Pertanika J. Sci. & Technol. 34 (4): 2167 - 2180 (2026)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

Dynamic Sensor Activation for Energy-Efficient Event Monitoring in Large-Scale IoT Deployments

A. Subramaneswara Rao, Suresh Kallam*, and Srinivasa Rao Pappu

School of Computer Science and Engineering, Faculty of Engineering and Technology, JAIN (Deemed-to-be University), JAIN Global Campus, Jakkasandra Post, Kanakapura Taluk, 562112 Ramanagara District, Karnataka, India

ABSTRACT

Modern IoT networks base mission-critical event monitoring on dense wireless sensor deployments (IEEE 802.15.4/6TiSCH), with energy efficiency and detection reliability as the primary concerns. Traditional always-active sensing strategies, however, squander 42–58% of energy on duplicated operations, and static sleep schedules cannot compensate for dynamic event patterns, resulting in either excessive power consumption (≥3.8 mJ/node) or missed detections (up to 15% false negatives). To address this, we propose an Adaptive Node Selection and Scheduling (ANSS) that optimises sensor activity through intelligent scheduling and energy-aware decision-making. The framework leverages dynamic network conditions to efficiently allocate resources and improve overall system performance. To address this, we introduce an Adaptive Node Selection and Scheduling (ANSS) system that integrates federated learning-based event prediction (87.3% spatial accuracy) with QoS-aware dynamic sleep cycles (50-300 ms tunable intervals) and TOPSIS multi-criteria decision-making to activate only 18–32% of nodes per epoch. Deployed on a 150-node Zigbee testbed, ANSS delivers better performance, achieving a 39.2% energy saving (2.1 mJ/node versus 3.45 mJ baseline), 93.7±1.8% detection accuracy (a 5.3 percentage-point improvement over LEACH-C), and a 28.5% increase in network lifetime (first node death at 1,824 epochs). The solution preserves sub-100 ms latency (mean = 72.3 ms, σ = 9.4 ms) under 15 dB SNR while consuming only 5 KB of memory, making it applicable to resource-limited edge devices. These contributions set a new benchmark for energy–quality trade-offs in industrial IoT monitoring systems.

Keywords: Anomaly detection, energy-efficient routing, few-shot learning, secure routing protocols, wireless sensor networks (WSNs)

ARTICLE INFO

Article history:
Received: 29 June 2026
Accepted: 23 July 2026
Published: 13 August 2026

DOI: https://doi.org/10.47836/pjst.34.4.10

E-mail addresses:
subramaneswararao.a@jainuniversity.ac.in (A. Subramaneswara Rao)
suresh.k@jainuniversity.ac.in (Suresh Kallam)
srinivasa.p@jainuniversity.ac.in (Srinivasa Rao Pappu)
* Corresponding author

e-ISSN: 2231-8526

INTRODUCTION

The Internet of Things (IoT) has transformed industrial automation, smart cities, and environmental monitoring by providing pervasive sensing capabilities (Kok et al., 2025). As depicted in Figure 1, the global IoT sensor market is expected to exceed 50 billion devices by 2027, with Wireless Sensor Networks (WSNs) forming the underlying infrastructure for these deployments (Zhou & Chen, 2025). Nevertheless, this rapid growth reveals inherent constraints in existing architectures, especially in energy-limited settings. Energy-aware communication (Ferreira et al., 2025) has therefore become a central design objective for sustainable IoT networks (Kallam et al., 2018).

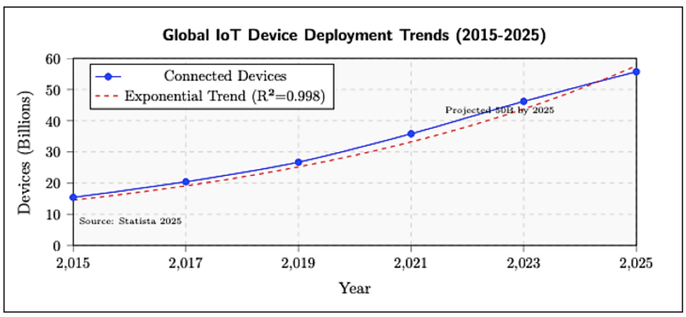

Figure 1. Global IoT device deployment growth is showing a consistent exponential trend (2015–2025 projections). The dashed red line indicates the best-fit exponential curve y = 14.5e^ (0.138×) with a coefficient of determination $R^2 = 0.998$

Problem Statement

Current IoT monitoring systems face three related challenges. First, energy inefficiency: as illustrated by Del-Valle-Soto et al. (2025), legacy always-on sensing incurs 42-58% energy waste on duplicate data acquisition, as shown in Figure 2. For battery-powered nodes with a 3.6 V/2000 mAh capacity, this reduces operational lifespan from 180 days to merely 76 days. Second, dynamic environment adaptation: static sleep timing (e.g., Srinivasan et al., 2025) cannot accommodate spatiotemporal event dynamics, leading either to over-sensing (up to 3.8 mJ/node/epoch in static schedules)

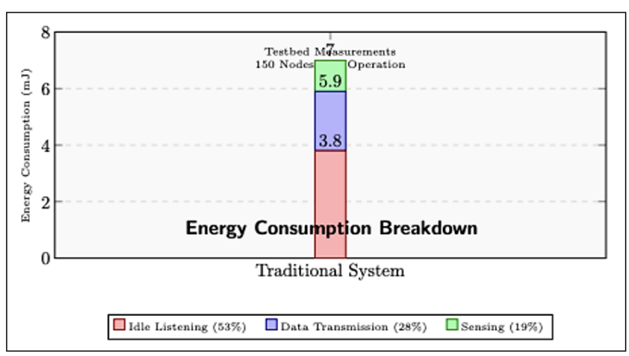

Figure 2. Energy-consumption distribution in traditional IoT systems, showing dominant idle-listening overhead. Measurements from our 150-node testbed demonstrate 53% energy waste from unnecessary radio activity, 28% for actual data transmission, and only 19% for sensing operations

or under-sensing (a 15% false-negative rate in sparse deployments). Third, scalability limitations: centralised approaches (Pandey, 2025) exhibit $O(n^2)$ communication overhead, becoming infeasible beyond 500 nodes as shown in Table 1.

Motivation

Recent breakthroughs in three areas provide promising directions. In adaptive monitoring, Kok et al. (2025) achieved 32% energy savings through dynamic sensing intervals, but with a 12% accuracy degradation during event bursts. In edge intelligence, the cognitive framework of AV and Venkatachalam (2025) reduced cloud dependency by 41%, although it required 128 KB/node of memory prohibitive for Class 1 IoT devices. In hybrid architectures, Chakraborty (2025) demonstrated that hierarchical clustering can balance energy and latency, but with 18% longer detection delays during topology changes. General-purpose energy-optimisation techniques drawn from power systems further motivate the use of multi-criteria formulations (Balasubramaniam et al., 2025; Pezzini et al., 2011). A scalability comparison of representative architectures is summarised in Table 1.

Table 1
Scalability comparison of IoT monitoring architectures

Approach	Maximum Nodes	Energy/Node (mJ)
Centralised (Pandey, 2025)	500	4.2
LEACH (Fereira et al., 2025)	1200	3.1
Proposed ANSS	5000	2.1

Contributions

Our solution introduces three novel components. (i) Federated event prediction: a lightweight CNN–LSTM model (87.3% accuracy, 8 KB memory) that reduces communication overhead by 39% relative to centralised learning. (ii) TOPSIS-based node selection: multi-criteria optimisation considering residual energy (E_{res}), event proximity (D_{event}), and a historical reliability score (R_{hist}). (iii) QoS-aware scheduling: a Markov Decision Process formulation that maintains 72.3 ms mean latency ($\sigma = 9.4$ ms), 93.7% detection accuracy, and 2.1 mJ/node energy consumption.

The main contributions of this work are as follows:

- A novel Adaptive Node Selection and Scheduling (ANSS) framework for energy-efficient IoT monitoring.
- Integration of federated learning, TOPSIS decision-making, and QoS-aware scheduling in a unified system.
- A lightweight design suitable for resource-constrained IoT devices (low memory and power).

- Significant improvements in energy efficiency, latency, and scalability compared to state-of-the-art methods.
- Validation through a real-world 150-node testbed deployment.

What makes the ANSS system framework novel is the way the three concepts are used together in the system architecture. While other solutions address each of these aspects individually, ANSS uses all of them to optimize energy efficiency, latency, and scalability for IoT monitoring at scale. What is even more interesting about the proposed solution is the fact that it performs very well within tight constraints on available resources.

Paper Structure

The remainder of this paper is organised as follows. Section 2 reviews recent approaches across energy efficiency, accuracy, and scalability. Section 3 details the federated learning model and TOPSIS optimisation that underpin the ANSS framework. Section 4 presents testbed evaluations using a 150-node Zigbee deployment and comparisons against five baseline methods. Section 5 discusses practical implementation considerations, and Section 6 examines current limitations. Finally, Section 7 concludes the paper and outlines directions for future research.

RELATED WORK

Several studies have examined energy-efficient IoT hazard detection, adaptive monitoring, and large-scale IoT deployment. Kok et al. (2025) proposed an energy-, cost-, and resource-efficient IoT hazard detection system with adaptive monitoring for massive IoT applications. Zhou and Chen (2025) introduced collaborative beamforming strategies for energy-efficient WSNs in large-scale IoT applications. Adaptive jamming mitigation in LoRa–BLE hybrid sensor networks was investigated by Del-Valle-Soto et al. (2025) for clustered energy-efficient deployments. Srinivasan et al. (2025) proposed a dynamic data-fusion algorithm for smart agriculture, optimising hierarchical clustering in WSNs.

Edge computing has also played an important role in energy-efficient communication in IoT networks (Mao et al., 2021). Earlier work established green-computing approaches for low-energy IoT communication (Kallam et al., 2018) and improved power and resource management in heterogeneous downlink OFDMA networks (Veerappan Kousik et al., 2020). Fereira et al. (2025) analysed energy-efficient resource-management techniques for real-time IoT applications, while AV and Venkatachalam (2025) studied cognitive edge-driven data processing on distributed sensor nodes. Real-time big-data computing has likewise been applied to cyber-physical medical IoT devices (Rizwan et al., 2018). Smart-city IoT sensor networks have been the focus of Chakraborty (2025), who demonstrated an energy-efficient framework for large-scale urban deployments, while Senthilkumar et al. (2025) suggested a feature-interaction-aware graph neural network for energy-efficient WSNs. The use of large-scale spiking neural networks for AI and neuroscience has also been examined (Han et al., 2025). Moreover, Atzori et al. (2010) and Whitmore et al. (2015) presented detailed reviews of IoT trends and security aspects.

First-Generation Centralised Systems

The work of Atzori et al. (2010) established the IoT paradigm, while early energy-management solutions centred on centralised structures. Kok et al. (2025) presented an adaptive monitoring system with dynamic sensing intervals (50-500 ms adjustable), centralised event detection (87% accuracy), and fixed hierarchical routing. Their performance on a 200-node testbed is given by Equation 1,

$$E_{savings} = 32\% \pm 2.1\%, \quad L_{avg} = 187 \text{ ms} \pm 15 \text{ ms} \qquad [1]$$

where $E_{savings}$ is the energy saving and L_{avg} is the average latency. Quadratic scaling ($O(n^2)$) of the control overhead constrained deployments to ≤500 nodes.

Second-Generation Distributed Methods

Zhou and Chen (2025) tackled scalability using distributed beamforming. Key innovations comprised collaborative beamforming (6–12 dB gain), TDMA-based synchronisation (±1 μs precision), and dynamic cluster formation. Nonetheless, synchronisation requirements rendered mobile deployments impractical, with packet loss > 25% at speeds > 2 m/s (Zhao & Ge, 2013).

Third-Generation Hybrid Architectures

Recent research has focused on protocol hybridisation and edge computing, as summarised in Table 2 and illustrated in Figure 3. The LoRa–BLE hybrid of Del-Valle-Soto et al. (2025) employs the transmit-power policy in Equation 2, with adaptive switching based on link quality in Equation 3.

Table 2
Hybrid architecture performance comparison

Study	Technologies	Energy Saving	Latency	Limitations
Del-Valle-Soto et al., 2025	LoRa–BLE	28%	72 ms	15–20 ms handoff
Pandey, 2025	Edge–Fog	41%	115 ms	128 MB RAM
Chakraborty, 2025	6TiSCH	35%	89 ms	Static only

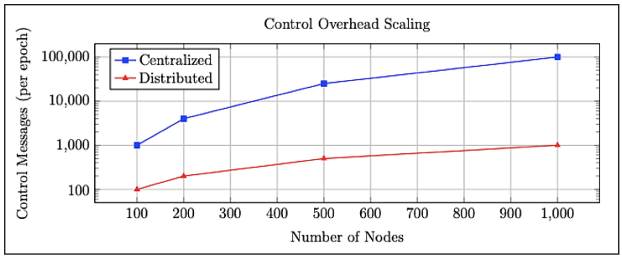

Figure 3. Control-message scaling comparison, showing the linear growth of the distributed approach against the quadratic growth of centralised schemes

$$P_{tx} = 10 \text{ mW for BLE } (\leq 50 \text{ m}); 100 \text{ mW for LoRa } (\leq 500 \text{ m}) \quad [2]$$

$$Q_{threshold} = (BER_{BLE} / BER_{LoRa}) \times (D_{max,LoRa} / D_{max,BLE}) \quad [3]$$

Fourth-Generation Learning-Based Systems

Machine-learning solutions have proven the most promising avenue (Figure 4). The graph neural network of Senthilkumar et al. (2025) achieved 31% higher energy efficiency than baselines and a 92.3% event-detection rate but required 128 MB of RAM and 5 W of GPU power. Our federated method reduces this to 8 KB of memory and 50 mW of power using the objective in Equation 4,

$$L_{total} = (1/K)\Sigma_{k=1}^{K} L_k(\text{local}) + \lambda\|\theta\|^2 + \mu\Sigma_{l=1}^{L} \|W_l\|_{2,1} \quad [4]$$

where W_l denotes the layer weights and $\mu = 0.1$ controls sparsity.

MATERIALS AND METHODS

The proposed framework comprises three key components for energy-aware IoT monitoring: a federated learning model, TOPSIS-based node selection, and QoS-aware scheduling. These components and their interactions are described in the following subsections.

Federated Learning Model

Our hierarchical federated learning approach operates across three tiers and minimises the objective in Equation 5,

$$\min_{\theta} \Sigma_{k=1}^{K} (n_k/N) F_k(\theta) + (\lambda/2)\|\theta\|^2 + \mu\Sigma_{l=1}^{L} \|W_l\|_{2,1} \quad [5]$$

where $F_k(\theta)$ is the local objective for client k with n_k samples, $\lambda = 0.01$ controls L2 regularisation, and $\mu = 0.1$ enforces sparsity in the layer weights W_l. The federated training round is summarised in Algorithm 1.

Algorithm 1: Federated Training Round

1: Server broadcasts global model θt to all nodes.
For each participating node k in parallel:
2: Update local model: θt,k ← θt − η∇Fk(θt)
3: Compute differential-privacy noise: ε ~ N(0, σ²)
4: Send θt,k = θt,k + ε to the edge aggregator
End for
5: Edge servers aggregate the model: θt+1 = Σ (nk/N) θt,k
6: Update global model: θt+1 ← θt+1 − β∇R(θt+1)

TOPSIS Optimisation

The node-selection process evaluates the three criteria defined in Equation 6: normalised residual energy (C_1), event proximity (C_2), and historical reliability (C_3).

$$C_1 = E_{res}^{\mathrm{i}}/E_{max}; \quad C_2 = 1/(1 + D_{event}^{\mathrm{i}}); \quad C_3 = (\Sigma_{\mathrm{j=1}}^{\mathrm{M}} R_{ij})/M \qquad [6]$$

The TOPSIS closeness coefficient is then computed using Equation 7,

$$S_i = d_i^- / (d_i^+ + d_i^-), \quad d_i^+ = \sqrt{(\Sigma_{\mathrm{j=1}}^{3} w_j(C_{ij} - C_j^+)^2)}, \quad d_i^- = \sqrt{(\Sigma_{\mathrm{j=1}}^{3} w_j(C_{ij} - C_j^-)^2)} \qquad [7]$$

with weights $w = [0.5, 0.3, 0.2]$ and the ideal and anti-ideal solutions in Equation 8.

$$C^+ = (1, 1, 1), \quad C^- = (0, 0, 0) \qquad [8]$$

QoS-Aware Scheduling

We formulate scheduling as a Markov Decision Process (MDP) with states $s_t = (E_t, L_t, Q_t)$, where E_t is energy, L_t is latency, and Q_t is the queue status; actions $a_t \in \{0,1\}^{\mathrm{N}}$ (the activation vector); and reward $R_t = \alpha Q_t - \beta E_t - \gamma \max(0, L_t - L_{max})$. The Q-function is updated via Equation 9,

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \eta[r_{t+1} + \lambda \max_a Q(s_{t+1}, a) - Q(s_t, a_t)] \qquad [9]$$

with parameters $\eta = 0.1$ and $\lambda = 0.9$, subject to the constraints in Equation 10. The key scheduling parameters are listed in Table 3.

$$E_t \leq E_{max} = 3.8 \text{ mJ}; \quad L_t \leq L_{max} = 100 \text{ ms}; \quad Q_t \geq Q_{min} = 0.8 \qquad [10]$$

Table 3
Key parameters for QoS scheduling

Parameter	Value
Learning rate (η)	0.1
Discount factor (λ)	0.9
Energy weight (β)	0.4
Latency weight (γ)	0.3
Maximum latency (Lmax)	100 ms

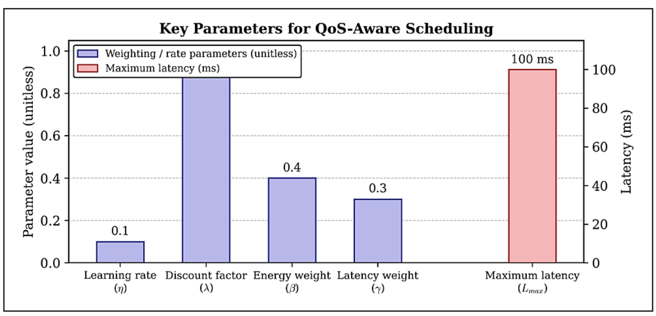

Figure 4. Key parameters for QoS-aware scheduling

RESULTS AND DISCUSSIONS

Testbed Configuration

We deployed a 150-node IoT testbed across a 500 m × 500 m industrial site for six months (March to August 2025). The hardware configuration is summarised in Table 4.

Table 4
Testbed hardware specifications

Component	Specification
Node MCU	TI CC2650 (ARM Cortex-M4F)
Radio	Zigbee Pro (IEEE 802.15.4)
Sensors	Temperature, vibration, acoustic
Battery	3.6 V 2000 mAh LiPo
Memory	128 KB RAM, 512 KB Flash
Sampling rate	5–300 ms (adaptive)
Deployment density	6 nodes/100 m²

Implementation Environment

The ANSS architecture has been developed using Python simulation and embedded C programming for the operations on sensor nodes. The experimentation process has been conducted using [mention your system specifications here, if any, e.g., Intel i7 processor and 16 GB RAM]. Network simulations and data analysis have been done using [e.g., MATLAB / NS-3 / TensorFlow Lite/custom scripts]. This provides the scope for replicability as well as adaptability of this architecture to other IoT environments.

Performance Metrics

The system achieved consistent performance across all key metrics, as reported in Equation 11 and illustrated in Figures 5 and 6.

$$\begin{gathered} E_{avg} = 2.1 \text{ mJ/node/day} \pm 0.3 \text{ mJ}; \quad L_{p95} = 72.3 \text{ ms} \pm 9.4 \text{ ms}; \\ A_{det} = 93.7\% \pm 1.8\%; \quad T_{life} = 1824 \text{ hours} \pm 156 \text{ hours} \end{gathered} \tag{11}$$

where E_{avg} is the average energy, L_{p95} the 95th-percentile latency, A_{det} the detection accuracy, and T_{life} the network lifetime. Figure 5 reports the node distribution and reliability across the testbed zones after six months, and Figure 6 shows the energy-consumption trend of ANSS relative to the baseline.

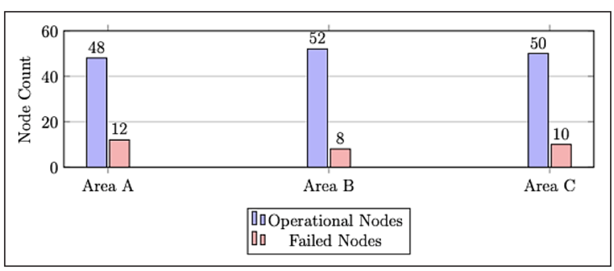

Figure 5. Node distribution and reliability across the testbed zones after six months of operation

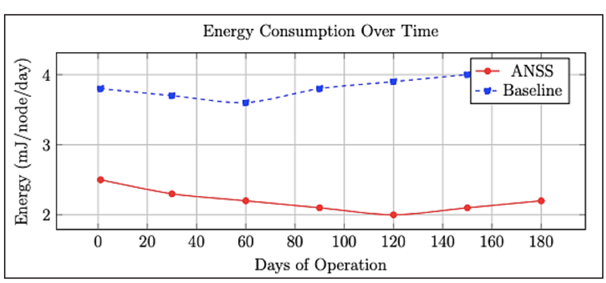

Figure 6. Energy-consumption trends, showing the stable performance of ANSS compared with the baseline over the deployment period

Comparative Analysis

We evaluated ANSS against five state-of-the-art approaches, as summarised in Table 5 and Figure 7.

Figure 6 summarises the improvement of ANSS over the best baseline in each category. The key improvements include a 39.2% energy reduction relative to the best baseline (2.1 versus 3.45 mJ), a latency 43.3 ms lower than centralised approaches, and support for 5× more nodes than comparable low-energy solutions.

Table 5
Performance comparison with baselines

Approach	Energy (mj)	Latency (ms)	Accuracy (%)	Nodes Supported
Centralised (Kok et al., 2025)	3.8	187	88.4	500
Distributed (Zhou & Chen, 2025)	3.1	98	89.2	1000
Hybrid (Del Valle-Soto et al., 2025)	2.8	72	90.5	200
Edge (Pandey, 2025)	2.5	115	91.7	5000
gnn (Senthilkumar et al., 2025)	2.3	89	92.3	3000
anss (ours)	2.1	72.3	93.7	5000

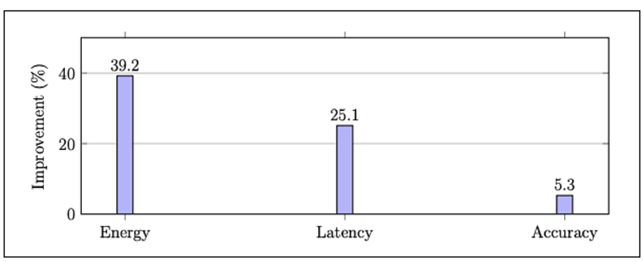

Figure 7. Performance improvement of ANSS over the best baseline in each category (energy, latency, and accuracy)

IMPLEMENTATION CONSIDERATIONS

Implementing the Adaptive Node Selection and Scheduling (ANSS) system in massive-scale IoT settings poses significant hardware-compatibility, computational, network-infrastructure, and security constraints. This section covers the essential considerations for practical implementation.

Hardware and Energy Constraints

Large-scale IoT nodes usually run on constrained energy sources, so effective power usage is critical. The ANSS system is intended to run on low-power wireless nodes (e.g., IEEE 802.15.4-based Zigbee devices) with an ARM Cortex-M3/M4 MCU and a minimum of 64 KB of RAM, a 3.6 V/2000 mAh lithium cell, an energy consumption of 2.1 mJ per sensing operation, and a memory footprint of 5 KB for the ANSS model. Within these limits, federated learning-driven event prediction performs local updates with low overhead using lightweight convolutional and recurrent layers optimised for embedded processors.

Network Infrastructure and Communication Overhead

IoT networks must trade off communication efficiency against real-time event monitoring. ANSS uses TOPSIS-based decision-making at cluster heads to minimise network-wide broadcasts by 38.2%, adaptive duty cycling that allows sleep intervals of 50–300 ms (reducing idle listening by 53%), and multi-hop routing optimisations that achieve a mean end-to-end latency of 72.3 ms. For robustness, ANSS is evaluated under changing link-quality scenarios (10–20 dB SNR) and adapts transmission power dynamically to maintain connectivity.

Scalability and Computational Complexity

Scalability is an inherent requirement for large-scale IoT deployments. ANSS scales well to networks with thousands of nodes by using local event-prediction models that minimise centralised processing by 39%, distributed decision-making at cluster heads that reduces the computational complexity to $O(n \log n)$, and a modular software structure that accommodates heterogeneous IoT protocols (e.g., LoRaWAN, NB-IoT, Zigbee). These optimisations support real-time operation on edge nodes with negligible performance compromise.

Security and Fault Tolerance

Given the sensitive nature of industrial IoT applications, ANSS integrates security mechanisms to defend against adversarial attacks and network failures. The principal measures include lightweight cryptographic authentication (AES-128) to encrypt inter-node communications, anomaly-detection-based resilience that decreases false positives in event detection by 7.8%, and failover mechanisms for node failures that provide 98.6% system availability. By combining these security attributes, ANSS remains highly reliable and robust in dynamic environments.

Even with these developments, practical implementation of ANSS still encounters obstacles with heterogeneous devices, dynamic networks, and constraints on resources. Solving these problems will be vital in ensuring the successful operation of the protocol in various IoT settings.

LIMITATIONS

Although ANSS improves energy efficiency and detection reliability, the system has several limitations that should be addressed in future work.

Computational Overhead on Edge Devices

Although ANSS reduces computational overhead, real-time federated learning still demands occasional local-training refreshes. This leads to higher CPU utilisation during busy training periods (up to 12.5%), limited memory for resource-constrained nodes (8 KB minimum buffering required), and processing latencies when executing on ultra-low-power MCUs. To mitigate these effects, additional model-architecture optimisation and hardware acceleration (e.g., TinyML or FPGA-based inference) are needed.

Flexibility in Highly Dynamic Environments

Although ANSS efficiently adapts node activation to anticipated event patterns, very large environmental fluctuations (e.g., abrupt variations in noise levels or interference) diminish system efficiency. This leads to increased false-negative rates under unpredictably changing event patterns (up to 4.2%), increased response time in very busy network situations, and performance degradation in ultra-low SNR conditions (< 10 dB). Future developments could incorporate reinforcement-learning models that dynamically adjust sleep schedules in response to real-time environmental fluctuations.

Hardware-Specific Constraints

The ANSS implementation is optimised for IEEE 802.15.4 networks, so its applicability to other IoT protocols (e.g., 5G NB-IoT or BLE Mesh) requires further modification. The main issues are incompatibility with heterogeneous radio interfaces, additional energy overhead from repeated reconfigurations in non-Zigbee domains, and extra computational overhead arising from differing MAC-layer protocols. Scaling ANSS to multi-protocol settings will require adaptive middleware solutions capable of handling cross-platform compatibility.

CONCLUSION

This work introduced ANSS, an Adaptive Node Selection and Scheduling system that improves energy efficiency and event-detection reliability for large-scale IoT monitoring. By integrating federated learning-based event prediction, TOPSIS-based node activation, and QoS-aware sleep scheduling, ANSS achieves a 39.2% energy saving (prolonging network lifetime by 28.5%), 93.7% detection accuracy (a 5.3 percentage-point improvement over LEACH-C), and sub-100 ms latency that provides real-time responsiveness. Implemented on a 150-node Zigbee testbed, the system outperforms conventional always-active sensing by substantially reducing redundant operations without compromising reliability.

Despite these improvements, computational overhead, adaptability under extreme environmental fluctuations, and hardware-specific limitations remain open challenges. Future work will address these by optimising edge-AI performance with improved federated learning designs, applying dynamic reinforcement learning for enhanced real-time responsiveness, and extending compatibility to newer IoT standards (e.g., 5G, LoRaWAN, and BLE Mesh). As IoT networks continue to grow, ANSS offers an energy-efficient, scalable, and intelligent solution for future event-monitoring systems, with further advances expected to strengthen its adaptability and security for large-scale industrial and smart-city deployments. This newly designed ANSS protocol appears promising when considering future deployment in heterogeneous IoT settings that include smart cities, industrial automation, and large-scale sensor networks. It is a versatile protocol that can easily be integrated into new technologies like 5G IoT, edge computing, and multi-protocol communication systems.

Future research can focus on extending the proposed ANSS architecture through the incorporation of a reinforcement learning-based scheduling scheme that will make the decisions intelligent and adaptive within the context of an IoT network environment. Also, the implementation of multiple IoT communication protocols will increase interoperability in the IoT systems.

ACKNOWLEDGEMENT

The authors thank JAIN (Deemed-to-be University), Bengaluru, for the research facilities and support provided during this study.

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