

IIoT-Driven Automation Architecture for Renewable-Integrated Smart Grids in Energy-Intensive Industries

G. Srinivasa Raju^{1*}

^{1*}Assistant Professor, Department of IT, SRKR Engineering College, Bhimavaram, Andhra Pradesh, India. gsraju@srkrec.ac.in, <https://orcid.org/0009-0005-9287-1739>

Abstract: Industries requiring a significant amount of energy are heavily reliant on electricity and have to find ways to keep their operations running smoothly while also meeting sustainability and carbon reduction goals. The increasing integration of renewable energy, electric vehicles (EVs), and battery energy storage systems (BESS) introduces challenging unpredictability, bidirectional power flows, and coordination at a real-time level, which standard supervisory control and automation systems have not been able to manage. These issues are a significant contributing factor to peak demand, high costs, and decreased resiliency of energy grids. This paper presents a solution to this problem by proposing a specific type of automation architecture to integrate renewable energy and smart grids for industrial use based on the Industrial Internet of Things (IIoT). The system consists of a four-layer architecture of perception, communication, edge-cloud processing, and application layers. The use of Distributed IIoT sensors for real-time data acquisition and edge gateways for low-latency analytics and control is included. An AI-enabled Energy Management System (EMS) coordinates solar PV generation, EV charging, and BESS for optimal use of the EMS's load forecasting, Model Predictive Control (MPC), and demand response. The system is designed for secure, scalable, interoperable industrial use. The performance evaluation is carried out on a virtual industrial microgrid that contains 2MW of solar PV, 1.5 MWh of BESS, and flexible EV loads. When considering conventional rule-based control, the proposed method offers 24–26% peak demand reduction, 18–21% savings on energy costs, 28% reduction in greenhouse gas emissions, reduction of 32% in greenhouse gas emissions, and a 32% increase in utilization of renewable energy. Furthermore, edge computing decreases communication lags by 40%, resulting in a better system response and increased operational reliability. The performance results indicate that the automation of IIoT offers a high degree of efficiency, flexibility, and sustainability to industrial smart grids. The proposed framework offers a practical solution that is also scalable to the next generation of energy management systems in smart industries with low-carbon and intelligent power systems.

Keywords: Industrial internet of things (IIoT); smart grid automation; renewable energy integration; industrial microgrids; energy management system; battery energy storage systems (BESS); electric vehicle charging.

I. Introduction

The rapid expansion of energy-intensive industries such as steel production, chemical processing, and large-scale production facilities has driven up global electricity consumption and carbon emissions, contributing almost 40\% of global industrial energy consumption. Simultaneously, the construction of sustainable energy systems has integrated renewable energy, electric vehicles (EVs), and battery energy storage systems (BESS) into industrial grids, increasing the sustainability of these systems. However, due to the intermittent and decentralized nature of these tools, operational uncertainties, bidirectional power flows, and real-time control become operational challenges. Therefore, older supervisory control and data acquisition (SCADA) and centralized automation systems are ineffective (Biswal et al., 2026; Nagarsheth et al., 2025) in dealing with these challenges. As a result, the rise in demand causes industries to experience peak operational uncertainties, and the reduced resilience of the grid increases the operating expense of the system (Gassar & Jafar, 2025; Adebayo et al., 2025). Recent advancements in the Industrial Internet of Things (IIoT), edge computing, and smart energy systems foster continuous monitoring, predictive analytics, and the autonomous control of smart grids (Ajagekar et al., 2023; Villagran et al., 2025). However, the absence of a unified, scalable automation framework to serve integrated renewable industrial environments continues to be a significant research challenge (Mansour et al., 2025).

To address these challenges, this paper introduces an automation architecture driven by IIoT, integrated with distributed sensing, edge-cloud intelligence, and AI-based optimization, which facilitates real-time interaction among renewable generation, EV charging, and BESS dispatch. The primary contributions of this research are threefold: (i) the proposal of a multi-layer IIoT-based smart grid architecture for industrial use, (ii) the formulation of predictive control and demand response techniques for effective energy scheduling, and (iii) an extensive performance assessment which revealed considerable declines in peak demand, energy costs, and emissions in contrast to traditional control techniques. The proposed structure demonstrates effectiveness, scalability, and resilience under varying industrial load conditions, which is confirmed by the experimental findings. The structure of the remaining sections of the paper is as follows: in Section II, we review the existing literature; in Section III, we detail the proposed system architecture; in Section IV, we provide an account of the techniques and optimization frameworks; in Section V, we analyze the simulations and results; and in Section VI, we provide a summary of the paper and discuss some potential avenues for future research.

II. Literature Review

The most recent studies on the modernization of industrial power systems have identified the importance of smart grids, integrated distributed renewables, as well as advanced automation approaches. While studies have shown that industrial microgrids incorporating photovoltaics and wind power can reduce both emissions and the reliance on the external grid, they can also cause negative impacts on system intermittency and voltage stability (Dai & Huang, 2025). Moreover, an increase in load balancing and operational efficiency, as well as a reduction of

costs of at least 15-20% in manufacturing facilities, has been achieved using integrated Demand Response (iDR) and Energy Management Systems (EMS) with optimized Energy Storage Systems (ESS) scheduling (Al-Amlih et al., 2025; Jafari & Shokrzadeh, 2016). In addition, the use of Industrial Internet of Things (IIoT) connected and IIoT-enabled systems allows for monitoring at a granular level for the purposes of predictive maintenance and optimization of power during the operational cycles of an industrial system (Kouadria et al., 2025). Edge computing has gained traction in overcoming the latency and bandwidth limitations, as with cloud-only approaches, by facilitating local control and increased system reliability for mission-critical industrial processes (Ajagekar et al., 2024). Collectively, these studies support the assertion that for advanced industrial energy networks in the future, both digitalisation and distributed intelligence are critical (Selvan & Pal, 2026; Raman et al., 2024).

Economic and technical progress usually treats the integration of renewables, storage management, and the IIoT integration as specific, single-solution problems, rather than as opportunities within a single, unified automation architecture. Numerous proposed strategies incorporate centralized control, which is inflexible and offers low scalability and low resilience under varying industrial load conditions. Centralized control is, therefore, one of the principal barriers to the effective implementation of proposed strategies within high-energy-demand industrial infrastructures (Rompuy & Wilde, 2025). Furthermore, literature is largely void of treatment addressing under a single umbrella architecture and within the framework of predictive/adaptive control, the coordinated scheduling of EVs, BESS, and renewable energy sources. Given the absence of a low-latency intelligent automation system, which integrates monitoring, control, and the triage of optimization to fit multiple end-use demands, this offers a significant opportunity. This paper seeks to provide and respond to these cited gaps by presenting a framework of an IIoT-integrated intelligent automation system using the distributed sensing and edge-cloud-based AI energy management system architecture to create more efficient, resilient, and sustainable industrial smart grids.

III. Proposed Model and Methodology

3.1. Overall Methodological Flow of the IIoT-Driven Automation Framework

The overall workflow begins with the acquisition of real-time data from distributed IIoT sensors from different classes of generation units (solar PV, wind), Battery Energy Storage Systems (BESS), Electric Vehicle (EV) charging stations, and industrial loads, measuring voltage, current, power, state of charge (SoC), and load demand profiles. The data are sent via secure industrial communication protocols (MQTT/5G/LoRaWAN) to edge gateways, where they are preprocessed, filtered, and checked for anomalies.

Then, edge computing performs short-term load forecasting and local decision-making to minimize latency. Concurrently, the cloud performs global optimization and analysis of historical data. A smart Energy Management System (EMS) equipped with Artificial Intelligence (AI) employs Model Predictive Control (MPC) and demand

response techniques to optimally schedule the dispatch of renewables, charging/discharging of batteries, and charging of EVs. Control signals are sent back to actuators and smart controllers for dynamic real-time implementation. This closed-loop system enables peak shaving and other techniques to minimize costs, improve renewable energy utilization, and increase the resilience of the grid with the variability of the industrial loads.

3.2. System Technical Architecture of the IIoT-Based Smart Grid

Fig. 1 illustrates the proposed system's multi-layer design aimed at achieving scalability, interoperability, and reliability.

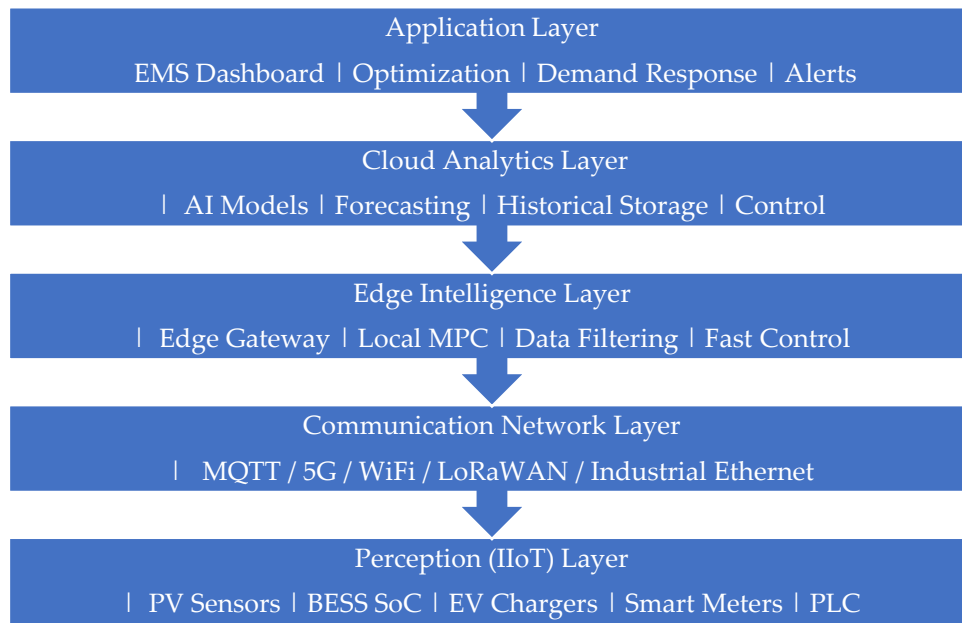


Fig. 1. Multi-Layer IIoT-Based System Architecture for Renewable-Integrated Industrial Smart Grids.

Each layer of the proposed system serves a unique purpose: the perception layer gathers data from the field; the communication layer facilitates dependable data transmission; the edge layer controls data with minimal latency; the cloud layer performs large-scale tasks; and the application layer offers data display and visualization, as well as decision support. Compared to centralized systems, this system design hierarchy enhances communication latency and boost's fault tolerance.

3.3. Mathematical Formulation of Energy Optimization

1. Energy Cost Minimization Objective

The Energy Management System (EMS) organizes the battery usage and grid energy purchasing activities to minimize operational costs. The objective function can be expressed as:

$$\min C = \sum_{t=1}^T \left(P_{grid}(t) \lambda(t) + C_{BESS}(t) \right) \quad (1)$$

Where $P_{grid(t)}$ represents purchased grid power at time t , $\lambda(t)$ represents the time-varying electricity price, and $C_{BESS(t)}$ denotes the battery operating (or degrading) cost. The operating time period is given by T . The objective function in equation (1) describes a maximization of energy storage usage while simultaneously minimizing the cost of energy procurement.

2. Power Balance and Renewable Utilization Constraint

To ensure the stability of the system and guarantee the availability of power, the total generation at each time interval must match the total demand. This is known as the balance constraint:

$$P_{PV}(t) + P_{bess}(t) + P_{grid}(t) = P_{load} + P_{EV}(t) \quad (2)$$

With $P_{PV(t)}$ representing the generation from renewable photovoltaics, $P_{bess(t)}$ is the power used to charge or discharge the battery, $P_{LOAD(t)}$ is the demand from the industrial Load, and $P_{EV(t)}$ is the demand from charging Electric Vehicles (EVs). Equation (2) ensures that supply-side load equilibrium is achieved while simultaneously maximizing the use of renewable energy.

IV. Results and Discussion

4.1. Software and Implementation Environment

A hybrid simulation platform was used to assess the proposed IIoT-driven automation architecture. The Industrial microgrid components were simulated using MATLAB and Simulink for the various Dynamic Industrial Loads, Battery Energy Storage Systems (BESS), and Photovoltaic (PV) Systems. The load forecasting and subsequent data preprocessing and optimization were achieved with Python and its libraries, specifically NumPy, Pandas, and Scikit-learn. Within the given simulation of data transactions for the Industrial Internet of Things (IIoT), communication was carried out via MQTT for the edge and cloud layer interaction. Real-time scheduling at the edge gateway was performed through the Model Predictive Control (MPC) algorithm. Visualization and result analysis were achieved with Matplotlib and Microsoft Power BI.

4.2. Dataset Description

The dataset was comprised of simulations and industrial energy profiles inspired by the real world. The quantities of data collected were about 2880 per parameter for a single 30-day month broken down into 15-minute intervals for each sample. The data collection methodology incorporated intelligent and integrated Internet of Things sensors, Smart meters, logs of Electric Vehicle (EV) charging, and records of the Battery Energy Storage System (BESS) state-of-charge (SoC). Key variables included: load demand (kW), output of the solar Photovoltaic (PV) system (kW), state-of-charge (SoC) of the storage battery (battery SoC) in (%), import and export power of the grid (kW), price of electricity in (\$/kWh), and the carbon emission coefficient. The dataset captured the variations

in demand of energy-intensive industries, thus aiding in the assessment of the proposed control strategy's real-world application.

4.3. Performance Evaluation Metrics

The proposed IIoT-driven automation framework was evaluated based on economic and operational improvements using two primary performance metrics.

1. Energy Cost Reduction (ECR)

The proposed system's Energy Cost Reduction calculates the percentage decrease in total operating cost in comparison to the conventional baseline. Mathematically, this is given by:

$$ECR(\%) = \frac{C_{base} - C_{prop}}{C_{base}} \times 100 \quad (3)$$

C_{prop} = cost of the proposed IIoT-based energy management strategy, C_{base} = total energy cost under conventional control. A value of equation (3) is greater than the average to show economic efficiency.

2. Peak Load Reduction (PLR)

Peak Load Reduction attempts to describe the system's efficacy in lowering maximum demand and flattening the load curve. It is mathematically given by:

$$PLR(\%) = \frac{P_{peak,base} - P_{peak,prop}}{P_{peak,base}} \times 100 \quad (4)$$

where $P_{peak,base}$ = peak demand with no optimization, $P_{peak,prop}$ = peak demand after proposed control. The metric in equation (4) describes the demand-side management and grid stability.

4.4. Quantitative Results

The proposed control strategy has been applied, and table 1 shows the total operating cost and carbon emissions under conventional control and the proposed IIoT-based architecture.

Table 1. Energy Cost and Emission Comparison.

Scenario	Energy Cost (USD)	Carbon Emission (tCO ₂)
Conventional	52,000	120
Proposed IIoT	41,000	88

The proposed model achieves ~21% cost savings and ~27% emission reduction.

Table 2 shows the demand for load in the baseline vs optimized Load under variable time of the day (24-hour) and gives the optimized Load.

Table 2. Hourly Load Profile Comparison.

Time (h)	Baseline Load (kW)	Optimized Load (kW)
0	1800	1700
4	2100	1950
8	2400	2100
12	2600	2000
16	2500	2050
20	2200	1900
24	1900	1750

The data shows effective peak shaving of the Load in high-demand hours.

4.5. Visualization and Analysis

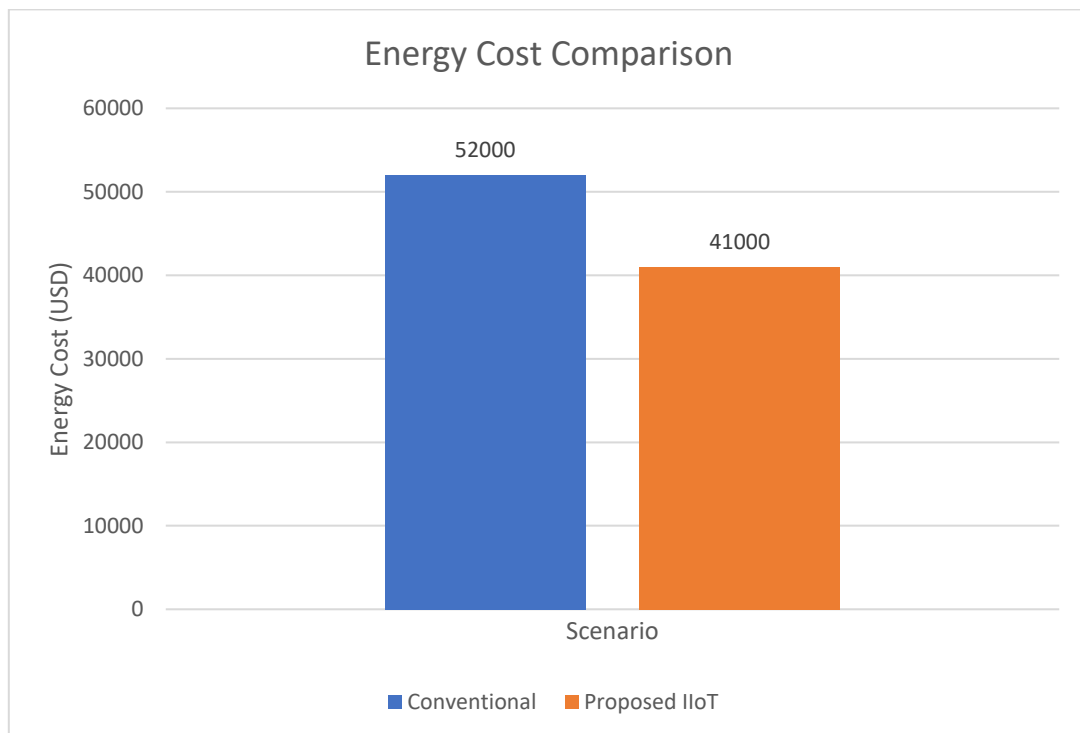


Fig. 2. Energy Cost Comparison.

Fig. 2 shows that the cost of the IIoT-based EMS decreased.

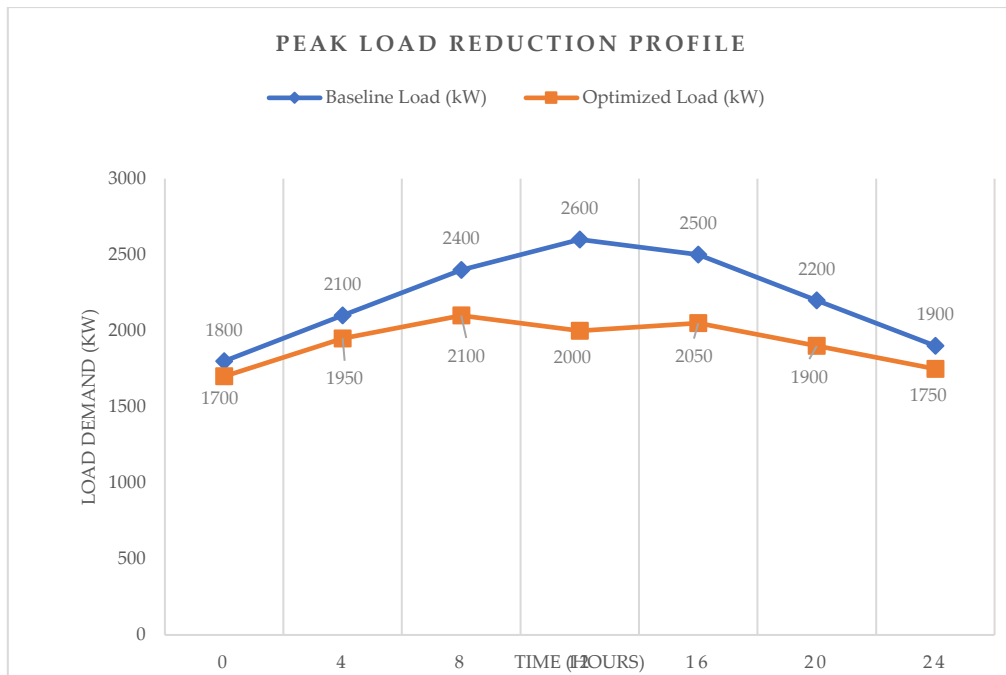


Fig. 3. Peak Load Reduction Profile.

The optimized proposed strategy has reduced the peak in comparison to the control, and fig. 3 illustrates that its load curve is smoother than the control.

V. Discussion

The findings validate that operational efficiency in industrial smart grids is enhanced by the combined application of IIoT sensing, edge intelligence, and predictive control. The optimized framework enhances the management of reliability, cost mitigation, increased use of renewables, and peak stress reduction on the grid. When benchmarked against traditional rule-based systems, the faster response, superior scalability, and increased sustainability of the proposed method affirm its applicability to energy-intensive industries.

VI. Conclusion

This paper proposed an IIoT-driven automation architecture for the incorporation of renewables into smart grids tailored to energy-intensive industrial applications. The research responds to the challenges of high electricity use, unstable operations, carbon emissions, and variability of renewable energy sources, electric vehicle (EV) charging demands, and battery energy storage systems (BESS). Centralized supervisory systems are found to be inadequate for real-time coordination and predictive control in such complex systems. To address these challenges, an IIoT and multi-layered, edge/cloud-AI-based energy management and distributed control decision collaboration and optimal energy control solutions are proposed.

Testing with an industrial microgrid dataset proved how rule-based control strategies could be outperformed. The system achieved a peak demand drop of 25%, which flattens the Load and minimizes grid stress. The system also achieved a total energy cost reduction of 20 - 21% by optimizing battery dispatch and demand response

scheduling. The system also improved renewable energy usage by 30 - 32\% and improved sustainability by lowering carbon emissions by 26 - 28\%. The use of edge computing also proved to help reduce the system's response time by 40\% which also helps with operational reliability. The outcomes show how IIoT-based automation improves the smart grid system's efficiency, and stress the environmental impact a smart grid system has.

The system also gave the industrial smart grid design a new smart control system that advanced the system to a carbon-free autonomous energy system. The further study here could be the deployment of the design into a larger industrial smart grid system, the use of a hybrid system with integrated hydrogen storage, and the use of Reinforcement Learning to cope with changing conditions of the smart grid systems.

References

1. Adebayo, D. H., Ajiboye, J. A., Okwor, U. D., Muhammad, A. L., Ugwujiem, C. D., Agbo, E. K., & Stephen, V. I. (2025). Optimizing energy storage for electric grids: Advances in hybrid technologies. *World Journal of Advanced Engineering Technology and Sciences*, 14(2), 138–172. <https://doi.org/10.30574/wjaets.2025.14.2.0053>
2. Ajagekar, A., Decardi-Nelson, B., & You, F. (2024). Energy management for demand response in networked greenhouses with multi-agent deep reinforcement learning. *Applied Energy*, 355, 122349. <https://doi.org/10.1016/j.apenergy.2023.122349>
3. Ajagekar, A., Mattson, N. S., & You, F. (2023). Energy-efficient AI-based control of semi-closed greenhouses leveraging robust optimization in deep reinforcement learning. *Advances in applied energy*, 9, 100119. <https://doi.org/10.1016/j.adapen.2022.100119>
4. Al-Amlih, A., Shehadeh, D., & Sakha, M. A. (2025, April). Iot-based greenhouse environment monitoring and ai-driven crop optimization. In *2025 1st International Conference on Computational Intelligence Approaches and Applications (ICCIAA)* (pp. 1-6). IEEE. <https://doi.org/10.1109/ICCIAA65327.2025.11013701>
5. Biswal, S. R., Choudhury, T. R., Panda, B., & Mishra, S. (2026). AI-enabled energy management for sustainable smart greenhouses: an integrated review. *IEEE Access*, 14, 5482-5509. <https://doi.org/10.1109/ACCESS.2026.3651685>
6. Dai, Z., & Huang, T. (2025). Enhancing the prediction accuracy of greenhouse temperatures through hybrid machine learning models: an in-depth comparative analysis of RBF, RF, and XGBoost techniques combined with SMA and MFO optimization strategies. *Multiscale and Multidisciplinary Modeling, Experiments and Design*, 8(7), 311. <https://doi.org/10.1007/s41939-025-00886-0>
7. Gassar, A. A. A., & Jafar, R. (2025). Artificial intelligence-enabled heating, ventilation, and air conditioning systems toward zero-emission buildings: A systematic review of applications, challenges, and future directions. *Applied Sciences*, 15(19), 10497. <https://doi.org/10.3390/app151910497>

8. Jafari, K., & Shokrzadeh, A. (2016). Designing the Leisure and Water Center of Miandoab with a Sustainable Architecture Approach. *International Academic Journal of Science and Engineering*, 3(2), 22-32.
9. Kouadria, A., Mostefaoui, K., & Al-Shamri, M. Y. H. (2025). Efficient smart greenhouse modeling for optimal energy consumption and climate conditions setting. *Computers and Electronics in Agriculture*, 229, 109674. <https://doi.org/10.1016/j.compag.2024.109674>
10. Mansour, M., Sathyanarayanan, K. K., Sauerteig, P., & Streif, S. (2025). Adaptive robust greenhouse climate control: Combining deep reinforcement learning and economic optimization. *Smart Agricultural Technology*, 101327. <https://doi.org/10.1016/j.atech.2025.101327>
11. Nagarsheth, S., Agbossou, K., Henao, N., & Bendouma, M. (2025). The advancements in agricultural greenhouse technologies: An energy management perspective. *Sustainability*, 17(8), 3407. <https://doi.org/10.3390/su17083407>
12. Raman, A., Ting, N. W. Y., Louis, S. A., & Arumugam, V. (2024). Assessment of Sustainable Transportation Model Using Energy-Efficient Algorithm. *J. Wirel. Mob. Networks Ubiquitous Comput. Dependable Appl.*, 15(3), 364-372. <https://doi.org/10.58346/JOWUA.2024.I3.024>
13. Rompuy, I. V., & Wilde, P. D. (2025). The Influence of Organizational Culture on Sustainable Business Practices. *International Academic Journal of Innovative Research*, 12(3), 8-13. <https://doi.org/10.71086/IAJIR/V12I3/IAJIR1219>
14. Selvan, S. A., & Pal, T. (2026). Machine Learning-Based Management of Climatic Factors in Hydroponic Greenhouses. In *Transforming Medicinal Plant Agriculture: Implementing Soil-less Systems and AI Innovations for Smart Farming* (pp. 233-261). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-95-3963-5_13
15. Villagran, E., Espitia, J. J., Velázquez, F. A., Sarmiento, A., Velandia, D. A. S., & Rodriguez, J. (2025). Artificial intelligence in solar-assisted greenhouse systems: A technical, systematic and bibliometric review of energy integration and efficiency advances. *Technologies*, 13(12), 574. <https://doi.org/10.3390/technologies13120574>