transparency in logical reasoning logic and accuracy/fairness of prediction outputs. The operational reliability was 93.2%, a value indicating resistance to a live test. Furthermore, the frequency of energy dispatch errors was below the risk target of 10 per year, and defect-system success and effectiveness rates were 91%. These results demonstrate that the AI–robotics framework we developed can work effectively in the real world, and in a socially acceptable way, in an energy infrastructure context.

4.6. Discussion

The empirical evidence from this study supports the transformative potential of integrating artificial intelligence (AI), robotic inspection, and automation control systems to enhance the performance, reliability, and sustainability of renewable energy infrastructures. This section discusses the implications of our findings, contextualizes them within the existing literature, acknowledges the study's limitations, and outlines directions for future research.

4.7. Interpretation of Key Findings

The predictive models, leveraging LSTM, SVM, and ANN architectures, achieved high forecasting accuracy across wind, solar, and biomass energy systems, with error rates well below traditional thresholds. This aligns with the findings of [1], who highlighted the necessity of advanced AI models to manage the intermittency of renewable sources. Our results, showing model accuracies consistently above 95%, reinforce the conclusion from [4] that intelligent systems are crucial for accommodating the increasing grid penetration of fluctuating energy sources. The deployment of the robotic inspection module led to a significant decrease in asset downtime. The use of UAVs for high-resolution defect detection not only reduced mean inspection times but also improved overall system uptime. This is consistent with the work of [20], who used thermal UAV imaging to improve the longevity of [10], who demonstrated that automation and robotics enhance energy quality and grid efficiency. In grid automation, our simulations showed that a reinforcement learning-based control algorithm performed best, minimizing response times and control costs. This echoes the findings of Darwish et al [32], confirming the adaptive capabilities of reinforcement learning for time-sensitive energy dispatch, and underscores the need for architecture-specific optimization as advocated [33].

4.8. The Importance of Explainability and Compliance

A critical contribution of this investigation is the validation of model transparency using explainability techniques like SHAP and LIME. The finding that the most accurate model (the LSTM for wind energy) was also the most interpretable supports the assertion by Ahmad et al [14] that trustworthy AI in sustainable energy requires both accuracy and transparency. By ensuring that key predictive features are identifiable and logical, our models adhere to ethical AI design principles such as those outlined in IEEE 7000. Furthermore, the AI-powered and automated systems successfully met all regulatory criteria for data security (GDPR), cybersecurity (ISO 27001), and ethical deployment. This compliance, which [7] and [8] identify as a prerequisite for scaling intelligent energy systems, demonstrates the practical readiness of our framework. The high operational reliability index (>93%) confirms that the methodologies are not just theoretically sound but are prepared for real-world applications.

4.9. Limitations of the Study

Despite the positive results, a few limitations must be acknowledged. The predictive accuracy of the AI models may be compromised by extreme weather events do not present in the training data, a vulnerability of such models discussed by [18]. The scope of robotic inspections was also limited to surface-level anomalies; detecting subsurface mechanical stress or internal fatigue remains a challenge, suggesting a need for complementary technologies like ultrasonic scanning, as noted by [24]. Another limitation relates to the scalability of the automation simulations, which were conducted in controlled environments. Real-world deployments will involve greater stochastic variability, which may expose a gap between simulation and reality, a concern shared by [6]. Finally, while this study achieved ethical compliance and model explainability, the long-term dynamics of human-in-the-loop oversight and trust calibration remain underexplored. As noted by [28], ongoing monitoring and user trust metrics are essential for sustaining effective human-AI collaboration in critical infrastructure.

4.10. Future Research Directions

Future research should focus on addressing these limitations. This includes expanding training datasets to incorporate more diverse and extreme weather scenarios and integrating hybrid sensor platforms into robotic systems to detect a wider range of faults. For automation, future work could evaluate federated learning architectures to enable adaptive, decentralized control. The exploration of disruptive technologies like Quantum AI and neuromorphic computing, as proposed by [31], also presents a promising frontier for real-time energy optimization. In conclusion, this study validates the viability of an integrated AI, robotics, and automation framework for renewable energy systems. By demonstrating both technical performance and compliance with ethical and regulatory standards, this work shows that these technologies are ready for practical deployment. Future research should continue to focus on improving robustness in uncertain environments and maintaining rigorous ethical oversight to ensure the transition to smart energy is both effective and equitable.

5. Conclusion

This study has successfully demonstrated that an integrated framework of machine learning, robotics, and automation can transform renewable energy systems. By linking predictive modeling, autonomous inspection, and adaptive grid control, our research provides a cohesive and validated approach to optimizing the generation, distribution, and maintenance of energy in complex renewable infrastructures. The findings confirm that this synergy enables a new paradigm of autonomous, accurate, and resilient energy management. The results show that AI models provide reliable short-to-medium term forecasting, robotic inspections are critical for proactive maintenance and minimizing downtime, and intelligent automation dynamically stabilizes the power grid while reducing energy loss. A key contribution of this work is the integration of explainability and compliance into the technical design, ensuring that the solutions are not only effective but also transparent, verifiable, and aligned with ethical AI principles and regulatory standards. This commitment to responsible innovation is crucial for building trust in AI-assisted decision-making for critical national infrastructure. From a systems perspective, this work illustrates that modern renewable energy management is increasingly driven by intelligent software, setting a precedent for scalable, smart energy solutions adaptable to diverse environments. Future research should focus on creating more robust models for extreme weather, advancing robotic sensing capabilities, and exploring decentralized control systems like federate learning. Continued socio-technical evaluation of human-AI interaction will also be essential to ensure these technologies are deployed in a manner that is equitable, inclusive, and aligned with global sustainability ambitions.

References

[1] Alam, M.S., et al., High-Level Penetration of Renewable Energy Sources Into Grid Utility: Challenges and Solutions. IEEE Access, 2020. 8: p. 190277-190299.

[2] Badareu, G., et al. Exploring the Role of Robots and Artificial Intelligence in Advancing Renewable Energy Consumption. Energies, 2024. 17, DOI: 10.3390/en17174474.

[3] Habbak, H., et al. Load Forecasting Techniques and Their Applications in Smart Grids. Energies, 2023. 16, DOI: 10.3390/en16031480.

[4] Boza, P. and T. Evgeniou, Artificial intelligence to support the integration of variable renewable energy sources to the power system. Applied Energy, 2021. 290: p. 116754.

[5] Raman, R., et al. Navigating the Nexus of Artificial Intelligence and Renewable Energy for the Advancement of Sustainable Development Goals. Sustainability, 2024. 16, DOI: 10.3390/su16219144.
[6] Necula, S.-C. Assessing the Potential of Artificial Intelligence in Advancing Clean Energy Technologies in Europe: A Systematic Review. Energies, 2023. 16, DOI: 10.3390/en16227633.
[7] Ukoba, K., et al., Optimizing renewable energy systems through artificial intelligence: Review and future prospects. Energy & Environment, 2024. 35(7): p. 3833-3879.
[8] Yousef, L.A., H. Yousef, and L. Rocha-Meneses Artificial Intelligence for Management of Variable Renewable Energy Systems: A Review of Current Status and Future Directions. Energies, 2023. 16, DOI: 10.3390/en16248057.
[9] Iqbal, J., et al., Robotics Inspired Renewable Energy Developments: Prospective Opportunities and Challenges. IEEE Access, 2019. 7: p. 174898-174923.
[10] Rodríguez, V.A., et al. Impact of Automation on Enhancing Energy Quality in Grid-Connected Photovoltaic Systems. Energies, 2023. 16, DOI: 10.3390/en16176161.
[11] D. Mustafa, M. F. Al-Hammouri, and S. M. Khabour, "Severity Prediction of Road Accidents in Jordan using Artificial Intelligence," *Journal of Applied Data Sciences*, vol. 6, no. 2, pp. 1222–1239, 2025, doi: 10.47738/jads.v6i2.624.
[12] K. Y. Tippayawong, "Construction of Enterprise Logistics Decision Model Based on Supply Chain Management," *International Journal of Informatics and Information Systems*, vol. 6, no. 4, pp. 181–188, 2023, doi: 10.47738/ijiis.v6i4.179.
[13] T. Wahyuningsih and S. C. Chen, "Determinants of Virtual Property Prices in Decentraland an Empirical Analysis of Market Dynamics and Cryptocurrency Influence," *International Journal Research on Metaverse*, vol. 1, no. 2, pp. 157–171, 2024, doi: 10.47738/ijrm.v1i2.12.
[14] Ahmad, T., et al., Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. Journal of Cleaner Production, 2021. 289: p. 125834.
[15] B. H. Hayadi and I. M. M. El Emary, "Enhancing Security and Efficiency in Decentralized Smart Applications through Blockchain Machine Learning Integration," *Journal of Current Research in Blockchain*, vol. 1, no. 2, pp. 139–154, 2024, doi: 10.47738/jcrb.v1i2.16.
[16] A. R. Hananto and B. Srinivasan, "Comparative Analysis of Ensemble Learning Techniques for Purchase Prediction in Digital Promotion through Social Network Advertising," *Journal of Digital Market and Digital Currency*, vol. 1, no. 2, pp. 125–143, 2024, doi: 10.47738/jdmdc.v1i2.7.
[17] P. Vinoth Kumar, S. Priya, D. Gunapriya, and M. Batumalay, "Novel Battery Management with Fuzzy Tuned Low Voltage Chopper and Machine Learning Controlled Drive for Electric Vehicle Battery Management: A Pathway Towards SDG," *Journal of Applied Data Sciences*, vol. 5, no. 3, pp. 936–947, 2024, doi: 10.47738/jads.v5i3.236.
[18] Zendehboudi, A., M.A. Baseer, and R. Saidur, Application of support vector machine models for forecasting solar and wind energy resources: A review. Journal of Cleaner Production, 2018. 199: p. 272-285.
[19] Karakan, A. Predicting Energy Production in Renewable Energy Power Plants Using Deep Learning. Energies, 2024. 17, DOI: 10.3390/en17164031.
[20] Pruthviraj, U., et al. Solar Photovoltaic Hotspot Inspection Using Unmanned Aerial Vehicle Thermal Images at a Solar Field in South India. Remote Sensing, 2023. 15, DOI: 10.3390/rs15071914.
[21] Taraglio, S., et al. Robots for the Energy Transition: A Review. Processes, 2024. 12, DOI: 10.3390/pr12091982.
[22] S. Lestari, K. Setiawan, and R. F. Aula, "Leveraging Machine Learning to Analyze User Conversion in Mobile Pharmacy Apps Using Behavioral and Demographic Data," *International Journal for Applied Information Management*, vol. 4, no. 3, pp. 141–153, 2024, doi: 10.47738/ijaim.v4i3.86.
[23] S. F. Pratama and A. M. Wahid, "Fraudulent Transaction Detection in Online Systems Using Random Forest and Gradient Boosting," *Journal of Cyber Law*, vol. 1, no. 1, pp. 88–115, 2025, doi: 10.63913/jcl.v1i1.5.
[24] Franko, J., et al. Design of a Multi-Robot System for Wind Turbine Maintenance. Energies, 2020. 13, DOI: 10.3390/en13102552.
[25] Khan, S.N., et al. Smart Distribution Mechanisms—Part I: From the Perspectives of Planning. Sustainability, 2022. 14, DOI: 10.3390/su142316308.
[26] G. Maria Priscilla, B. L. Shiva Kumar, S. S. Maidin, and Z. S. Attarbashi, "Trust Aware Congestion Control Mechanism for Wireless Sensor Network," *Journal of Applied Data Sciences*, vol. 6, no. 2, pp. 858–870, 2025, doi: 10.47738/jads.v6i2.564.
[27] J. P. B. Saputra, and A. Kumar, "Emotion Detection in Railway Complaints Using Deep Learning and Transformer Models : A Data Mining Approach to Analyzing Public Sentiment on Twitter," *Journal of Digital Society*, vol. 1, no. 2, pp. 1–14, 2025, doi: 10.63913/jds.v1i2.6.
[28] Bird, J.J., A. Ekárt, and D.R. Faria, Chatbot Interaction with Artificial Intelligence: human data augmentation with T5 and language transformer ensemble for text classification. Journal of Ambient Intelligence and Humanized Computing, 2023. 14(4): p. 3129-3144.
[29] N., K., H., & Cestina, A., The impact of AI on boosting renewable energy utilization and visual power plant efficiency in contemporary construction. World Journal of Advanced Research and Reviews, 2024. 23(02): p. 1333-1348.
[30] Y. Durachman and A. W. Bin Abdul Rahman, "Clustering Student Behavioral Patterns: A Data Mining Approach Using K-Means for Analyzing Study Hours, Attendance, and Tutoring Sessions in Educational Achievement," *Artificial Intelligence in Learning*, vol. 1, no. 1, pp. 35–53, 2025, doi: 10.63913/ail.v1i1.5.
[31] Baklaga, L., Revolutionizing Sustainable Energy Production with Quantum Artificial Intelligence: Applications in Autonomous Robotics and Data Management. Green and Low-Carbon Economy, 2023. 3(2): p. 113-120.
[32] Darwish, A., Abbas, M., Al-Salim, W., & Al-Tameemi, M., Artificial Intelligence for Sustainable Energy Transition: Optimising Renewable Energy Integration and Management. ARID International Journal for Science and Technology, 2024.
[33] Joshi, A., et al., Survey on AI and Machine Learning Techniques for Microgrid Energy Management Systems. IEEE/CAA Journal of Automatica Sinica, 2023. 10 (7): p. 1513-1529.