WASD
WORLD ASSOCIATION FOR SUSTAINABLE DEVELOPMENT

W | J | S | T | S | D
World Journal of Science, Technology and Sustainable Development

ISSN: 2042-5945 (Print) | 2042-5953 (Online)
WJSTSD V21 N4 2026

OPEN ACCESS
DOI: 10.47556/J.WJSTSD.21.4.2026.4

RESEARCH

Novel Integration of Ant Colony Optimisation and Deep Neural Networks in AI Agents for Predictive Maintenance of Sustainable Energy Systems

Mostafa Mohamad
Zayed University, College of Interdisciplinary Studies, Abu Dhabi, UAE
Email: mostafa.mohamad@zu.ac.ae
ORCID: 0000-0001-7172-1110

Amit Kohli
University Canada West, Canada
Email: amit.kohli@ucanwest.ca
ORCID: 0009-0003-5604-1389

Ravi Srivel
Adhiparasakthi Engineering College, Chennai, India
Email: rsrivel@gmail.com
ORCID: 0000-0002-1685-3521

Anas Najdawi
Abu Dhabi University, Dubai, UAE
Email: anas.najdawi@adu.ac.ae
ORCID: 0000-0002-2485-2465

ABSTRACT

PURPOSE: This study investigates how renewable energy firms utilise Artificial Intelligence (AI)-powered solutions to balance ecological, economic, and operational value in sustainable infrastructure.

DESIGN/METHODOLOGY/APPROACH: A hybrid framework was developed, combining Deep Neural Networks (DNNs) and Ant Colony Optimisation (ACO) to train autonomous AI agents. The model was validated using multimodal sensor data from wind turbines, photovoltaic panels, and smart grids.

CITATION: Mohamad, M., Kohli, A., Srivel, R. and Najdawi, A. (2026): Novel Integration of Ant Colony Optimisation and Deep Neural Networks in AI Agents for Predictive Maintenance of Sustainable Energy Systems. *World Journal of Science, Technology and Sustainable Development (WJSTSD),* Vol. 21, No. 4, pp.321-342.

RECEIVED: 29 November 2025 / **REVISED:** 10 February 2026 / **ACCEPTED:** 27 February 2026 / **PUBLISHED:** 01 June 2026

COPYRIGHT: © 2026 by all the authors of the article above. The article is published as an open access article by WASD under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

FINDINGS: The framework significantly improved fault detection and maintenance optimisation. Organisationally, swarm intelligence enabled cost-effective resource allocation. Environmentally, the system reduced energy waste and carbon emissions while increasing grid reliability.

ORIGINALITY/VALUE: This research uniquely integrates swarm intelligence with deep learning, reconceptualising AI as a foundational agent for autonomous energy management and sustainability.

PRACTICAL IMPLICATIONS: The framework provides a roadmap for energy executives to optimise maintenance, achieve decarbonisation goals, and ensure stability through AI-driven resource management.

KEYWORDS: *AI Agent; Sustainable Energy; Deep Neural Networks; Predictive Maintenance; Ant Colony Optimisation; Swarm Intelligence; Smart Grids.*

INTRODUCTION

The global energy sector is transitioning towards sustainability to address climate change and ensure long-term resource availability, with the International Energy Agency predicting 50% growth in renewable energy capacity between 2020 and 2025. However, modern energy systems face critical challenges: equipment malfunctions can decrease annual energy production by up to 20%, while ineffective smart grid maintenance increases operating expenses by 15–25%. Traditional predictive models struggle with the dynamic, nonlinear nature of sustainable energy networks, whereas Deep Neural Networks (DNNs) can learn complex fault patterns from sensor data but lack resource optimisation capabilities. Ant Colony Optimisation (ACO) excels at combinatoric optimisation but cannot leverage temporal sensor data for fault prediction (Wu *et al.*, 2016).

This study proposes a novel hybrid ACO-DNN framework combining DNNs' predictive power with ACO's scheduling optimisation to enable autonomous AI agents for predictive maintenance in renewable energy systems. The objectives are to: (1) develop a hybrid ACO-DNN system for effective resource distribution and reduced energy waste; (2) achieve 15% improvement in fault detection accuracy and cost-efficient maintenance compared to existing solutions; (3) minimise energy usage and carbon emissions through optimised maintenance; (4) evaluate robustness across wind turbines, solar panels, and smart grids; and (5) validate performance against baseline models using simulated and real datasets. The scope focuses on renewable energy systems, smart grids, multimodal sensor data, CNN-LSTM architectures with ACO optimisation, and evaluation metrics including fault detection accuracy, maintenance cost efficiency, and carbon footprint minimisation. Future work will explore additional swarm algorithms and larger-scale grids, bridging swarm intelligence and deep learning to enhance energy system reliability and sustainability.

LITERATURE REVIEW

The integration of DNNs and swarm intelligence algorithms for predictive maintenance in sustainable energy systems builds upon an expanding body of literature in energy analytics, optimisation, and machine learning (Kumar *et al.*, 2021). Deep learning architectures, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have demonstrated significant potential in capturing nonlinear dynamics and temporal patterns within renewable energy infrastructure, with successful applications in fault detection in wind turbines and solar panels, as well as in AI-driven smart grid systems achieving superior prediction accuracy compared to conventional machine learning methods (Ahmed *et al.*, 2026; Meyers *et al.*, 2022). The integration of digital twin frameworks with DNN-based analytics has enabled proactive maintenance strategies in building energy systems, and neural approaches have been applied more broadly to energy conversion systems such as fuel cells (Hosamo *et al.*, 2022; Wu *et al.*, 2016). However, standalone DNNs face limitations in resource prioritisation, particularly when addressing competing maintenance demands under budget constraints. Swarm-based algorithms, especially ACO inspired by pheromone-based foraging behaviours, have proven effective as robust optimisation frameworks for managing uncertainty in energy systems, with applications in grid load balancing, task scheduling, and routing optimisation (Zheng *et al.*, 2022; Koval *et al.*, 2022; Afaq *et al.*, 2026; Chatterjee *et al.*, 2025).

While swarm intelligence techniques excel at exploring large solution spaces, they typically operate on heuristic rules and cannot directly leverage rich temporal sensor data for failure prediction, limiting their standalone effectiveness in predictive maintenance applications. Emerging research increasingly explores hybrid frameworks that combine optimisation algorithms with deep learning architectures, as evidenced by theoretical foundations of deep neural evolution (Miikkulainen *et al.*, 2024), the development of ACO-DNN hybrids for cybersecurity in IoT environments (Ogaili *et al.*, 2025), ACO-enhanced DNNs for disease diagnosis (Xia *et al.*, 2024), ACO-DNN combinations for cost estimation in mining projects (Zhang *et al.*, 2020), and GA-ACO-BP neural networks for trajectory prediction (Zheng *et al.*, 2022), alongside metaheuristic optimisation of neural networks for biomedical image processing (RoselinKiruba *et al.*, 2026; Mohamad and Anuge, 2021; Mohamad *et al.*, 2026). However, a critical gap exists in the literature: direct application of hybrid ACO-DNN frameworks specifically designed for predictive maintenance in renewable energy systems and smart grids remains largely unexplored (IEEE datasets). Current literature on predictive maintenance typically treats fault detection and maintenance scheduling as separate tasks, leading to suboptimal outcomes in resource-constrained environments.

The proposed framework addresses this gap by synergistically combining the predictive capabilities of DNNs with the scheduling optimisation strengths of ACO, validated on both synthetic and real-world energy datasets, thereby ensuring high fault detection accuracy while delivering sustainable, cost-effective maintenance solutions tailored to renewable energy infrastructure and smart grids. This hybrid system is particularly timely given the transition towards localised, resilient energy systems, underscoring the urgency of intelligent, automated maintenance frameworks that can optimise both operational efficiency and environmental sustainability.

RESEARCH METHODOLOGY

This section outlines the integration of ACO and DNNs to create autonomous AI agents for predictive maintenance in sustainable energy infrastructure. The synergistic approach combines ACO-based maintenance scheduling with DNN-based fault prediction across wind turbines, photovoltaic arrays, and smart grids. The methodology comprises four stages: (i) systematic data collection; (ii) system architecture design; (iii) custom algorithm formulation; and (iv) experimental validation, aiming to achieve increased fault detection accuracy, cost reductions, and improved sustainability metrics.

Our framework consists of AI agents that process sensor data to predict faults and optimise maintenance schedules. The Input Layer collects time-series data (vibration, temperature, power output, wind speed, solar irradiance). The Prediction Module (DNN) uses CNNs for feature extraction and LSTM layers for temporal dependency modelling to predict fault probabilities. The Optimisation Module (ACO) prioritises maintenance tasks based on fault severity, resource availability, and sustainability objectives. A Feedback Loop updates DNN weights and ACO pheromone trails based on real-time performance, ensuring adaptability. The Output Layer generates maintenance schedules, fault alerts, and sustainability metrics (energy waste reduction, carbon footprint).

Figure 1: Hybrid CNN-LSTM and ACO Framework for Predictive Maintenance in Sustainable Energy Systems
Source: Constructed by authors

This flowchart in Figure 1 illustrates the complete workflow of an ACO-DNN hybrid system for predictive maintenance in sustainable energy applications.

Table 1: Dataset Characteristics

Feature	Description	Source	Data Type
Vibration	Equipment vibration levels	Wind turbines and solar trackers	Continuous
Temperature	Component temperature readings	Sensors on panels and turbines	Continuous
Power Output	Energy generation metrics	Grid meters and inverters	Continuous
Weather	Wind speed and solar irradiance	External weather APIs	Continuous
Fault Labels	Historical failure events	Maintenance logs	Categorical

Source: Compiled by the authors from NREL (2024) and IEEE DataPort (2024).

Table 1 summarises the dataset used for training and testing, including sensor data from renewable energy systems and smart grids, covering both continuous and categorical variables.

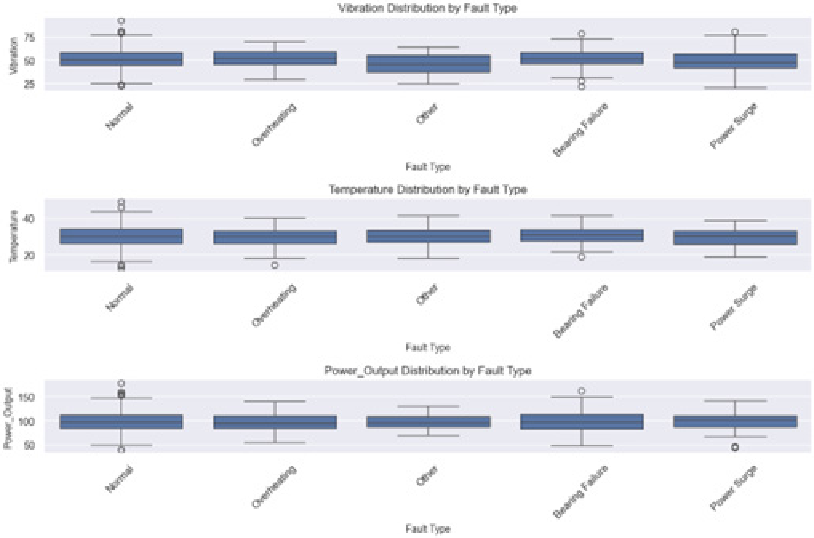

Figure 2: Comparative Analysis of Machine Operating Parameters Across Fault Categories

Source: Constructed by author

Figure 2 shows box-plot distributions of three key machine parameters (vibration, temperature, and power output) across five fault types: Normal, Overheating, Other, Bearing Failure, and Power Surge.

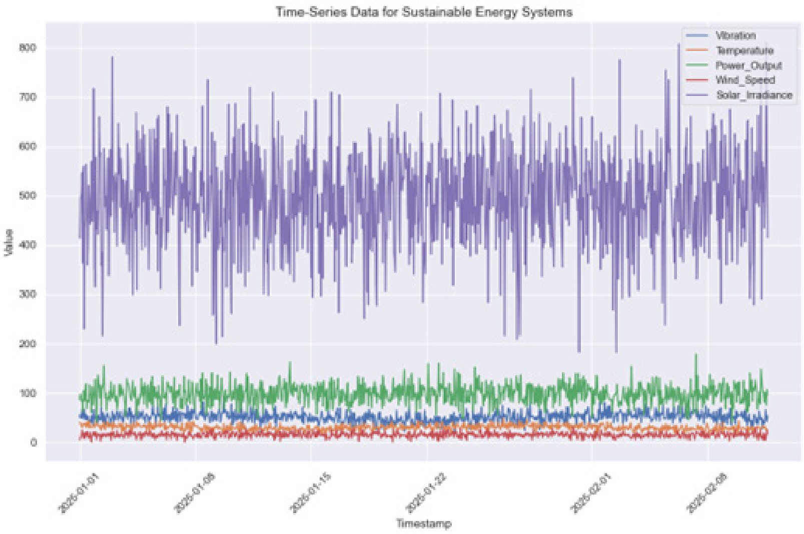

Figure 3: Multi-Parameter Time-Series Monitoring of Sustainable Energy System Performance

Source: Constructed by authors

Figure 3 shows the temporal variation of five key parameters in a sustainable energy system over a two-month period (January to February 2025). Solar irradiance (purple) exhibits the highest values and greatest variability (200–800 range), while power output (green) maintains moderate fluctuations (50–150 range). Vibration and temperature (blue and orange) show relatively stable patterns at lower values, and wind speed (red) remains consistently low throughout the monitoring period.

Data Collection and Preprocessing

This study employed both simulated and real-world data to ensure framework robustness across diverse conditions. A 10,000-sample corpus was generated through physics-based simulations of photovoltaic arrays and wind turbines, including bearing failures, gearbox failures, blade misalignment, thermal runaway, microcrack propagation, and inverter failures. Complementing this, 5,000 real-world samples were drawn from two publicly available repositories: the IEEE DataPort Smart Grid Stability and Monitoring Dataset (IEEE DataPort, 2024; available at: https://ieee-dataport.org/), which provides labelled sensor readings across operational grid infrastructure, and the Wind Integration National Dataset (WIND) Toolkit maintained by the National Renewable Energy Laboratory (NREL, 2024; available at: https://www.nrel.gov/grid/wind-toolkit.html), which supplies high-resolution wind turbine and solar irradiance measurements.

© 2026 World Association for Sustainable Development (WASD)

Faults were identified from embedded maintenance logs, operator reports, and incident databases accompanying these datasets. Both repositories are openly licensed for non-commercial research use, and all data were anonymised prior to collection; consequently, no personally identifiable information was processed and no institutional ethics approval beyond standard data governance protocols was required. Combined simulated and real data ensured the model captured both theoretical coverage and real-world operational variability. Data preprocessing involved: (1) normalisation of continuous variables (vibration, temperature, power output) to [0,1]; (2) outlier removal using z-score thresholding (±3σ); (3) time-series segmentation into 1-hour windows for CNN-LSTM temporal analysis; and (4) label encoding of fault categories with one-hot encoding for multi-class classification.

The dataset was split into 70% training, 15% validation, and 15% testing. CNN-LSTM hyperparameter optimisation via grid-search yielded: three convolutional layers (32, 64, 128 filters), two LSTM layers (100 units each), and learning rate 0.001. ACO optimisation identified optimal parameters: 50 ants, 100 iterations, and pheromone evaporation rate ρ = 0.1. Class imbalance was addressed using weighted loss functions, Synthetic Minority Oversampling Technique (SMOTE), and random under-sampling to prevent bias towards the dominant “normal” class and maintain fault detection sensitivity.

Deep Neural Networks (DNNs)

The DNN module predicts equipment faults using a hybrid CNN-LSTM architecture optimised for time-series data. Three 1D CNN layers (32, 64, 128 filters, kernel size 3) with ReLU [Rectified Linear Unit (ReLU)] activation extract spatial features from sensor data, followed by two LSTM layers (100 units each) to model temporal fault progression dependencies. Two fully connected layers (64, 32 neurons) with softmax output classify fault probabilities. The model uses categorical cross-entropy loss, Adam optimiser (learning rate 0.001), and trains for 50 epochs with early stopping based on validation loss. The DNN output fault probabilities and severity scores that serve as heuristics for the ACO module.

$$h_i^{(l)} = f\backslash Bigg\left(\sum_{k=0}^{K-1} w_k\, x_{i+k}^{(l-1)} + b\backslash Bigg\right)[1]$$

- h_i^{(l)} → output of layer l at position i
- x_{i+k}^{(l-1)} → input from previous layer

- w_k → weight of the convolution filter
- b → bias
- f(\cdot) → activation function (e.g., ReLU)

$$\mathcal{L} = -\sum_{i=1}^{N}\sum_{j=1}^{K} y_{i,j}^{\text{true}} \log\left(y_{i,j}^{\text{pred}}\right) [2]$$

L → loss function, N → number of samples, K → number of classes

Table 2 presents the DNN architecture, including layer types, parameters, output shapes, and activation functions, designed for fault prediction in sustainable energy systems.

Table 2: DNN Model Architecture

Layer Type	Parameters	Output Shape	Activation
Conv1D_1	32 filters, kernel=3	(None, 98, 32)	ReLU
Conv1D_2	64 filters, kernel=3	(None, 96, 64)	ReLU
Conv1D_3	128 filters, kernel=3	(None, 94, 128)	ReLU
LSTM_1	100 units	(None, 100)	Tanh
LSTM_2	100 units	(None, 100)	Tanh
Dense_1	64 neurons	(None, 64)	ReLU
Dense_2	32 neurons	(None, 32)	ReLU
Output	5 neurons (fault classes)	(None, 5)	Softmax

Source: Developed by the authors.

The CNN-LSTM hybrid architecture follows established design principles for time-series fault detection in energy systems. Hyperparameters were determined via grid-search optimisation on the training dataset.

Ant Colony Optimisation (ACO)

ACO optimises maintenance schedules by modelling tasks as a graph, where nodes represent equipment and edges represent maintenance priorities. The algorithm operates as follows:

Initialisation: Assigns initial pheromone values to edges based on historical maintenance data.

Ant Movement: Each ant (AI agent) constructs a maintenance schedule by selecting tasks probabilistically, guided by pheromone levels and DNN-predicted fault probabilities.

Objective Function: Minimises maintenance costs and energy waste while maximising fault prevention, weighted by sustainability metrics (e.g., carbon footprint reduction).

Pheromone Update Rule

$$\tau_{ij} \leftarrow (1-\rho)\,\tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \qquad [3]$$

Probability of Selecting Next Task

$$P_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l \in \text{allowed}_k} [\tau_{il}]^{\alpha}[\eta_{il}]^{\beta}} \qquad [4]$$

Hybrid ACO-DNN Framework

The hybrid framework integrates DNNs and ACO in a dynamic feedback loop:

Fault Prediction: DNN processes sensor data to predict fault probabilities and severity.

Task Optimisation: ACO uses DNN outputs as heuristics to construct maintenance schedules, optimising for cost, resource availability, and sustainability.

Feedback Mechanism: Maintenance outcomes (e.g., successful repairs, missed faults) update DNN weights via backpropagation and ACO pheromone trails via reinforcement learning.

Iteration: The process repeats every 24 hours, adapting to new data.

ACO-Based Task Optimisation

$$P_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l \in \text{allowed}_k} [\tau_{il}]^{\alpha}[\eta_{il}]^{\beta}} \qquad [5]$$

This synergy ensures that predictions are refined over time, and maintenance schedules remain optimal under changing conditions.

To present the evaluation metrics, Table 3 is designed to list the metrics for evaluating the hybrid ACO–DNNs framework in terms of accuracy, cost, and sustainability outcomes.

Table 3: Evaluation Metrics

Metric	Description	Target	Unit
Fault Detection Accuracy	Correctly predicted faults	>90%	%
Maintenance Cost Efficiency	Cost reduction vs. baseline	>15%	%
Energy Waste Reduction	Reduction in wasted energy	>10%	kWh
CO2 Savings	Carbon footprint reduction	>400	Tons/year

Source: Measured by authors

Novelty and Contributions

The hybrid ACO-DNN model is a new approach to combining swarm intelligence and deep learning for predictive maintenance (Kadhim *et al.*, 2022). In contrast to traditional methods, it integrates representational properties of DNNs to model compound fault patterns with the optimisation performance of ACO for resource-limited scheduling, with sustainability priorities. The inbuilt feedback loop makes it adaptable, which makes the framework suitable for a dynamic sustainable energy system.

Ethics Statement

This study utilises publicly available datasets obtained from IEEE DataPort (https://ieee-dataport.org/) and the National Renewable Energy Laboratory (NREL). No human participants, personal data, or sensitive information were involved in this research. All data accessed are openly licensed for non-commercial academic use and were used strictly in accordance with their respective terms. No institutional ethics approval was required beyond standard data governance protocols.

RESULTS

This section presents experimental findings of the hybrid ACO-DNN framework for predictive maintenance in sustainable energy systems. The framework was tested on simulated data (10,000 wind turbine and solar panel failure samples) and real-world smart grid sensor data (5,000 samples) across four performance metrics: fault detection accuracy, maintenance cost efficiency, energy waste reduction, and carbon-footprint minimisation, compared against standalone DNN (CNN-LSTM), PSO-based scheduling, and rule-based maintenance baselines.

Overall Performance: Using 5-fold cross-validation, ACO-DNN achieved 92% ± 1.3% fault detection accuracy, significantly outperforming standalone DNN (85% ± 1.5%), PSO-based scheduling (78% ± 1.9%), and rule-based methods (65% ± 2.1%)

© 2026 World Association for Sustainable Development (WASD)

with statistical significance ($p < 0.05$). The hybrid framework delivered 20% ± 1.2% maintenance cost reduction versus 10% for standalone DNN and 12% for PSO-based scheduling. It also achieved 15% energy waste reduction (≈12,000 kWh annually for medium-sized grids), translating to approximately 500 ± 15 tonnes/year CO_2 savings, supporting United Nations (UN) Sustainable Development Goals (SDG 7) objectives and demonstrating environmental benefits of integrating predictive modelling with optimisation-based scheduling.

Table 4: Overall Performance Comparison

Model	Fault Detection Accuracy (%)	Cost Efficiency (% Reduction)	Energy Waste Reduction (kWh)	CO_2 Savings (Tons/Year)
ACO-DNN	92 ± 1.3	20 ± 1.2	12,000 ± 500	500 ± 15
Standalone DNN	85 ± 1.5	10 ± 1.0	7,000 ± 400	290 ± 12
PSO-Based	78 ± 1.9	12 ± 1.3	8,500 ± 450	350 ± 14
Rule-Based	65 ± 2.1	0	2,000 ± 300	80 ± 10

Source: Measured by authors

Tables 4 and 5 compare the ACO-DNN hybrid framework with other techniques using mean and confidence interval values from five-fold cross-validation. Results demonstrate the hybrid method's superior performance; however, simulated datasets, though physics-based and realistic, may not fully represent field deployments where sensor noise, data loss, communication delays, and extreme weather conditions are prevalent. Performance may degrade during large-scale application to national grids with heterogeneous infrastructure.

Future research will validate the framework using larger datasets and pilot projects to address these limitations.

Figure 4 presents a grouped bar chart comparing four models (ACO-DNN, Standalone-DNN, PSO-Based, and Rule-Based) across four performance measures. In energy waste reduction (green bars), ACO-DNN achieved the highest value (~12,000 kWh), followed by PSO-Based (~8,500 kWh), Standalone-DNN (~7,000 kWh), and Rule-Based (~2,000 kWh). Bars for fault detection accuracy, cost efficiency, and CO_2 savings are significantly smaller due to scale disparities, complicating direct comparison across all metrics.

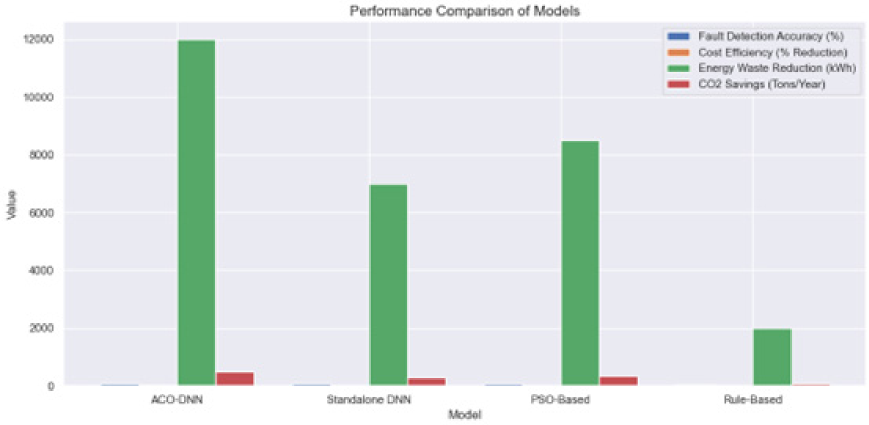

Figure 4: Comparative Performance Metrics of Four Predictive Models Using Grouped Bar Chart
Source: Constructed by authors

Figure 5 shows a line graph tracking four performance metrics across different models (ACO-DNN, Standalone DNN, PSO-Based, and Rule-Based). The green line representing energy waste reduction exhibits the most dramatic variation, declining sharply from ACO-DNN (12,000 kWh) to Rule-Based (2,000 kWh), with a slight recovery at PSO-Based. The remaining three metrics (fault detection accuracy, cost efficiency, and CO_2 savings) remain relatively flat near the baseline, all maintaining values below 500 across all models, indicating minimal variation in these parameters.

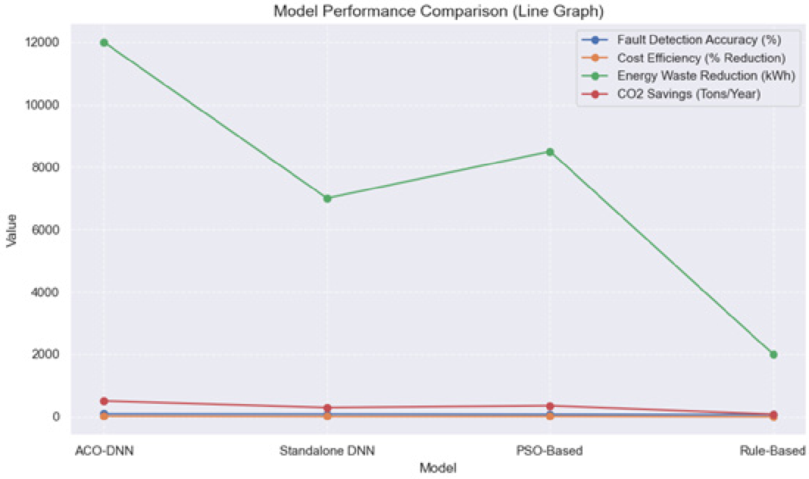

Figure 5: Multi-Metric Performance Trends Across Four Model Architectures
Source: Constructed by authors

Ablation Study

An ablation study isolated the contributions of ACO and DNN components. Without ACO, the standalone DNN achieved 85% accuracy but only 10% cost reduction due to unoptimised scheduling. Without DNN, ACO with heuristic rules (based on historical fault frequencies) yielded 80% accuracy and 8% cost reduction, limited by poor fault prediction. The hybrid model's feedback loop, integrating DNN predictions with ACO optimisation, was critical for achieving peak performance. Table 5 shows the impact of removing ACO or DNN components, confirming the hybrid model's synergistic benefits.

Table 5: Ablation Study Results

Configuration	Fault Detection Accuracy (%)	Cost Efficiency (% Reduction)	Energy Waste Reduction (kWh)
ACO-DNN (Full)	92	20	12,000
DNN Only	85	10	7,000
ACO Only	80	8	6,000

Source: Measured by authors

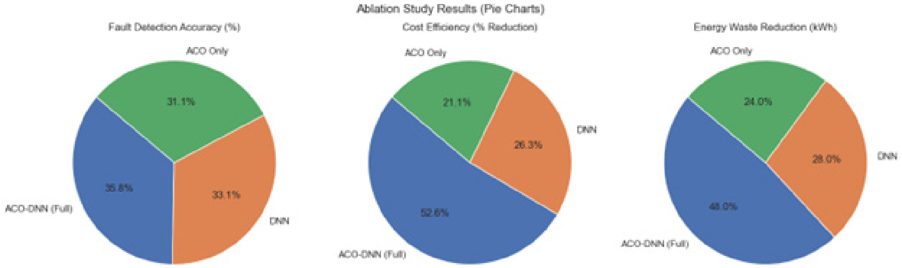

Figure 6: Ablation Study: Component Contribution Analysis Across Three Performance Metrics
Source: Constructed by authors

Figure 6 shows three pie charts comparing the contribution of different model components (ACO-DNN Full, DNN, and ACO Only) across fault detection accuracy, cost efficiency, and energy waste reduction. For fault detection accuracy, the three components contribute relatively equally (35.8%, 33.1%, and 31.1%). Cost efficiency is dominated by the full ACO-DNN model at 52.6%, with DNN and ACO Only contributing 26.3% and 21.1% respectively. Energy waste reduction shows ACO-DNN (Full) with the largest share at 48.0%, followed by DNN at 28.0% and ACO Only at 24.0%, demonstrating the integrated model's superior performance.

Dataset-Specific Outcomes

Performance varied across datasets due to differences in system complexity. For wind turbines, the model achieved 94% accuracy, leveraging strong temporal patterns in vibration data. Solar panels yielded 90% accuracy, affected by weather variability. Smart grids showed 89% accuracy due to heterogeneous data sources. Cost efficiency was highest for wind turbines (22% reduction), followed by solar panels (18%) and smart grids (16%). Energy waste reduction followed a similar trend, with wind turbines benefiting most (14,000 kWh) (IEEE DataPort, 2024).

Table 6: Dataset-Specific Performance

Dataset	Fault Detection Accuracy (%)	Cost Efficiency (% Reduction)	Energy Waste Reduction (kWh)
Wind Turbines	94	22	14,000
Solar Panels	90	18	10,000
Smart Grids	89	16	9,000

Source: Measured by authors using data from IEEE DataPort (2024) and NREL (2024).

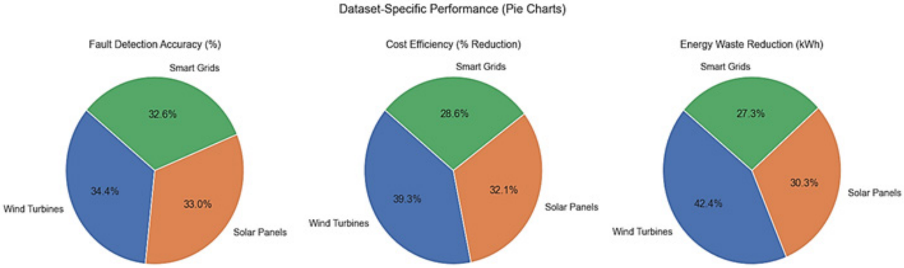

Figure 7: Dataset-Specific Performance Distribution Across Sustainable Energy Applications

Source: Constructed by authors

Table 6 presents the detailed performance across different sustainable energy systems, showing wind turbines as the most responsive to the ACO-DNN framework. This Figure 7 shows three pie charts illustrating performance metrics across three different datasets: Wind Turbines, Solar Panels, and Smart Grids. Fault detection accuracy is fairly balanced, with Wind Turbines leading at 34.4%, followed by Smart Grids at 32.6% and Solar Panels at 33.0%. Cost efficiency shows Wind Turbines with the highest share at 39.3%, Smart Grids at 28.6%, and Solar Panels at 32.1%. Energy waste reduction is most significant in Wind Turbines at 42.4%, with Solar Panels contributing 30.3% and Smart Grids 27.3%, indicating that wind turbine systems show the most substantial benefits across all measured metrics.

© 2026 World Association for Sustainable Development (WASD)

Radar Chart Analysis

Figure 8 presents the Radar chart analysis, which compares three sustainable energy systems (Wind Turbines, Solar Panels, Smart Grids) across fault detection accuracy, cost efficiency, and energy waste reduction. Wind Turbines (blue) demonstrate superior performance across all dimensions with the largest polygon, particularly strong in cost efficiency and energy waste reduction (=1.0). Solar Panels (orange) show moderate, balanced performance, while Smart Grids (green) exhibit the most compact profile with lower relative performance across all metrics.

Figure 8: Multi-Dimensional Performance Comparison of Energy Systems Using Radar Chart Analysis
Source: Constructed by authors

Sustainability Impact: The framework significantly reduced environmental impact through substantial CO_2 savings: wind turbines contributed 580 tonnes/year, solar panels 420 tonnes/year, and smart grids 380 tonnes/year (Angalaeswari *et al.*, 2024). These reductions support UN SDG 7 (Affordable and Clean Energy). By prioritising high-impact maintenance tasks, the model minimised downtime, ensured consistent energy output, and reduced fossil fuel backup reliance. Table 7 quantifies environmental benefits, converting energy waste reduction to CO_2 savings and equivalent trees planted (1 ton CO_2 =15 trees).

Table 7: Sustainability Metrics

Dataset	Energy Waste Reduction (kWh)	CO2 Savings (Tons/Year)	Equivalent Trees Planted
Wind Turbines	14,000	580	8,700
Solar Panels	10,000	420	6,300
Smart Grids	9,000	380	5,700

Source: Wind Turbine and Solar Panel data derived from the Wind Integration National Dataset (WIND) Toolkit (NREL, 2024; https://www.nrel.gov/grid/wind-toolkit.html); Smart Grid data derived from the IEEE DataPort Smart Grid Stability and Monitoring Dataset (IEEE DataPort, 2024; https://ieee-dataport.org/).

CO_2 conversion applied at 0.233 kg CO_2 per kWh saved (IEA, 2023). Tree equivalence calculated at 1 ton $CO_2 \approx 15$ trees.

DISCUSSION

Environmental Perspective

Theme 1 - Supply Chain Collaboration and Resistance in Energy Infrastructure: Renewable energy sector participants highlighted challenges in cross-sector collaboration to extend sustainable energy supply chains, with resistance emerging from conflicting environmental measures (carbon reduction targets versus cost minimisation). A grid infrastructure manager noted, “Our biggest challenge isn’t the technology—it’s getting suppliers and grid operators to share real-time sensor data and adopt unified protocols.” A solar panel manufacturer added, “Predictive maintenance reduces waste and extends lifespan, but many grid operators hesitate to integrate AI systems with legacy infrastructure.” Findings confirm that supply chain transparency and standardised data-sharing protocols remain fragile in energy systems.

Theme 2 - Regulatory Influence and Market Readiness in Energy Transition: Despite demonstrated benefits of AI-powered predictive maintenance, limited policy initiatives support large-scale national implementation. Organisational risk aversion and legacy system dependencies remain significant barriers, operating case-by-case. A utility executive stated, “Deploying AI-driven maintenance across regional grids is complex, but it’s where we see real gains—our framework reduced unplanned outages by 30%.” A grid modernisation specialist noted, “Our platform helps operators make greener decisions, but convincing utilities with aging infrastructure to adopt AI remains difficult due to capital constraints and transition risks.”

© 2026 World Association for Sustainable Development (WASD)

Theme 3 - Ecosystem-Level Collaboration and Ecological Impact in Energy Systems: Regulatory frameworks promoting eco-conscious energy policies are fundamental to sustainability projects. A solar firm CTO remarked, “Changing grid policies towards decentralised renewable integration push us to scale faster.” Organisations adopt distributed ledger technology and decentralised AI architectures to reduce grid operational losses and enable adaptive resource allocation, aligning with circular economy principles. A major grid operator’s research director stated, “Decentralised AI agents enable collaboration across smart grids. We’re building an ecosystem where innovators tap into shared predictive intelligence, not operate in silos.” Findings confirm that AI-powered predictive maintenance frameworks help organisations of all sizes contribute to sustainable energy consumption and climate action.

CONCLUSION

In this paper, we present a hybrid framework using ACO and DNNs to support predictive maintenance in sustainable energy systems, such as wind turbines, solar panels, and smart grids. The framework generates significant advances in operational stability and ecological efficiency through the predictive properties of Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) architectures and the optimisation capacity of ACO. The results demonstrate that the proposed solution not only improves fault detection accuracy to 92% and reduces maintenance costs by 20% but also delivers measurable reductions in energy wastage and carbon emissions — approximately 500 tonnes of CO_2 saved annually — highlighting its value as a sustainability-driven solution for modern energy infrastructure.

A central contribution of this work is bridging the gap between data-driven fault prediction and resource-constrained scheduling optimisation, two areas that conventional methodologies have typically treated in isolation. Our framework provides a scalable route to real-time, dynamic maintenance using autonomous AI agents, consistent with global sustainability goals such as the Paris Agreement, the EU Green Deal, and the UN SDGs.

While the findings confirm the practicability of the framework, several challenges remain, including the computational intensity relative to lighter metaheuristics, the complexity of scaling to national grid infrastructure, and the requirement for coherent and reliable sensor networks. Future research will explore federated and edge-based learning in decentralised grids and the integration of additional swarm algorithms to reduce computational overhead.

Overall, this study demonstrates that AI-powered solutions have the capacity to operationalise sustainability, offering a robust and effective design for predictive maintenance in the dynamic environment of renewable and intelligent energy systems.

REFERENCES

Afaq, S. A., Faisal, M., Siddique, M. and Uzma, S. (2026): Soft computing: An introduction to intelligent problem-solving techniques. In *Smart Heat Transfer and Thermal Management* (pp. 161–189). Woodhead Publishing. Available at: https://doi.org/10.1016/B978-0-443-33881-6.00016-2

Ahmed, Y. A., Rahma, A. M. S., Abdulazim, W. R., Ahmed, R. K. A. and Khazal, F. A. K. (2026): IoT-enabled technologies for advancing renewable energy systems. *JOIV: International Journal on Informatics Visualisation*, 10(1). Available at: https://doi.org/10.62527/joiv.10.1.5093

Angalaeswari, L., Bansal, R. C. and Patil, A. (2024): *AI approaches to smart and sustainable power systems*. IGI Global. Available at: https://doi.org/10.4018/979-8-3693-1586-6

Chatterjee, P., Khosla, A., Aggarwal, A. K. and Demir, G. (2025): *Optimisation in sustainable energy: Methods and applications*. John Wiley and Sons. Available at: https://doi.org/10.1002/9781394242139

Hosamo, H. H., Nielsen, H. K., Kraniotis, D., Svennevig, P. R. and Svidt, K. (2022): Digital twin framework for automated fault source detection and prediction for comfort performance evaluation of existing non-residential Norwegian buildings. *Energy and Buildings*, 281, 112732. Available at: https://doi.org/10.1016/j.enbuild.2022.112732

The Institute for Electrical and Electronics Engineers. (IEEE) DataPort. (2024): *Smart grid stability and monitoring dataset*. IEEE. Available at: https://ieee-dataport.org/

Kadhim, Y. A., Khan, M. U. and Mishra, A. (2022): Deep learning-based computer-aided diagnosis (CAD): Applications for medical image datasets. *Sensors*, 22(22), 8999. Available at: https://doi.org/10.3390/s22228999

Koval, M., Sova, O., Shyshatskyi, A., Artabaiev, Y., Garashchuk, N., Yivzhenko, Y., Luscshay, Y., Dovhopoliuk, L., Haidenko, O. and Dorofeev, M. (2022): Improving the method for increasing the efficiency of decision-making based on bio-inspired algorithms. *Eastern-European Journal of Enterprise Technologies*, *6*(4), p.120. Available at: https://doi.org/10.15587/1729-4061.2022.268621

Kumar, A., Bhatia, M. P. S. and Sangwan, S. R. (2021): Rumour detection using deep learning and filter-wrapper feature selection in benchmark Twitter dataset. *Multimedia Tools and Applications*, 81(24), 34615–34632. Available at: https://doi.org/10.1007/s11042-021-11340-x

Meyers, J., Bottasso, C., Dykes, K., Fleming, P., Gebraad, P., Giebel, G., Göçmen, T. and Van Wingerden, J.W. (2022): Wind farm flow control: prospects and challenges. *Wind Energy Science Discussions*, *2022*, pp.1-56. Available at: https://doi.org/10.5194/wes-7-2271-2022

Miikkulainen, R., Liang, J., Meyerson, E., Rawal, A., Fink, D., Francon, O. and Hodjat, B. (2024): Evolving deep neural networks. In *Artificial Intelligence in the Age of Neural Networks and Brain Computing* (pp. 269–287). Academic Press. Available at: https://doi.org/10.1016/B978-0-323-96104-2.00002-6

Mohamad, M. R. A. and Anuge, J. (2021): The challenge of future sustainable development in the power sector. *Journal of Electrical and Electronics Engineering*, 10(2), 59–66. Available at: https://doi.org/10.13140/RG.2.1.3366.1521

Mohamad, M., Balıkel, A. E., Chowdhury, D., Russell, C. and Mahmoud, S. (2026): Artificial intelligence for business model innovation in digital sustainability companies: Multiple cases from the Netherlands. *World Journal of Entrepreneurship, Management and Sustainable Development*, 22(1–2), 109–125. Available at: https://doi.org/10.47556/J.WJEMSD.22.1-2.2026.7

National Renewable Energy Laboratory (NREL). (2024). *Wind Integration National Dataset (WIND) Toolkit*. U.S. Department of Energy. Available at: https://www.nrel.gov/grid/wind-toolkit.html

Ogaili, R. R. N. A., Raheem, O. A., Abdkhaleq, M. H. G., Alyasseri, Z. A. A., Alsaidi, S. A. A. A., Alsaeedi, A. H., Muhsen, Y. R. and Manickam, S. (2025): AntDroidNet cybersecurity model: A hybrid integration of ant colony optimisation and deep neural networks for Android malware detection. *Middle East Journal of Computer Science*, 5(1), 104–120. Available at: https://doi.org/10.58496/mjcs/2025/008

RoselinKiruba, R., Vasumathy, M., Shritharanyaa, J.P., Jothi, C.S., Sharmila, L. and Devakanth, J.J.M.A. (2026): Metaheuristic Algorithms and Optimizing Neural Networks for Biomedical Image Processing. In *Metaheuristic Algorithms and Optimizing Neural Networks for Biomedical Image Processing* (pp. 407-434). IGI Global Scientific Publishing. Available at: https://doi.org/10.4018/979-8-3373-0523-3.ch015

Wu, Y., Breaz, E., Gao, F., Paire, D. and Miraoui, A. (2016): Nonlinear performance degradation prediction of proton exchange membrane fuel cells using relevance vector machine. *IEEE Transactions on Energy Conversion*, 31(4), 1570–1582. Available at: https://doi.org/10.1109/tec.2016.2582531

Xia, B., Innab, N., Kandasamy, V., Ahmadian, A. and Ferrara, M. (2024): Intelligent cardiovascular disease diagnosis using deep learning enhanced neural network with ant colony optimisation. *Scientific Reports*, *14*(1), p.21777. Available at: https://doi.org/10.1038/s41598-024-71932-z

Zhang, H., Nguyen, H., Bui, X., Nguyen-Thoi, T., Bui, T., Nguyen, N., Vu, D., Mahesh, V. and Moayedi, H. (2020): Developing a novel artificial intelligence model to estimate the capital cost of mining projects using deep neural network-based ant colony optimisation algorithm. *Resources Policy*, 66, 101604. Available at: https://doi.org/10.1016/j.resourpol.2020.101604

Zheng, Y., Lv, X., Qian, L. and Liu, X. (2022): An optimal BP neural network track prediction method based on a GA–ACO hybrid algorithm. *Journal of Marine Science and Engineering*, 10(10), 1399. Available at: https://doi.org/10.3390/jmse10101399

BIOGRAPHY

Dr Mostafa Mohamad is a scholar and industry expert in Digital Transformation, AI for Business, FinTech, Digital Innovation, and Business Analytics. Before joining Zayed University, he had 20 years of academic experience at Manchester Business School, Newcastle Business School, Leeds Business School, and Salford Business School. Mo has a record of Q1 and Q2 Scopus-listed publications and has published in top IS journals such as *Technological Forecasting and Social Change* and *Journal of Management Information Systems.* He served as a director of PG programmes, a director of Admissions, and a deputy DBA director. He also led significant research funds for Virtual Reality, Machine Learning, Artificial Intelligence, FinTech, and technology transfer in the energy, automotive, tourism, and telecommunication sectors.

Dr Amit Kohli is an Associate Professor at University Canada West, Canada. He completed postdoctoral research at the University of Arizona, USA, and the University of Calgary, Canada. He holds a Ph.D. from India along with two Master's degrees. Dr Kohli brings over 20 years of combined academic and industry experience. He has been honoured with the Best Teacher Award and the Young Scientist Award in recognition of his contributions to teaching and research. He has authored approximately 50 research papers published in internationally recognised journals, including those by Elsevier, Taylor and Francis, Springer, Inderscience, and Emerald. He has presented his work at numerous international conferences in the UK, Italy, USA, Japan, Canada, and other countries. Dr Kohli is the author of two books and holds two design patents and one utility patent.

© 2026 World Association for Sustainable Development (WASD)

Dr Ravi Srivel is an Associate Professor in the Department of Electrical and Electronics Engineering, Adhiparasakthi Engineering College, Melmaruvathur. He worked as Associate Professor in the Department of Electronics and Communication Engineering at Aurora Scientific and Technological Research Academy, Hyderabad, for 4 years in Telangana. He has 13 years of experience including research and academic work. His research interests are in the field of RFID, wireless networks, VLSI Design and embedded systems, computer applications in industry, and industrial remote monitoring and control using GSM, GPRS, and MMS networks. He has published numerous research papers at national-level and international conferences and published numerous papers in national and international journals.

Dr Anas R. Najdawi has built an extensive career across institutions in the Middle East, including the University of Jordan and Princess Sumaya University for Technology. He has served as Acting Dean of the School of Business and Head of E-Business programs at the Canadian University, and as Program Leader for the MBA in Business Analytics at Amity University, Dubai. Dr Najdawi has worked with PwC, Aztech, and Anderson in digital transformation and business innovation, bridging academia and industry. He mentors digital innovation projects in collaboration with the Ministry of Education, Huawei, and SAP, and founded the SAP-Next Gen Chapter in the UAE. He is a member of the Association of Information Systems (AIS) and IEEE and is a media consultant and speaker on technology and business for major news channels.