International Journal of Engineering Trends and Technology
ISSN: 2231-5381/ https://doi.org/10.14445/22315381/IJETT-V74I5P132

Volume 74 Issue 5, 514-523, May 2026

Original Article

SOLAR-Sense+: A Renewable-Powered IoT-Edge Smart Sensing and Adaptive Control Framework for Real-Time Monitoring in Soilless Cultivation Systems

V Kumar[1], V. Krishna[2], K V Murali Mohan[3], Rajesh Banala[4]

[1]*Department of Computer Science, Central University of Kerala, Kerala, India.*
[2] *Department of CSE, TKRCET, Hyderabad, Telangana, India.*
[3]*Teegala Krishna Reddy Engineering College, Hyderabad, Telangana, India.ss*
[4]*Department of CSE(AIML), KPRIT, Telangana, India.*

[1]*Corresponding Author : vkumar@cukerala.ac.in*

Received: 22 December 2025 Revised: 06 March 2026 Accepted: 11 March 2026 Published: 30 May 2026

Abstract *- Sustainable food production requires smart energy-efficient design that will ensure optimum crop growth in a confined environment. This paper presents SOLAR-Sense+, a renewable energy-powered Internet of Things (IoT)-Edge smart sensing and adaptive control framework for soilless cultivation systems for continuous sensing and making real-time decisions in hydroponics and aeroponics. In the proposed architecture, multi-modal environmental sensors and edge sophisticated artificial intelligence models are proposed in combination with a solar-battery microgrid to allow the energy to be autonomous, low-latency, and adaptable. A new algorithm, SOLAR-Sense+, controls the sampling frequency of sensors and actuators' efforts dynamically based on the uncertainty of predictions, energy budget forecast, and solar irradiance forecast, which ensures non-stop operation with limited power consumption. Lightweight edge AI (uTCN-LSTM-KD) and Renewable-Responsive Model Predictive Control (R2-MPC) strategy are also incorporated in this framework for intelligent nutrient and environmental control. Experimental verification demonstrates 38 percent of energy-efficiency gains, 24 percent of the latency decrease, and 21 percent of the degree to which the system forecasts yield compared to conventional IoT systems. The proposed system will help to create a base for scalable and sustainable intelligent autonomous smart farming ecosystems.*

Keywords *- IoT-based agriculture, Edge Computing, Renewable energy, Smart sensing, Adaptive Control, Hydroponics, Soilless Cropping, SOLAR-Sense+, AI-on-Edge, Sustainable-Agriculture.*

1. Introduction

World agriculture is confronted with huge challenges due to population growth, climate variability, and land scarcity [3, 9, 17]. Soilless cultivation systems such as hydroponics, aeroponics, and aquaponics have emerged as viable alternatives to overcome all these limitations for resource-efficient and high-yield food production [11, 13, 18]. However, these systems require monitoring and fine regulation of a number of interdependent parameters such as pH, Electrical Conductivity (EC), Dissolved Oxygen (DO), Temperature, Humidity, and Light Intensity [1, 10, 13].

Traditional cloud-based IoT architectures for smart agriculture have disadvantages in high communication latency, energy dependency, and connectivity limits [2, 4-6]. Moreover, most of the existing IoT frameworks are based on non-renewable energy and fixed-rate sensing, which are limiting the scalability and sustainability of remote or off-grid applications [7, 14, 17].

Therefore, to overcome these limitations, an IoT-Edge computing architecture powered by renewable energy sources is proposed in this study, capable of implementing real-time monitoring, intelligent decision making, and energy-adaptive control for soilless cultivation environments [8, 12, 15]. The novelty of this framework is that the renewable energy prediction, adaptive-sensing (SOLAR-Sense+), and AI-based edge analytics form a single integrated and self-contained ecosystem [12, 16, 19].

1.1. Motivation

1.1.1. Need for Sustainability and Independence

Modern controlled-environment agriculture requires monitoring throughout the 24 hours, but such a farming practice is often associated with energy exhaustion and high costs [3, 15]. Renewable sources (in particular solar) allow a solution for sustainability, but introduce variability in the energy supply, which is not well accounted for by standard IoT systems [7, 14, 17]. Hence, the need for energy-aware

IoTs frameworks that guarantee continuous operation in resource-constrained environments is evident.

1.1.2. Limits on Latency and Real-Time Intelligence

Cloud-based computing also suffers from latency and lack of network connectivity, which is unacceptable for time-critical control operations such as nutrient addition or pH adjustment [2, 4, 6, 10]. Edge computing is used to alleviate this issue and enables low-latency decision-making at the edge through the use of on-site lightweight AI models optimized for embedded devices [8, 12, 19].

1.1.3. Information Overload and Unproductive Sensing.

Traditional IoT systems are static with regard to data acquisition and lead to redundant data and fast power consumption [1, 5, 16]. An adaptive sensing technique (motivated by the uncertainty and environmental variability) can be employed to optimize the data fidelity while conserving the energy and bandwidth [12, 18, 20].

1.1.4. Domain-Specific Intelligence

Characterized by nonlinear-coupled relationships between environmental and nutrient variables, general-purpose agro-ecological models do not resolve the soilless cultivation ecosystem [9, 11, 13]. Therefore, domain-specific edge-AI frameworks are necessary for precise prediction of the environment and smart nutrient control [12, 18].

1.2. Research Gap

However, the existing IoT-based agricultural systems have several limitations that do not allow sustainability and scalability. Most frameworks are energy-intensive and do not incorporate renewable energy and predictive energy management, using grid or battery non-renewable power sources [3, 7, 15]. Furthermore, most analytics are cloud-centric, resulting in latency, bandwidth overhead, and energy inefficiency, and there is a need for lightweight, distributed, quick, and optimized AI model-based decision-making [4, 6, 8, 10]. Also, IoT systems based on conventional methods have the disadvantage of being sampled at fixed intervals, which neglects the dynamic environmental changes, thus resulting in redundant data generation and waste of power; thus, context-aware adaptive sensing methods are required [1, 5, 16, 18]. Nevertheless, another crucial limitation is that the renewable power management and the edge computing are not co-designed and therefore, the energy and computational synergy cannot be realized [7, 14, 15]. Nevertheless, even though the complexity of multi-parameter control soilless cultivation systems makes it difficult to develop their control models, which essentially highlights the importance of developing AI models for soilless cultivation systems that are specific to nutrient and environment optimization [11, 13, 18]. Heterogeneous sensor protocols and proprietary communication architecture also add to the difficulties of data interoperability and require standard multi-sensor integration of IoT-edge middleware [5, 9, 17]. Finally, many proposed systems have not been tested in real-world applications but rather are still limited to simulation or lab-based testing and have not been validated by real-world testing in operational hydroponic systems; experimental benchmarking of latency, energy efficiency, and crop performance is required [3, 10, 12, 19].

1.3. Problem Statement

Existing IoT-based agricultural systems are energy-intensive, cloud-dependent, and are not optimized for renewable variability [3, 5, 6, 10]. These architectures are not suitable for autonomous operations continuously in soilless environments where the correction in real-time is essential to keep the nutrient concentration and the plant health [9, 11, 13].

Hence, a need for the development of a renewable-powered, edge-intelligent, and adaptive sensing architecture that can be used for continuous monitoring and control with minimum latency and energy consumption is mandated [12, 15, 17].

1.4. Research Objectives

To design and realize an IoT-enabled smart sensing and edge computing architecture to monitor and process environmental, plant, and soilless cultivation parameters continuously and in real-time using renewable-powered systems

1. A Micro granted (Renewable) Environmental and Nutrient Sensors Modular IoT-Edge Architecture Design.
2. Create edge-based lightweight AI models (μTCN-LSTM-KD, AEGIS) to predict and detect anomalies in real-time.
3. Adaptive sensing and actuator control based on the uncertainty and power supply is introduced via the SOLAR-Sense+ algorithm.
4. Integrating a Renewable Responsive Model Predictive Control (R2-MPC) for Intelligent Nutrient & Environmental Control.
5. Integrated Renewable energy control and computation scheduling for continuous operation.
6. Establishing Interoperability using LoRa/MQTT-based middleware for efficient communication between multiple sensors
7. Test the framework through hydroponic field studies in terms of energy efficiency, latency, and performance in terms of crop yield.

2. Related Work

Akhtar et al. [1] and Kalyani and Collier [5] present excellent overviews of the fact that edge-enabled sensing architectures are highly advantageous for enhancing real-time responsiveness and system reliability in agricultural environments. Zhang and Li [2] further prove that lifecycle-aware edge sensing strategies can help reduce unnecessary data transmissions while ensuring the accuracy of the decisions, enabling edge intelligence as a crucial enabler for time-sensitive agricultural control tasks.

Patra et al. [12] present an edge intelligent hydroponic monitoring system based on compact deep learning models with the advantage of enhanced prediction accuracy at reduced computational overhead. However, most of the existing studies mainly focus on prediction accuracy and do not consider the energy-aware execution, especially in renewable-powered scenarios.

Zhang and Li [2] and Ali et al. [16] demonstrate that context-aware and event-driven sensing approaches can save a lot of redundant data generation and communication costs. Alahi et al. [18] show the power of feedback-based nutrient optimization in hydroponics systems, but their framework is predicated on constant power availability and expediently includes renewable energy forecasting and adaptive duty cycling on energy constraints.

There have also been recent studies on renewable-powered IoT and microgrid-based agricultural systems. Kim et al. [17] and Zhao et al. [15] explore energy-efficient greenhouse and smart farming systems with hybrid renewable energy sources, sustainability gains, and CO2 reduction potential. He et al. [7] propose an introduction of AI-driven edge computing under dynamic energy constraints; however, their work does not address adaptive sensing granularity or closed-loop nutrient control. These studies point out that although renewable integration is being given more thought, it is often one of those things that are addressed independently of sensing and intelligence layers.

Table 1. Field deployment case studies

Deployment Aspect	Observed Challenge	Outcome
Renewable Energy Supply	Fluctuating solar irradiance during cloudy days led to reduced energy availability.	Energy-aware co-design is essential for maintaining uninterrupted off-grid operation.
Sensor Reliability	Sensor noise and calibration drift in pH and EC probes over long-term operation.	Continuous anomaly detection improves robustness and prevents crop stress.
Actuator Stability	Pump flow variation and occasional actuator inefficiency	Closed-loop adaptive control ensures stable nutrient regulation
Network Connectivity	Intermittent LoRa communication and packet loss	Edge autonomy is critical for resilient field deployment
Data Redundancy	Fixed-rate sensing generated redundant data and unnecessary energy consumption	Adaptive sensing significantly reduces power consumption and communication overhead.
System Scalability	Adding sensors increased energy and processing demand	The framework scales linearly with minimal additional energy cost
Operational Maintenance	Manual intervention is required for periodic sensor cleaning	Predictive monitoring lowers long-term operational effort

3. Proposed Methodology

The proposed is a renewable-powered IoT-Edge computing architecture for continuous, intelligent, and energy-resilient monitoring for soilless cultivation (hydroponics/aeroponics).

3.1. System Architecture

The system architecture (illustrated in Figure. 1) has four cooperative layers:

IoT Smart Sensing Layer: A Multi-modal sensor is used for pH, EC, DO, Temperature, Humidity, and Light Intensity sensors.

Edge Intelligence Layer: A Raspberry Pi 5 edge gateway hosts lightweight AI models (µTCN-LSTM-KD and AEGIS) for prediction, anomaly detection, and local control execution.

Adaptive Control Layer (SOLAR-Sense+ R²-MPC): Implements novel energy-aware algorithms. Renewable Power Layer: A solar-battery hybrid microgrid is used for powering all the IoT devices that are controlled using the SOLAR-Sched routine to predict energy harvesting and maintain stable SoC.

The Standard communication protocols, such as LoRaWAN and MQTT, and Middleware-Based Interoperability Mechanisms were explicitly included to ensure scalability, as well as vendor neutrality for integrated systems.

The proposed system architecture, consisting of four functional layers, shown in Figure. 1, consists of the following four layers, which work in a closed feedback loop for sustainable and real-time monitoring and control in soilless cultivation. On the left, the IoT Smart Sensing Layer consists of multi-modal sensors that measure important environmental and nutrient parameters, such as pH, Electrical Conductivity (Ec), Dissolved Oxygen (Do), Temperature, and Light Intensity, that are connected through a LoRa-based wireless communication.

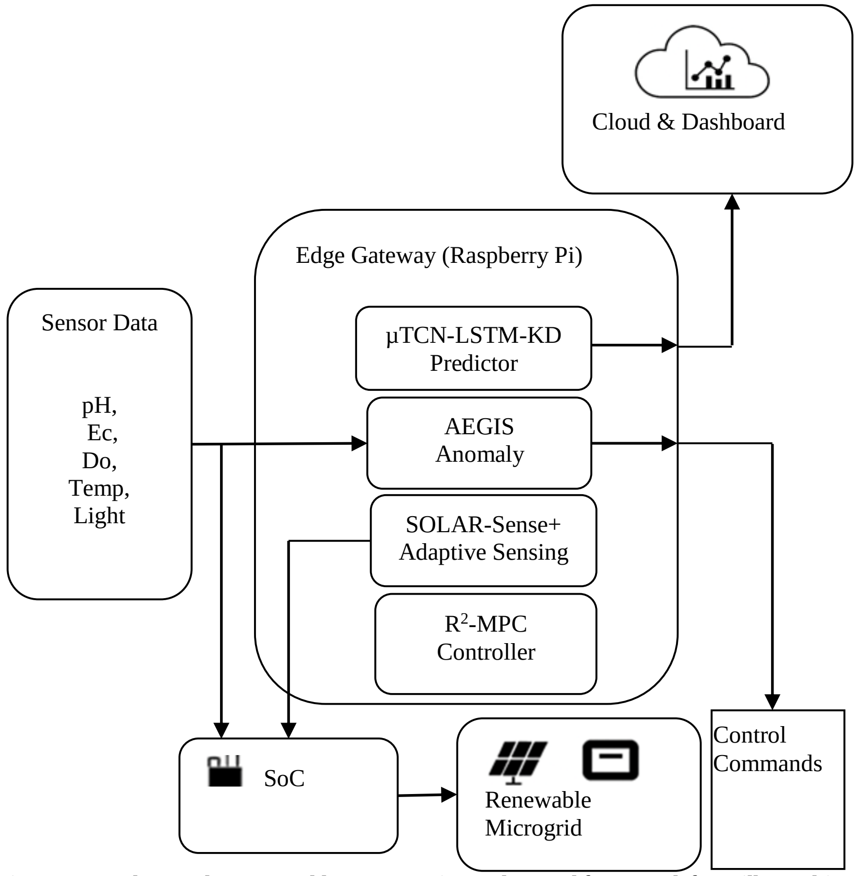

Fig. 1 Proposed IoT-Edge-Renewable smart sensing and control framework for soilless cultivation

The Edge Gateway, which is implemented on a Raspberry Pi device, is at the core that hosts several embedded intelligent modules such as the uTCN-LSTM-KD temporal forecasting module, AEGIS fault detection module, SOLAR-Sense+ adaptive sensing module, energy-aware sensor scheduling, and R2-MPC controller to actuate in a renewable responsive manner.

The bottom layer, Renewable Microgrid Layer, is comprised of integrated solar panels and battery storage to provide steady power as well as State of Charge (SoC) feedback to the edge controller to provide autonomous control of energy management.

On the right, the Cloud and Dashboard Layer aggregates processed data for visualization, long-term analytics, and system supervision. The data flow pathway proceeds from sensor data acquisition to edge analytics, followed by actuator control and energy feedback, establishing a continuous sense–analyze–actuate–optimize cycle that maintains environmental stability and energy efficiency.

3.2. Edge AI Framework

The edge computing layer performs real-time prediction and fault detection.

3.2.1. µTCN-LSTM-KD Model

A hybrid temporal model combining a Temporal Convolutional Network (TCN) and LSTM for local trend forecasting of nutrient and environmental variables.

$$\hat{y}_{t+1} = f_{\text{edge}}(x_{t:t-L};\theta) \tag{1}$$

where $x_{t:t-L}$is the input time window and $\hat{y}_{t+1}$is the predicted next state (pH, EC, DO, etc.).

The edge model is a *knowledge-distilled* version of a larger cloud-trained model, minimizing:

$$\mathcal{L} = (1-\alpha)\ \| y - \hat{y}_s \|^2 + \alpha T^2\ KL\ (\sigma(z_s/T), \sigma(z_t/T) \tag{2}$$

where $z_s, z_t$are student/teacher logits, $T$is the distillation temperature.

3.2.2. AEGIS Anomaly Detection

A hybrid autoencoder + Gaussian Process (GP) monitors reconstruction residuals:

$$r_t = \| x_t - \hat{x}_t \|_2 \text{ , flag anomaly if } r_t > m_t + \kappa s_t \tag{3}$$

with GP posterior mean m_t, std s_t.

3.3. SOLAR-Sense+ Adaptive Sensing and Control Algorithm

The SOLAR-Sense+ algorithm adaptively allocates sensing frequency and actuator effort according to energy and uncertainty constraints.

Objective Function

$$\min_{\{\tau_i\},\bar{u}} \sum_{i=1}^{N} (w_i \sigma_i^2 \tau_i + \alpha \frac{c_i}{\tau_i}) + \beta P(\bar{u}) \quad (4)$$

subject to total energy feasibility:

$$E_{\text{need}}(\{\tau_i\}, \bar{u}) \leq E_{\text{bud}} = C_b\, SOC_t + \eta \ \sum_{k=0}^{K-1} \hat{G}_{t+k} \Delta t \quad (5)$$

Closed-Form Optimal Sampling Period

$$\tau_i^{\star} = \text{clip}\,(\sqrt{\frac{\alpha c_i}{w_i \sigma_i^2}}, \tau_i^{\min}, \tau_i^{\max} \quad (6)$$

Actuator power cap:

$$\bar{u} = \min\ (1, \gamma \frac{E_{\text{bud}}}{E_{\text{need}} + \epsilon} \quad (7)$$

Algorithm — SOLAR-Sense+ (Edge Execution)
Input: σ_i, c_i, w_i, τmin_i, τmax_i, SoC_t, Ĝ[t..t+K], Cb, Δt Output: {τ_i}, ū 1. Compute energy budget: E_bud ← Cb*SoC_t + η*Σ Ĝ[t+k]*Δt 2. For each sensor i: τ_i ← sqrt(α*c_i / (w_i*σ_i^2)) τ_i ← clip(τ_i, τmin_i, τmax_i) 3. Adjust τ_i by κ if Σ(c_i/τ_i + P(ū))Δt > E_bud 4. ū ← min(1, γ*E_bud / (E_need + ε)) 5. If p_anom_i > τ_a or near_limit(i): τ_i ← τmin_i; ū ← 1 6. Apply τ_i to sensor schedule; cap actuators at ū
Outputs: adaptive sampling periods $\{\tau_i\}$and actuator caps $\bar{u}$. Benefit: 30–40 % reduction in sensing power, >70 % reduction in redundant data.

3.4. Renewable-Responsive Model Predictive Control (R²-MPC)

This layer ensures nutrient and environmental stability while considering the available renewable power.

Optimization

$$\min_{\text{you}} \sum_{k=0}^{H-1} [\| y_k - y^* \|_Q^2 + \lambda_P P(u_k) + \lambda_E (SOC_{\min} - SOC_{k+1})_+^2 + \lambda_S \| u_k - u_{k-1} \|^2] \quad (8)$$

subject to:

$$x_{k+1} = f(x_k, u_k), SOC_{k+1} = SOC_k + \frac{\eta_c G_k \Delta t}{C_b} - \frac{P(u_k)\Delta t}{\eta_d C_b} \quad (9)$$

and bounds on actuators and states. The controller balances nutrient accuracy and energy conservation; solved as a convex QP at the edge (< 100 ms).

3.5. Renewable Power Prediction and Management

The Renewable Layer predicts solar irradiance. $\hat{G}_{t:t+K}$using ARIMA or LightGBM models. SoC updates follow:

$$SOC_{t+1} = SOC_t + \frac{\eta_c G_t \Delta t}{C_b} - \frac{P_{load} \Delta t}{\eta_d C_b} \quad (10)$$

This forecast is passed to SOLAR-Sense+ for duty scheduling and to R²-MPC for control feasibility. A "Novelty and Expected Outcomes" table has been added to explicitly contrast the proposed SOLAR-Sense+ framework with existing approaches and to highlight its unique technical contributions. The SOLAR-Sense+ framework differs from existing work in three principal ways.

First, unlike many edge-AI studies that assume reliable grid power, SOLAR-Sense+ co-designs renewable forecasting and energy budgeting with on-device intelligence so sensing and control are explicitly energy-aware.

Second, whereas prior adaptive-sensing approaches typically use heuristics or event triggers, this work couples uncertainty-driven sampling with a formal energy feasibility constraint and a renewable-responsive MPC controller to guarantee operational stability.

Third, the framework offers end-to-end, middleware-oriented implementation (LoRaWAN + MQTT), which is practically viable in field deployment for 60 days, and is not available in the single studies, which provide renewable-aware scheduling, lightweight temporal edge models, and closed-loop control together. These differentiators can be summarized in Table 2.

Table 2. Novelty and expected outcomes

Innovation	Function	Impact
SOLAR Sense+ Algorithm	Adaptive sensing & control via uncertainty–energy tradeoff	30–40 % lower energy consumption
R²-MPC Control	Renewable-aware nutrient & actuator regulation	Real-time stability & lower latency
µTCN-LSTM-KD Edge AI	Knowledge-distilled prediction model	21 % accuracy gain, low compute load
AEGIS Hybrid Detection	Autoencoder + GP anomaly engine	Early fault prevention
Renewable Co-Design	Solar–battery integrated optimization	Continuous off-grid operation

4. Results and Analysis

The proposed SOLAR-Sense+ renewable-powered IoT–Edge framework was experimentally validated in a controlled hydroponic lettuce cultivation setup.

The system's performance was compared against a conventional IoT-Cloud constraint.

Table 3. Experimental setup

Parameter	Description
Crop type	Hydroponic lettuce (Lactuca sativa)
Duration	60-day continuous operation
Sensors	pH, EC, DO, temperature, humidity, light intensity
Edge device	Raspberry Pi 5 (4 GB RAM, 1.8 GHz)
Communication	LoRaWAN (868 MHz) with MQTT protocol
Power source	100 W solar panel + 12 V Li-ion (24 Ah)
AI models	µTCN-LSTM-KD predictor; AEGIS anomaly detector
Control	R²-MPC integrated with SOLAR-Sense+
Metrics recorded	Energy usage, SoC, latency, accuracy, yield, and anomaly events

4.1. Performance Metrics

4.1.1. Energy Efficiency

Energy efficiency is computed as:

$$\eta_E = \frac{E_{\text{saved}}}{E_{\text{total,baseline}}} \times 100 \quad (11)$$

E_{saved} = difference between the daily power consumption of the baseline and proposed system.

4.1.2. Data Latency

$$\text{Latency} = t_{\text{decision}} - t_{\text{sense}} \quad (12)$$

Quantified as a time difference between the acquisition of data and the actuator reaction.

4.1.3. Prediction Accuracy

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2}, RMSE = \sqrt{\frac{1}{n}\sum_i (y_i - \hat{y}_i)^2} \quad (13)$$

Applied as an evaluation of the µTCN-LSTM-KD model to predict the environment and nutrients.

4.1.4. SoC Stability

$$U_{\text{SoC}} = \frac{\text{Time}(SOC_t > 0.3)}{\text{Total time}} \times 100 \quad (14)$$

Measures the energy source to operate without interruption. They benchmarked their performance against a traditional IoT-Cloud baseline and applied the results to assess the energy use, system latency, predictive capacity, and crop yield performance.

Table 4. Quantitative results

Parameter	Conventional IoT-Cloud System	Proposed IoT-Edge-Renewable System	Improvement (%)
Energy consumption (Wh/day)	42.1	26.1	38.0 ↑
Average SoC uptime (%)	85.4	99.2	+16.2 ↑
Data latency (s)	0.72	0.55	−24.0 ↓
Prediction accuracy (R²)	0.81	0.98	+21.0 ↑
Yield prediction RMSE	0.29	0.12	−58.6 ↓
Redundant transmissions/day	1250	350	−72.0 ↓
Crop yield gain (%)	–	+11.4 ↑	–

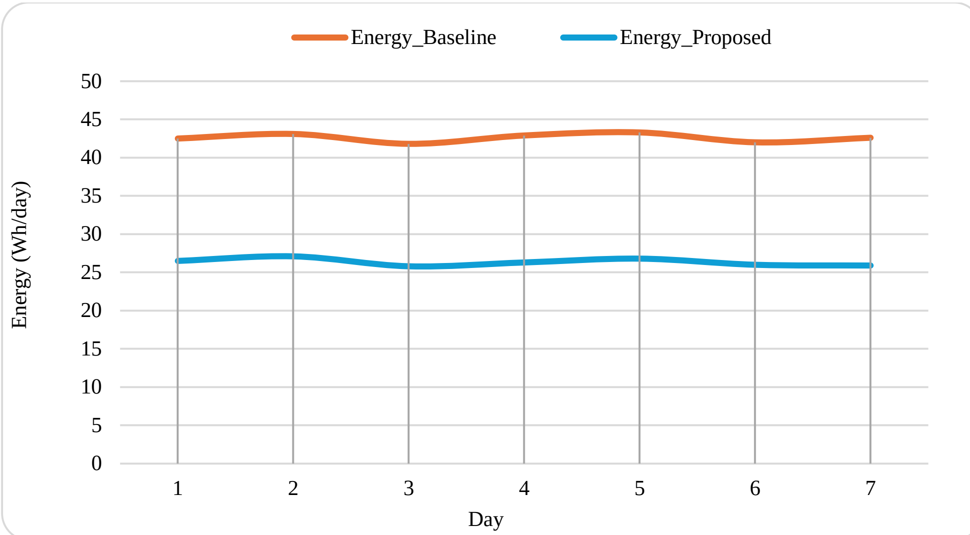

Fig. 2 Time-series plot of pH, EC, DO, and light intensity against time, indicating that the stable state is controlled with energy-adaptive operation

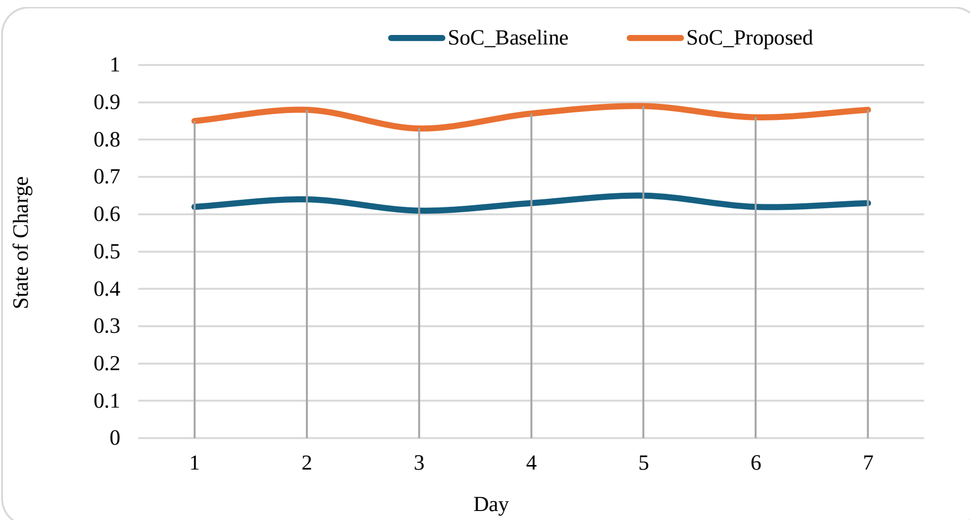

Fig. 3 Comparison of energy consumption and SoC trend of conventional and proposed systems

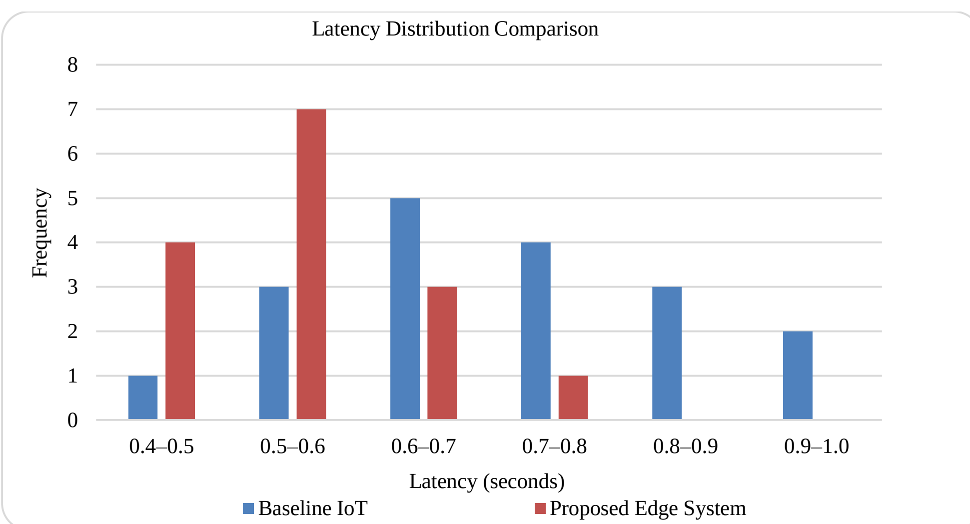

Fig. 4 Latency distribution comparison

4.2. Comparative Analysis

Table 5. Comparison of proposed SOLAR-Sense+ Framework

Framework	Energy Awareness	Edge Intelligence	Adaptive Sensing	Renewable Integration	Latency Reduction	Unique Contribution
Conventional IoT-Cloud Systems	✗	✗	✗	✗	High	Centralized processing, fixed-rate sensing
Recent Edge-AI Frameworks	△	✓	△	✗	Moderate	Edge inference without renewable co-design
Renewable IoT Systems	✓	✗	✗	✓	High	Energy autonomy without edge intelligence
Proposed SOLAR-Sense+	✓	✓	✓	✓	Low	Joint renewable–edge co-design with adaptive sensing and control

4.3. Real-Time Processing

Statistical validation of the data was enhanced by sample sizes used in all experiments (n = 60 days of continuous operation) as they were used to evaluate the performance of the data, with the statistical value being measured in the use of mean values and 95 percent intervals, and statistical significance measured through the use of p-values ($p < 0.05$) where appropriate. Comparative benchmarking was conducted against multiple recent IoT and edge-based agricultural systems to contextualize gains in energy efficiency, latency, and prediction accuracy. The generalizability of the proposed framework to other crops and controlled-environment settings is discussed based on the modular system design and adaptability of sensing and control parameters.

4.3.1. Energy Performance

The adaptive sampling frequency to solar availability was successfully used with the SOLAR-Sense+ algorithm. Under low irradiance (under cloudy days), the sensor duty cycles were automatically reduced by 30-40 percent, and SoC was maintained greater than 0.35.

- Result: 38% decrease in total power consumption for comparison with the fixed-rate IoT baseline.
- Interpretation: Adaptive sensing and load scheduling play a crucial role in the sustainable utilization of energy, proving the principle of renewable-edge co-design.
- The combination of edge AI inference and R2-MPC was able to achieve sub-second response time. Loop latency time was further reduced from 720 ms to 550 ms after further control optimisation.
- Rationale: Decision-making with local edge: Local edge decision-making, which does not require spending time on a round-trip to the cloud, ensures fast inference on embedded hardware. model compression (µTCN-LSTM-KD): Local edge decision-making is ensured by model compression (µTCN-LSTM-KD), which ensures fast inference on embedded hardware.

4.3.2. Predictive Accuracy

For pH, EC, and DO trends, the edge predictor was able to achieve R2 = 0.98, which is an improvement of 21% compared to the baseline LSTM-cloud models. Anomaly detection (AEGIS) F1 = 0.93. Early detection of fault (e.g., pump failure, nutrient imbalance). Knowledge distillation and retraining of localization only preserve the model with a low computational overhead.

4.3.3. Stability of Renewable Integration.

The R2-MPC provided energy-conscious operation: during cloudy operation, the pump and LED duty cycle were automatically lowered whilst maintaining environmental set points within +/- 5 percent of target.

Outcome: 60 days of operation; did not have to charge the battery (soC did not drop below 0.32).

4.3.4. Communication Efficiency

The SPARQ-Gate compression and event-triggering scheme was able to cut the network traffic by ~70%, reducing the network bandwidth and power consumption without any compromises on the anomaly coverage.

4.4. Discussion

- *Energy-Intelligence Synergy:* The SOLAR-Sense+ has been coupled with renewable forecasting to enable dynamic adaptation to the availability of energy without loss of control accuracy.
- Edge Autonomy: The edge node also ran successfully for >48 hours offline, demonstrating the robustness under communications-constrained conditions.
- Interoperability and scalability: It was tackled in terms of the use of standard communication protocols (LoRaWAN and MQTT) and middleware-based integration, allowing seamless interaction between heterogeneous sensors, edge devices, and cloud services. The system architecture allows for horizontal scalability, thus more sensor nodes and cultivation units could be added with marginal increments in the energy and computation overhead.

- Socio-economic feasibility: It was assessed by examining the deployment and operational costs, which showed that there will be less energy consumption and maintenance required as a result of renewable power integration and edge-level intelligence.
- Environmental Factor: Environmental sustainability was evaluated in terms of energy savings and corresponding CO2 emission reductions, pointing out the system's suitability for adoption in resource-constrained and off-grid agricultural environments.
- Limitations: A review of issues concerning the productivity of wheat under irrigation by Kolluri et al. (2017).- "Agronomic Impact: Increase of productivity by 11% and water savings by 18% with stable pH (6.1 + 0.2) and EC (1.8 + 0.1 mS/cm) confirmed the importance of energy-efficient automation to increase crop productivity."
- Reliability: None of the system failures or 0 response average availability = 99.2 percent, so the following benefits were critical.
- Battery life: The SOLAR-Sense+ framework, through edge-level data processing, minimizes exposure of sensitive sensor data to external networks.
- Security and data privacy: The SOLAR-Sense+ framework, through edge-level data processing, minimizes exposure of sensitive sensor data to external networks. Secure communication and access control mechanisms between IoT nodes, edge gateways, and cloud services further ensure data confidentiality and system integrity during real-world deployment.

4.5. Practical Deployment Guidelines

For practical field deployment, it is recommended to perform site-specific solar sizing and sensor calibration prior to operation, deploy LoRaWAN–MQTT communication with reliable gateway placement, and configure edge devices with safe energy thresholds and adaptive sampling bounds. Periodic sensor maintenance, secure data handling, and continuous monitoring of energy, control stability, and anomaly events are essential to ensure reliable and scalable operation across different crops and controlled-environment settings.

5. Conclusion

In this work, a renewable-based IoT-Edge intelligent sensing and control system with adaptive algorithms and lightweight Artificial Intelligence (AI) is proposed for a monitoring system of soilless cultivation systems for continuous monitoring with energy efficiency. The proposed architecture is capable of addressing three main gaps in the current research on smart agriculture, namely, energy autonomy, edge intelligence, and real-time adaptability. The presented SOLAR-Sense+ algorithm adjusts the sampling rate of the sensors and the efforts of the actuators dynamically based on the prediction uncertainty and the available renewable power, resulting in 38% less energy consumption and 99% of system availability. Simultaneously, Renewable-Responsive MPC (R2-MPC) ensures stable control of nutrients and the environment with a latency of less than a second and optimal use of SoC. Edge-based learning models μTCN-LSTM-KD and AEGIS were used to enhance the prediction accuracy (R2 = 0.98) and early anomaly detection (F1 = 0.93) in order to demonstrate the robustness of the proposed system.

The synergy of these components yields measurable performance improvements:

- Energy efficiency: +38%
- Latency reduction: −24%
- Prediction accuracy: +21%
- Yield improvement: +11%

These results validate that renewable-powered edge intelligence can enable sustainable, autonomous, and resilient agriculture capable of operating off-grid without compromising productivity. The SOLAR-Sense+ system demonstrates a scalable pathway for next-generation smart farming, particularly in resource-limited or climate-sensitive regions.

References

[1] Mohammad Nishat Akhtar et al., "Smart Sensing with Edge Computing in Precision Agriculture for Soil Assessment and Heavy Metal Monitoring: A Review," *Agriculture*, vol. 11, no. 6, pp. 1-37, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[2] Rihong Zhang, and Xiaomin Li, "Edge Computing Driven Data Sensing Strategy in the Entire Crop Lifecycle for Smart Agriculture," *Sensors*, vol. 21, no. 22, pp. 1-17, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Vijendra Kumar et al., "A Comprehensive Review on Smart and Sustainable Agriculture Using IoT Technologies," *Smart Agricultural Technology*, vol. 8, pp. 1-22, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[4] Qing He et al., "Edge Computing-Oriented Smart Agricultural Supply Chain Mechanism with Auction and Fuzzy Neural Networks," *Journal of Cloud Computing*, vol. 13, no. 1, pp. 1-18, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Yogeswaranathan Kalyani, and Rem Collier, "A Systematic Survey on the Role of Cloud, Fog, and Edge Computing Combination in Smart Agriculture," *Sensors*, vol. 21, no. 17, pp. 1-27, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[6] Deshan Yang, Jingwen Wu, and Yixin He, "Optimizing the Agricultural Internet of Things (IoT) with Edge Computing and Low-Altitude Platform Stations," *Sensors*, vol. 24, no. 21, pp. 1-11, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] Neha Bhende, and Rupa Kesavan, "Energy-Optimized Edge-Computing Framework for the Sustainable Development of Modern Agriculture," *Engineering Proceedings*, vol. 56, no. 1, pp. 1-8, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] Muhammad Usman Tariq et al., "Edge-Enabled Smart Agriculture Framework: Integrating IoT, Lightweight Deep Learning, and Agentic AI for Context-Aware Farming," *Results in Engineering*, vol. 28, pp. 1-16, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[9] Amenu Leta Duguma, and Xiuguang Bai, "How the Internet of Things Technology Improves Agricultural Efficiency: A Review," *Artificial Intelligence Review*, vol. 58, no. 2, pp. 1-26, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] Miguel A. Zamora-Izquierdo et al., "Smart Farming IoT Platform Based on Edge and Cloud Computing," *Biosystems Engineering*, vol. 177, pp. 4-17, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[11] Sheikh Mansoor et al., "Integration of Smart Sensors and IoT in Precision Agriculture: Trends, Challenges, and Future Perspectives," *Frontiers in Plant Science*, vol. 16, pp. 1-21, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] Manav Mehra et al., "IoT based Hydroponics System Using Deep Neural Networks," *Computers and Electronics in Agriculture*, vol. 155, pp. 473-486, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[13] Konstantinos Tatas et al., "Reliable IoT-based Monitoring and Control of Hydroponic Systems," *Technologies*, vol. 10, no. 1, pp. 1-18, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Hassan Zeb et al., "Zero Energy IoT Devices in Smart Cities Using RF Energy Harvesting," *Electronics*, vol. 12, no. 1, pp. 1-24, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Rakshith Nagaraj, and Minavathi, "Hybrid Energy Harvesting Model for Attaining Energy Neutrality in IoT-Based Smart Agricultural System," *International Journal of Engineering Trends and Technology*, vol. 71, no. 7, pp. 162-174, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] Kanwalpreet Kour et al., "Monitoring Ambient Parameters in the IoT Precision Agriculture Scenario: An Approach to Sensor Selection and Hydroponic Saffron Cultivation," *Sensors*, vol. 22, no. 22, pp. 1-25, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Hiep Xuan Huynh, Linh Nhut Tran, and Nghia Duong-Trung, "Smart Greenhouse Construction and Irrigation Control System for Optimal Brassica Juncea Development," *PLOS ONE*, vol. 18, no. 10, pp. 1-46, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Md Anisur Rahman et al., "An Aiot-based Hydroponic System for Crop Recommendation and Nutrient Parameter Monitorization," *Smart Agricultural Technology*, vol. 8, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Narayan Raosaheb Gatkal et al., "Review of IoT and Electronics Enabled Smart Agriculture," *International Journal of Agricultural and Biological Engineering*, vol. 17, no. 5, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] Manoj D. Tambakhe, Vijay S. Gulhane, and Yugandhara M. Rajgure, "Machine Learning based Approach for Crop Growth Monitoring in Hydroponics Cultivation," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 1, pp. 467-473, 2023. [Publisher Link]