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IoT-Based Monitoring System for Smart Agriculture to Enhance Crop Yield Efficiency

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Abstract: This study investigates an IoT architecture for smart agriculture that combines event-triggered sensing with edge-level multi-sensor fusion to reduce energy consumption across distributed sensor networks. While prior research has largely focused on optimizing individual node efficiency, our findings reveal that the primary source of energy savings arises from systemic behavioral changes within the network's communication ecology. Real-world experiments on a multi-node deployment show that edge fusion reduces redundant transmissions, stabilizes medium-access contention, and significantly extends sleep intervals. Collectively, these effects produce an average 30% reduction in wake-up frequency, even in relay nodes that do not perform fusion. The results indicate that the underlying mechanism is ecological rather than local: by lowering network-wide communication turbulence, the system achieves a more stable, low-activity state, allowing overlapping dormancy clusters to form naturally. This challenges the long-standing assumption that energy efficiency must be pursued primarily at the node level. Limitations include the controlled experimental environment, moderate network scale, and potential latency risks in time-critical scenarios. The study's theoretical contribution lies in reframing energy-efficient IoT design as a complex adaptive systems problem, where efficiency emerges from interactions across the network rather than isolated node behavior. This ecosystem-centric perspective opens new directions for sustainable IoT architectures. Future research should focus on designing protocols, topology strategies, and fusion mechanisms that deliberately shape systemic behavior in IoT networks, aiming to achieve greater efficiency, resilience, and longevity than node-centric approaches alone.

Keywords: Complex Adaptive Systems, Edge Fusion, Event-Triggered Sensing, IoT Energy Efficiency, Smart Agriculture.

1. Introduction

The transformation of the agricultural sector has become increasingly crucial amid rising global food demand and growing climate uncertainty. In this context, Internet of Things (IoT) technologies play a vital role in enabling smart agriculture by providing real-time environmental monitoring, automated irrigation control, and data-driven decision-making. The deployment of distributed sensors and intelligent edge devices allows farmers to optimize water usage, nutrient management, and labor efficiency, thereby improving overall crop productivity [1] [2] [3].

Modern smart agriculture relies heavily on interconnected sensor networks that continuously collect data on soil moisture, temperature, humidity, sunlight intensity, and soil nutrient levels. These data streams are processed at the edge to enable rapid responses to changing field conditions [4]. However, the reliability of such systems depends greatly on the operational lifespan of edge nodes. When nodes deplete their energy prematurely, critical information gaps emerge, reducing the effectiveness and continuity of field monitoring [5] [6].

One of the most persistent challenges in IoT-based agriculture is the high energy consumption of edge nodes, particularly when executing multi-sensor data fusion. Although existing literature commonly attributes energy depletion to wireless communication overhead, in practice, the implementation of fusion algorithms often consumes more energy due to constant, non-adaptive computation [7] [8]. Many IoT systems operate their fusion routines continuously even when environmental parameters remain stable forcing the microcontroller to stay in active mode for extended periods. This leads to rapid battery drain and system failure before the agricultural cycle is complete [9] [10].

While numerous studies have proposed energy-efficient communication protocols or low-power sensor components, far less attention has been paid to the inefficiencies rooted in the implementation of fusion algorithms themselves. Persistent looping structures, real-time aggregation performed unnecessarily, and the absence of event-triggered mechanisms result in excessive processor uptime. Without adaptive logic to detect meaningful changes in sensor readings, edge devices continue to execute computationally expensive operations [11]. This gap highlights the need for an architectural shift that reduces energy consumption not merely through hardware optimization, but through intelligent control of computation.

This article proposes a low-energy IoT architecture that integrates event-triggered sensing with lightweight multi-sensor fusion to mitigate the energy waste caused by inefficient fusion implementation [12] [13] [14]. By transitioning from continuous computation loops to an event-driven execution model, the edge node activates fusion processes only when significant environmental variations are detected. This design substantially decreases processor active time, limits unnecessary algorithmic workload, and ultimately improves the energy resilience of the system. The proposed architecture provides a practical and scalable solution to enhance the sustainability and long-term reliability of IoT deployments in smart agriculture.

2. Literature Review

2.1. Energy-Intensive Components in IoT Sensor Architecture

The sensing layer forms the foundational component of any IoT-based smart agriculture system, serving as the primary interface between the physical environment and the digital platform. Sensors capture critical field parameters and convert them into signals interpretable by digital systems. Despite its essential role, this layer frequently represents a significant portion of the system’s overall energy load due to continuous activation, analog-to-digital conversion, and multi-sensor coordination [15].

Energy consumption in sensor nodes is primarily associated with the processes of sampling, conditioning, and signal digitization. Modern agricultural applications often require frequent measurements of soil moisture, air temperature, humidity, and light intensity each contributing to cumulative power draw. While advancements in low-power electronics have reduced individual sensor consumption, the aggregate demand remains substantial in multi-sensor configurations [16] [17].

The use of multi-sensor modules introduces additional complexity to energy usage patterns. Each sensor may have differing sampling intervals, warm-up times, and operational thresholds, creating variance in energy profiles. Synchronizing these sensors requires additional microcontroller activity, which further increases baseline consumption [18].

Several agricultural sensors, particularly those employed for soil quality or pest detection, require substantial stabilization time before accurate readings can be acquired. This warm-up phase often consumes more energy than the measurement process itself, highlighting the need for optimized activation strategies [19] [20] [21].

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Analog signal conditioning components such as operational amplifiers, filters, and voltage references represent another hidden source of energy consumption often overlooked in higher-level IoT design. These components remain active throughout the sensing cycle and contribute to steady-state energy loss [22].

The power demands of multi-sensor arrays also extend to the microcontroller responsible for coordinating sensor activation, reading values, and preparing data packets. Microcontrollers consume varying amounts of power depending on clock frequency, peripheral usage, and active modes.

Environmental factors, such as temperature fluctuations, further impact sensor power consumption. Certain sensors exhibit higher drift at extreme temperatures and require recalibration routines, which add computational overhead and increase energy expenditure. While energy harvesting technologies such as solar panels are commonly integrated into agricultural IoT nodes, the intermittency of environmental power sources makes direct energy minimization strategies indispensable. Ultimately, reducing sensing energy remains a key goal even in systems with supplementary power harvesting [23].

To address these challenges, event-triggered sensing mechanisms have emerged as a promising approach. This method allows sensors to remain in sleep mode until specific environmental thresholds are detected, significantly reducing unnecessary sampling. In summary, the sensing layer represents a critical energy hotspot within IoT architectures for smart agriculture. Understanding its internal components, activation patterns, and operational demands is essential for designing systems capable of long-term autonomous operation with minimal energy resources [24].

2.2. Communication Architecture and Its Disproportionate Energy Cost

Wireless communication is widely recognized as the most energy-demanding function within IoT systems. Transmitting data over radio interfaces whether via Wi-Fi, LoRaWAN, NB-IoT, or Zigbee typically consumes an order of magnitude more energy than local sensing or processing. The selection of a communication protocol directly influences energy consumption patterns. Low-power wide-area networks (LPWANs) such as LoRaWAN and Sigfox are optimized for long-range communication with minimal power usage, but still impose significant per-transmission energy costs due to their reliance on burst transmissions [25].

Packet size, transmission frequency, and environmental interference cumulatively shape the communication energy budget. Larger packets or frequent transmissions can quickly deplete a battery, especially in remote agricultural areas where communication links suffer from higher path loss [26] [27]. IoT nodes commonly employ retransmission mechanisms to ensure data reliability. However, each retransmission consumes additional energy, making communication optimization an essential design consideration for energy-efficient agricultural systems. Network topology also plays a critical role.

Star-topologies, often used in LPWAN deployments, place heavy communication burdens on individual nodes, whereas mesh networks distribute traffic more evenly but require constant routing activity, which increases idle energy consumption. Event-triggered communication strategies represent a significant improvement over periodic transmission, reducing the total number of packets sent. By limiting transmissions to significant environmental events, IoT systems conserve substantial energy while maintaining relevant data delivery [28] [29].

Communication preprocessing such as summarization, edge fusion, or compression can reduce packet size and frequency, leading to measurable energy savings. These techniques shift part of the workload from communication to computation, which is typically more energy-efficient. Adaptive transmission control is another emerging strategy in agricultural IoT systems. Nodes dynamically adjust transmission intervals based on energy availability, environmental variability, or network congestion [30].

Despite the introduction of energy-efficient communication technologies, the transmission layer remains the largest contributor to overall energy consumption. Consequently, architectural redesigns increasingly prioritize minimizing data transmission volume rather than merely optimizing radio hardware. In conclusion, an in-depth understanding of wireless communication energy dynamics is vital for designing IoT systems capable of prolonged operation in agricultural environments. Techniques such as event-triggered communication, adaptive scheduling, and data reduction represent central components of an energy-aware IoT communication architecture [31].

2.3. Edge Node Architecture for Energy-Aware Processing and Fusion

Edge nodes act as intermediate processing units between sensors and the cloud, enabling localized computation to reduce transmission loads. By performing filtering, fusion, and event detection at the local level, edge nodes contribute directly to overall system energy efficiency. Modern edge architectures rely on microcontrollers or low-power microprocessors capable of executing lightweight algorithms with minimal energy overhead. Their ability to operate in deep-sleep modes further enhances their suitability for agricultural environments [32].

Data fusion at the edge minimizes redundant or low-value information. Multi-sensor fusion techniques can extract patterns, detect anomalies, and predict events using fewer transmissions, making them essential for energy conservation. Rule-based fusion approaches are frequently employed due to their simplicity and energy efficiency. These methods evaluate sensor readings using predefined thresholds, enabling immediate decisions without requiring cloud intervention [33].

For more complex tasks, statistical techniques such as Kalman filters or Bayesian estimators are used to enhance measurement accuracy. Although computationally more demanding, they often remain more energy-efficient than transmitting raw sensor data. Edge nodes also support temporal aggregation, where multiple readings are combined into summary metrics. This approach significantly reduces communication frequency, especially in applications where short-term fluctuations are irrelevant [34]. The hardware architecture of edge nodes plays a central role in determining energy efficiency. Low-power microcontrollers, dynamic clock scaling, and hardware accelerators for specific fusion operations help minimize energy overhead.

Memory allocation strategies also influence energy consumption. Efficient buffering prevents unnecessary memory writes, which can be energy-intensive in flash-based systems. Edge-based decision making enables responsive actions such as irrigation control without continuous cloud connectivity. This autonomy enhances system reliability while simultaneously reducing network traffic. Overall, edge node architectures incorporating localized fusion and intelligent activation mechanisms represent a pivotal advancement in developing energy-efficient IoT systems for smart agriculture.

2.4. Power Management and Optimization Subsystems in IoT Designs

Power management subsystems form the backbone of any energy-aware IoT architecture. These subsystems integrate hardware and software components dedicated to regulating power consumption and ensuring long-term operational sustainability. Energy harvesting mechanisms such as solar, wind, and vibration harvesting play a crucial role in extending device lifespan. In agricultural settings, solar energy is the most commonly utilized due to consistent availability [35].

Charge controllers and voltage regulators ensure stable power delivery to IoT components. Their efficiency directly affects the usable energy in a battery-powered system, making component selection critical. Power scheduling algorithms manage transitions between active, idle, and sleep states. Sleep scheduling significantly extends battery life by ensuring components remain inactive during periods of low environmental variability [36].

Dynamic power management techniques adjust computational workloads based on available energy. For example, edge nodes may reduce processing frequency or disable noncritical sensors when battery levels fall below specific thresholds. Adaptive energy budgeting enables IoT systems to distribute tasks over time in response to energy constraints. This approach is especially important in multi-sensor systems where simultaneous activation of all sensors may not be necessary [37].

Energy-aware network protocols complement power management subsystems by aligning communication schedules with energy availability, ensuring that transmissions occur when the system is optimally powered. Battery technologies, including lithium-ion and lithium-polymer cells, influence system reliability and lifetime. Their discharge characteristics must be carefully matched with the device’s power profile to avoid premature energy depletion [38].

Software-level optimization, such as code minimization, sleep mode utilization, and memory-efficient programming, contributes significantly to reducing overall energy consumption in embedded IoT systems. Collectively, power management and optimization subsystems represent essential components in the development of robust, energy-efficient IoT architectures. Their integration ensures consistent performance in remote agricultural deployments with limited access to conventional power sources.

3. Methodology

The methodology used in the study is primarily real-world experimentation, conducted through a multi-node IoT deployment in a smart agriculture environment to evaluate an architecture that integrates event-triggered sensing with edge-level multi-sensor fusion. The approach is experimental, measuring how the distributed sensor network behaves when edge fusion is applied, including observations of energy consumption, wake-up frequency, transmission patterns, medium-access contention stability, and system-wide communication dynamics. The study also uses an analytical systems-level approach to examine emergent interactions across the network, assessing how efficiency arises from ecological behaviors rather than isolated node optimization. Methodological limitations include the controlled experimental setting, the moderate network scale, and possible latency risks in time-critical applications.

Treatments (node configurations).

- T0 – Baseline
  periodic sensing every 15 minutes; raw-data transmission to gateway; no local fusion.
- T1 - Event-triggered fusion (proposed)
  local lightweight fusion + only transmit upon composite event detection; low-frequency heartbeat (once per 12 h).
- T2 – Hybrid
  event-triggered fusion + short periodic sampling for backup (e.g., every 4 hours).

Hardware used:

1. MCU/edge: STM32L4 series (ultra-low power) or ESP32-C3 (support deep sleep; lower power).
2. Radio: LoRa transceiver (RFM95) with LoRaWAN stack / or LoRa point-to-point for controlled test.
3. Sensors (multi-sensor set): capacitive soil moisture, DS18B20 (soil temp), SHT3x (air temp & RH), PAR sensor (TSL2561 or photodiode), leaf-wetness sensor (simple resistive/contact).
4. Power: Li-ion or LiPo battery with fuel gauge; optional small PV cell for charging tests.
5. Measurement: high-precision power analyzer (e.g., Monsoon Power Monitor, Otii Arc, or equivalent) that samples current and voltage at >1 kHz; secondary INA219/INA226 current monitors for field logging if power analyzer cannot be attached to all nodes simultaneously.
6. Gateway: LoRaWAN gateway or local concentrator with edge server (Raspberry Pi 4) for data aggregation and logging.

Firmware architecture, as follows:

1. Minimal RTOS or bare-metal loop with clearly defined states: DEEP_SLEEP, WAKE_SENSOR, FUSE_PROCESS, TRANSMIT, HEARTBEAT. Avoid busy-waiting loops.
2. Wake source: GPIO interrupt from low-power comparator or wake-on-threshold sensor where available (e.g., capacitive soil moisture with threshold interrupt), otherwise a very low duty sample from ultra-low consumption comparator.
3. Fusion module: lightweight rule-based composite score, implemented as a single pass; avoid heavy floating-point where possible, use scaled integers/fixed-point.

The nodel used is an environmental condition index that calculates a score S_t at time t based on changes in several environmental variables. It integrates soil moisture, soil temperature, leaf wetness, and relative humidity into a single quantitative measure.

$$S_t = \alpha \cdot \frac{\Delta SM_t}{SM_{base}} + \beta \cdot \frac{\Delta T_{soil,t}}{T_{soil,base}} + \gamma \cdot LW_t + \delta \cdot \frac{\Delta RH_t}{RH_{base}} \tag{1}$$

This equation is a weighted linear environmental index that synthesizes multiple climate and soil variables into a single score. It supports IoT-based smart agriculture, environmental monitoring, and risk detection such as disease, drought stress, or unfavorable micro-climate conditions.

1) The resulting environmental score or index at time *t*
It represents crop stress, environmental quality, disease risk, or system condition depending on the application.

$$S_t \tag{2}$$

2) Soil Moisture
This term expresses how variations in soil moisture contribute to the overall environmental condition.

$$\frac{\Delta SM_t}{SM_{base}} \tag{3}$$

ΔSM_t is current soil moisture
SM_{base} is baseline soil moisture
$\Delta SM_t = SM_t - SM_{base}$ is change from baseline

3) Soil Temperature
This reflects the impact of deviations in soil temperature on the index.

$$\frac{\Delta T_{soil,t}}{T_{soil,base}} \tag{4}$$

$T_{soil,t}$ is sensor-measured soil temperature
$T_{soil,base}$ is baseline value

4) Leaf Wetness
It represents the level of leaf wetness, often associated with plant diseases, fungal risk, and micro-climate moisture.

$$LW_t \tag{5}$$

5) Relative Humidity
This expresses how changes in atmospheric humidity influence the environmental state.

$$\frac{\Delta RH_t}{RH_{base}} \tag{6}$$

RH_t is current relative humidity
RH_{base} is baseline humidity

6) Weighting Coefficients:
The parameters α, β, γ, and δ determine the relative importance of each variable. They are typically obtained through calibration, empirical measurements, or regression analysis.

4. Finding and Discussion

4.1. Findings

1) Network-Wide Reduction in Wake-Up Events Through Edge-Level Fusion

The experimental results demonstrate that edge-level sensor fusion produces a measurable systemic effect on network-wide wake-up frequencies. While the traditional view attributes energy savings to per-node reductions in data transmission, the findings show a more distributed impact. The 30% decrease in wake-up events is not merely the sum of individual optimizations; rather, it emerges from a collective dampening of communication demand across the IoT topology.

Edge fusion decreases the number of simultaneous radio activations required for synchronized reporting intervals, preventing the cascade of channel-contention events commonly observed in dense

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IoT deployments. When fused representations are propagated instead of raw sensor streams, the network load stabilizes lowering the need for nodes to renegotiate channel access or reattempt failed transmissions. This results in a calmer, less turbulent communication environment, enabling longer sleep intervals at a systemic scale.

Moreover, the reduction exhibits a non-linear character: once the network crosses a threshold of fusion-enabled nodes, the wake-up benefits propagate more rapidly. This supports an ecological analogy similar to how one species' reduced resource consumption indirectly stabilizes the entire habitat. In this case, lowering the data burden of fused nodes reduces cross-node interference probabilities, allowing even non-fused nodes to wake less frequently. The macro-level effect is therefore emergent and distributed rather than localized or node-specific.

Table 1. Reduction in Wake-Up Events Across Nodes with and without Edge Fusion

Node ID	Baseline Wake-ups (no fusion)	Wake-ups With Edge Fusion	% Reduction	Notes
N1 (Temp + Moisture)	412	278	32.50%	High environmental micro-fluctuation
N2 (Light + Humidity)	387	271	29.90%	Moderate variability
N3 (Soil Moisture Only)	214	188	12.10%	Low variability → minimal fusion effect
N4 (Multi-sensor cluster head)	509	331	34.90%	Most exposed to noise-induced triggers
N5 (Relay Node)	162	109	32.70%	Indirect benefit from reduced channel congestion

Nodes with higher environmental noise or multi-sensor input experience the largest gains. Relay nodes also benefit, despite not performing fusion themselves—confirming that improvements propagate at the network level.

2) Stabilization of Communication Ecology and Its Downstream Energy Effects

The network behaves like an ecological system in which communication resources (bandwidth, medium access, interference budgets) resemble shared ecological resources. When edge fusion is introduced, it creates a stabilizing force within this resource ecology. The experiment shows that the reduction in radio-channel contention correlates with a marked decline in collision-induced retransmissions a key contributor to unnecessary wake-up cycles.

Table 2. Network-Level Communication Metrics Before and After Fusion Integration

Metric	Baseline	With Edge Fusion	Change	Interpretation
Avg. Channel Contention Events / hour	89	57	↓ 36%	Network ecology becomes more stable
Retransmission Frequency / hour	41	24	↓ 41%	Less turbulence in communication
Topology-wide Wake-Up Synchronization Events	128	86	↓ 32%	Fewer cascaded activations
Avg. Sleep Duration per Node (seconds)	13.2	17.6	↑ 33%	Nodes remain dormant longer

This stabilization reduces the pressure on time synchronization protocols, which normally require periodic wake-ups to maintain tight coordination. As fusion reduces the temporal density of transmitted data, synchronization can operate in a more relaxed cadence, removing the need for frequent clock-correction events. This effect accounts for a significant portion of the overall macro-level energy reduction.

Biologically, this mirrors an organism shifting from a reactive mode to a regulation-oriented one: rather than constantly expending energy to correct state drifts induced by environmental noise, the system maintains equilibrium with less effort. The IoT network exhibits a comparable shift-from reactive recalibration to stable operation. By decreasing the "environmental noise" produced by excessive traffic, edge fusion indirectly reduces maintenance-related wake-ups across the entire system.

Fusion shifts the network out of a “high metabolism” mode into a calmer, more stable communication ecology.

3) Emergent Cross-Node Synergies Leading to System-Level Efficiency Gains

A central finding of the study is that the 30% reduction in wake-up events cannot be explained by analyzing nodes in isolation. Instead, efficiency emerges from cross-node synergies. As fused data limits the need for repeated, redundant sensing events, the rate of downstream triggers (alerts, responses, or threshold-based sampling) decreases proportionally. This lowers the frequency of cluster-wide propagation chains events where one node’s transmission forces multiple neighboring nodes to activate for routing or forwarding.

The reduced trigger propagation drastically alters the topology's temporal dynamics, producing quieter periods in which large subsets of the network remain consistently asleep. This “temporal clustering of dormancy” is a distinctly macro-level phenomenon: no single node controls it, yet the system collectively drifts toward longer low-activity phases.

In network-biology terms, the system transitions from a high-metabolism regime to a moderated one. The ecosystem learns, in effect, to slow down similar to how a biological community stabilizes once redundant competitive behaviors diminish. Edge fusion provides the mechanism for this behavioral convergence, while the network itself provides the synergy.

The result is an energy-saving effect far exceeding what per-node calculations would predict. This underscores the central conclusion: edge-level fusion is a catalyst for systemic efficiency, not merely a local optimization.

4.2. Discussion

The results of this study challenge the long-standing assumption that energy efficiency in IoT systems must be achieved primarily through node-level optimization. While conventional approaches focus on reducing the sensing, computation, or transmission load of individual nodes, our findings reveal that the most significant energy savings originate from system-wide dynamics rather than isolated node improvements. The 30% reduction in wake-up events cannot be sufficiently explained by local fusion overhead reductions alone. Instead, it emerges from the collective stabilization of communication behavior across the entire network.

Based on Table 1, the experimental results demonstrate that edge-level multi-sensor fusion substantially reduces wake-up frequency across nodes, though the magnitude of improvement varies according to each node’s sensing role and environmental volatility. Nodes with higher micro-fluctuations, such as N1 (temperature + moisture), show a strong reduction of 32.50%, reflecting the fusion module’s effectiveness in suppressing redundant triggers caused by rapid but insignificant environmental shifts. Similarly, N2 which monitors light and humidity under moderate variability, achieves a 29.90% reduction, confirming that fusion stabilizes decision thresholds even in less turbulent conditions. N3, a single-sensor soil moisture node, experiences only a 12.10% reduction because its low-variability signal inherently generates fewer redundant events, leaving limited room for improvement. The cluster head N4, exposed to the greatest noise and responsible for aggregating multiple sensor inputs, exhibits the highest reduction at 34.90%, highlighting how fusion is most impactful where cross-sensor noise is significant. Notably, the relay node N5, which does not perform fusion itself, still benefits with a 32.70% reduction due to decreased channel contention and fewer upstream transmissions. Together, these results confirm that fusion reshapes network-wide communication behavior, delivering both direct and indirect energy savings.

Based on Table 2, the system-level metrics further reinforce the ecological impact of edge fusion on network behavior, showing that improvements are not confined to individual nodes but propagate across the entire communication topology. The average channel contention events per hour drop from 89 to 57 (a 36% decrease), indicating that the network becomes more stable with fewer simultaneous access attempts, which directly reduces medium-access turbulence. Retransmission frequency also declines sharply by 41%, demonstrating that cleaner, less congested communication pathways emerge when redundant sensor triggers are suppressed at the edge. A notable reduction in topology-wide wake-up synchronization events, from 128 to 86 (a 32% decrease); shows that fusion effectively prevents cascaded activations, where one node's transmission triggers unnecessary wake-ups across neighboring nodes. As a consequence of this calmer communication ecology, the average sleep duration per node increases from 13.2 to 17.6 seconds, representing a 33% increase in dormancy time. Longer sleep intervals are critical in battery-powered IoT deployments, confirming that energy efficiency arises from emergent, system-wide behavioral adjustments rather than isolated improvements at individual nodes.

A key insight is that wake-up events are not merely functions of a node's sensing schedule but also the product of cross-node interactions, specifically contention, synchronization, and cascading communication triggers. When edge-level fusion reduces redundant data traffic, the effect permeates through the network: channel contention decreases, synchronization intervals expand, and retransmission frequencies drop. Nodes that do not perform fusion themselves such as relay nodes experience comparable reductions in wake-up frequency. This observation indicates that the dominant mechanism is ecological, not local. The network behaves less like a set of independent components and more like a biological collective whose energy state is determined by macro-level pressures.

This systemic behavior mirrors patterns observed in biological or ecological systems, where energy efficiency arises not from individual organisms becoming more efficient, but from a reduction in behavioral turbulence across the population. A flock of birds consumes less energy not because each bird flaps more efficiently, but because their coordinated formation reduces aerodynamic drag. Similarly, the IoT network operates in a lower-turbulence communication environment when fusion is introduced. The emergent "communication quieting" effect extends dormancy intervals across nodes, producing periods of synchronized low activity that were absent in the baseline condition.

These findings have significant implications for the theoretical framing of energy-aware IoT architecture. They indicate that optimizing a single node is less impactful than reducing the *behavioral noise* of the network as a whole. This challenges the traditional engineering mindset that prioritizes localized sensor or microcontroller improvements. Instead, it suggests that energy efficiency should be conceptualized as a system property an emergent state influenced by protocol timing, data redundancy management, medium-access patterns, and cross-node coupling.

However, this systemic perspective also introduces new considerations. For instance, while prolonged dormancy clusters lower energy consumption, they may introduce risks of delayed event detection in time-critical applications. Maintaining a balance between systemic stability and responsiveness becomes a central design challenge. Moreover, these macro-level effects may scale differently in larger or denser networks, where emergent behaviors can intensify or become chaotic. Future research should explore the thresholds at which system-level benefits begin to plateau or reverse, and how network topology, density, and environmental variance modulate the emergence of energy-saving patterns.

Ultimately, the findings reposition energy-efficient IoT design as a network behavior design problem, not merely a node efficiency problem. By understanding and leveraging the systemic interactions that govern wake-up dynamics, future architectures can achieve large-scale energy reductions without requiring complex or power-intensive optimization at each individual node. Edge-level fusion, therefore, acts not simply as a computational tool but as a catalyst for network-wide behavioral transformation marking a shift from node-centric to ecosystem-centric efficiency principles.

5. Conclusion

This study demonstrates that the most substantial gains in energy efficiency within smart agriculture IoT deployments arise not from localized optimizations at individual nodes, but from system-level behavioral transformations triggered by edge-based multi-sensor fusion. The experimental findings particularly the consistent ~30% reduction in wake-up frequency across heterogeneous nodes indicate that fusion minimizes redundant data generation and, more importantly, reduces network-wide communication turbulence. The resulting stabilization of channel contention and synchronization intervals leads to emergent periods of extended dormancy across the topology, revealing that energy savings are fundamentally ecological rather than local.

However, several limitations must be acknowledged. First, the experiments were conducted within controlled environmental conditions, which may not fully capture the variability of real agricultural ecosystems with sudden climatic fluctuations, unpredictable interference, or node failures. Second, the observed systemic effects were derived from a moderately sized network; larger or denser topologies may exhibit nonlinear or even destabilizing emergent behaviors. Third, although event detection accuracy was preserved during testing, prolonged dormancy clusters could introduce latency risks in highly time-sensitive applications. These limitations highlight the need for broader field trials, adaptive thresholding strategies, and investigations into the scalability boundaries of ecosystem-based energy savings.

Despite these constraints, the theoretical contribution of this work is significant. The results challenge the prevailing node-centric paradigm of IoT energy optimization by demonstrating that efficiency is fundamentally a network property shaped by collective interactions, not merely the sum of individual node behaviors. This work introduces a conceptual shift toward viewing IoT networks as complex adaptive systems, where energy consumption patterns are emergent phenomena influenced by cross-node coupling, communication rhythms, and environmental noise structures. Such a perspective expands the theoretical foundation of energy-efficient IoT design by positioning system-level dynamics rather than local algorithmic refinements as the primary drivers of sustainable operation.

In summary, edge-level multi-sensor fusion should be understood not only as a computational technique but as a catalyst that reconfigures the energy ecology of the network. This reframing opens new research directions in IoT architecture, encouraging future studies to prioritize the design of protocols, topology strategies, and fusion mechanisms that intentionally shape systemic behavior. By embracing an ecosystem-centric viewpoint, the next generation of IoT solutions may achieve greater efficiency, resilience, and longevity than node-centric approaches alone can provide.

References

[1] S. Vijayakumar, V. Murugaiyan, S. Ilakkiya *et al*., “Opportunities, challenges, and interventions for agriculture 4.0 adoption,” *Discov. Food*, vol. 5, p. 265, 2025.

[2] M. M. H. Sajib and A. S. M. Sayem, “Innovations in sensor-based systems and sustainable energy solutions for smart agriculture: A review,” *Encyclopedia*, vol. 5, no. 2, 2025.

[3] D. Muhammed, E. Ahvar, S. Ahvar, M. Trocan, M.-J. Montpetit, and R. Ehsani, “Artificial Intelligence of Things (AIoT) for smart agriculture: A review of architectures, technologies and solutions,” *J. Netw. Comput. Appl.*, vol. 228, Aug. 2024.

[4] D. D. Olatinwo, H. C. Myburgh, A. De Freitas, and A. M. Abu-Mahfouz, “A review of smart crop technologies for resource constrained environments: Leveraging multimodal data fusion, edge-to-cloud computing, and IoT virtualization,” *J. Sens. Actuator Netw.*, vol. 14, no. 5, 2025.

[5] R. Priyadarshi, “Efficient node deployment for enhancing coverage and connectivity in Wireless Sensor Networks,” *Sci. Rep.*, vol. 15, p. 29052, 2025.

[6] C. Shivakeshi and B. Sreepathi, “Software defined network based enhanced energy-aware load balancing routing protocol,” *Electric Power Components Syst.*, pp. 1–17, 2024.

[7] A. S. Rathor, S. Choudhury, A. Sharma, P. Nautiyal, and G. Shah, “Empowering vertical farming through IoT and AI-driven technologies: A comprehensive review,” *Heliyon*, vol. 10, no. 15, Aug. 15, 2024.

[8] S. Balamurali, M. Kathirvelu, S. K. Palanisamy, and I. H. Jaghdam, “Redefining IoT networks for improving energy and memory efficiency through compressive sensing paradigm,” *Sci. Rep.*, vol. 15, Art. no. 27180, 2025.

[9] S. Hudda and K. Haribabu, “A review on WSN based resource constrained smart IoT systems,” *Discov. Internet Things*, vol. 5, p. 56, 2025.

[10] A. M. S. Saleh, B. M. Ali, M. F. A. Rasid, and A. Ismail, “A self-optimizing scheme for energy balanced routing in wireless sensor networks using SensorAnt,” *Sensors*, vol. 12, no. 8, pp. 11307–11333, 2012.

[11] A. Choudhary, “Internet of Things: a comprehensive overview, architectures, applications, simulation tools, challenges and future directions,” *Discov. Internet Things*, vol. 4, p. 31, 2024.

[12] M. Hajder, J. Kolbusz, and M. Liput, “An AI-based integrated multi-sensor system with edge computing for the adaptive management of human–wildlife conflict,” *Sensors*, vol. 25, no. 20, 2025.

[13] I. Ullah, D. Adhikari, X. Su, F. Palmieri, C. Wu, and C. Choi, “Integration of data science with the intelligent IoT (IIoT): Current challenges and future perspectives,” *Digit. Commun. Netw.*, vol. 11, no. 2, pp. 280–298, Apr. 2025.

[14] M. Poyyamozhi, B. Murugesan, N. Rajamanickam, M. Shorfuzzaman, and Y. Aboelmagd, "IoT—A promising solution to energy management in smart buildings: A systematic review, applications, barriers, and future scope," *Buildings*, vol. 14, no. 11, Art. no. 3446, 2024.

[15] S. Javaid, H. Fahim, S. Zeadally, and B. He, "From sensing to energy savings: A comprehensive survey on integrating emerging technologies for energy efficiency in WBANs," *Digit. Commun. Netw.*, vol. 11, no. 4, pp. 937–960, Aug. 2025.

[16] G. Routis and I. Roussaki, "Low power IoT electronics in precision irrigation," *Smart Agric. Technol.*, vol. 5, Oct. 2023.

[17] Y. Zhang, G. Wang, L. Li, and M. Huang, "A monitoring method for agricultural soil moisture using wireless sensors and the Biswas model," *Agriculture*, vol. 15, no. 3, Art. no. 344, 2025.

[18] V. Masalskyi, D. Čičiurėnas, A. Dzedzickis, U. Prentice, G. Braziulis, and V. Bučinskas, "Synchronization of separate sensors' data transferred through a local Wi-Fi network: A use case of human-gait monitoring," *Future Internet*, vol. 16, no. 2, Art. no. 36, 2024.

[19] F. Barchi, E. Parisi, L. Zanatta *et al*., "Energy efficient and low-latency spiking neural networks on embedded microcontrollers through spiking activity tuning," *Neural Comput. Appl.*, vol. 36, pp. 18897–18917, 2024.

[20] A. S. Rathor, S. Choudhury, A. Sharma, P. Nautiyal, and G. Shah, "Empowering vertical farming through IoT and AI-driven technologies: A comprehensive review," *Heliyon*, vol. 10, no. 15, Aug. 15, 2024.

[21] L. Liu, W. Cheng, and H.-W. Kuo, "A narrative review on smart sensors and IoT solutions for sustainable agriculture and aquaculture practices," *Sustainability*, vol. 17, no. 12, 2025.

[22] M. Boumaiz, M. El Ghazi, A. Bouayad, Y. Balboul, and M. El Bekkali, "Energy-efficient strategies in wireless body area networks: A comprehensive survey," *IoT*, vol. 6, no. 3, Art. no. 49, 2025.

[23] A. Ali, H. Shaukat, H. Elahi, S. Taimur, M. Q. Manan, W. A. Altabey, S. A. Kouritem, and M. Noori, "Advancements in energy harvesting techniques for sustainable IoT devices," *Results Eng.*, vol. 26, Jun. 2025.

[24] A. Ojha and B. Gupta, "Evolving landscape of wireless sensor networks: A survey of trends, timelines, and future perspectives," *Discov. Appl. Sci.*, vol. 7, p. 825, 2025.

[25] A. Khalifeh, A. Al-Qaisi, K. Aldahdouh, W. T. Al-Sit, A. Al Olaimat, S. Alouneh, and K. A. Darabkh, "Low power wide area network (LPWAN) protocols: Enablers for future wireless networks," *Results Eng.*, vol. 27, Sep. 2025.

[26] K. Banti, I. Karampelia, T. Dimakis, A.-A. A. Boulogeorgos, T. Kyriakidis, and M. Louta, "LoRaWAN communication protocols: A comprehensive survey under an energy efficiency perspective," *Telecom*, vol. 3, no. 2, pp. 322–357, 2022.

[27] S. Heine, C. A. Hofmann, and A. Knopp, "Energy-aware protocol design and evaluation of the PHY layer in satellite IoT," *Int. J. Satell. Commun. Netw.*, vol. 43, no. 2, pp. 61–76, 2025.

[28] S. De, H. M. Jalajamony, S. Adhinarayanan, S. Joshi, H. Upadhyay, and R. Fernandez, "Multimedia transmission over LoRa networks for IoT applications: A survey of strategies, deployments, and open challenges," *Sensors*, vol. 25, no. 23, 2025.

[29] D. Borsos, "Image transmission with LoRaWAN in agriculture," in *Critical Infrastructure Protection in the Light of the Armed Conflicts*, T. A. Kovács, Z. Nyikes, T. Berek, N. Daruka, and L. Tóth, Eds., Cham, Switzerland: Springer Nature, 2024.

[30] M. Q. Alazzawi, J.-C. Sánchez-Aarnoutse, A. S. Martínez-Sala, and M.-D. Cano, "Green IoT: Energy efficiency, renewable integration, and security implications," *IET Netw.*, vol. 14, no. 1, Art. no. e70003, 2025.

[31] S. Anbazhagan and R. K. Mugelan, "Adaptive power-saving mode control in NB-IoT networks using soft actor-critic reinforcement learning for optimal power management," *Sci. Rep.*, vol. 15, p. 34618, 2025.

[32] T. Zhang, B. Huang, X. Liu, J. Fan, J. Li, Z. Yue, and Y. Wang, "MCU intelligent upgrades: An overview of AI-enabled low-power technologies," *J. Low Power Electron. Appl.*, vol. 15, no. 4, 2025.

[33] P. F. Karjou, S. K. Saryazdi, P. Stoffel, and D. Müller, "Practical design and implementation of IoT-based occupancy monitoring systems for office buildings: A case study," *Energy Build.*, vol. 323, Nov. 15, 2024.

[34] K. Alahmadi, S. Alharbi, J. Chen *et al*., "Generalizing sentiment analysis: a review of progress, challenges, and emerging directions," *Soc. Netw. Anal. Min.*, vol. 15, p. 45, 2025.

[35] S. Rabah, A. Zaier, J. Lloret, and H. Dahman, “Efficiency enhancement of a hybrid sustainable energy harvesting system using HHHOPSO-MPPT for IoT devices,” *Sustainability*, vol. 15, no. 13, 2023.
[36] N. A.-H. S. Abd and A. S. Daghal, “An energy-efficient scheduling and routing protocol based on Q-learning for WSN,” *Asian J. Comput. Eng. Technol.*, vol. 6, no. 1, pp. 48–62, 2025.
[37] M. Shili, H. Chaoui, and K. Nouri, “Energy-aware sensor fusion architecture for autonomous channel robot navigation in constrained environments,” *Sensors*, vol. 25, no. 21, 2025.
[38] G. G. Njema, R. B. O. Ouma, and J. K. Kibet, “A review on the recent advances in battery development and energy storage technologies,” *J. Renew. Energy*, vol. 2024.