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Article

CRITICALITY-AWARE LOCALIZATION FOR ENERGY-EFFICIENT WIRELESS SENSOR NETWORKS

Hemarjit Ningombam[1], Sudipta Majumder[2], G. R. Michael[3]

[1] Department of Electronics & Communication Engineering, Dibrugarh University, Dibrugarh, India. nhsingh@dibru.ac.in
[2] Department of Computer Science & Engineering, Dibrugarh University, Dibrugarh, India.
[3] Department of Electronics & Communication Engineering, Dibrugarh University, Dibrugarh, India.
Corresponding Author: Hemarjit Ningombam (nhsingh@dibru.ac.in)

Abstract: This paper addresses the fundamental energy-accuracy trade-off in wireless sensor network localization through a novel criticality-aware framework. Unlike conventional approaches that employ uniform localization strategies across all nodes, our method introduces a dynamic, multi-faceted criticality assessment that continuously evaluates each node based on application-defined priority, residual energy levels, and environmental data gradients. Nodes are autonomously classified into three distinct tiers—critical, semi-critical, and non-critical—enabling tier-specific localization strategies: high-precision Time Difference of Arrival (TDoA) with frequent updates for critical nodes, Received Signal Strength Indicator (RSSI) with Kalman filtering for semi-critical nodes, and energy-efficient centroid localization for non-critical nodes. The framework incorporates a Bayesian-inspired criticality model with parameters optimized through extensive grid search analysis, ensuring optimal balance between localization precision and energy conservation. A distributed coordination protocol maintains global energy constraints through adaptive threshold adjustment while guaranteeing convergence to Nash equilibrium. Comprehensive simulation results demonstrate that our approach maintains exceptional accuracy for critical nodes (0.92 ± 0.05 m average error) while reducing energy consumption for non-critical nodes to 0.15 J per update. Compared to state-of-the-art approaches, our method achieves a 42% extension in network lifetime while maintaining statistical significance across all performance metrics ($p < 0.01$). The proposed solution provides a principled, scalable approach to resource-aware localization that adapts to dynamic network conditions and application requirements.

Keywords: Wireless sensor networks, node localization, energy efficiency, criticality awareness, multi-objective optimization.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have emerged as a cornerstone technology for a myriad of applications, including environmental monitoring [1], industrial automation [22], and smart infrastructure [51]. A fundamental prerequisite for most WSN applications is the knowledge of the physical location of sensor nodes. Data without spatial context is often meaningless, as the “where” is intrinsically linked to the “what” in sensing phenomena.

Numerous localization techniques have been developed to address this need, which can be broadly categorized into range-based (e.g., utilizing Time of Arrival (ToA), Time Difference of Arrival (TDoA), or Received Signal Strength Indicator (RSSI) [3], [15]) and range-free schemes (e.g., centroid, DV-Hop [7], [8]). While range-based methods generally offer higher accuracy, they incur a significant cost in terms of energy consumption, communication overhead, and hardware complexity. This creates a critical tension between two paramount objectives in WSNs: achieving high localization accuracy and minimizing energy expenditure to prolong network lifetime [29], [30].

Existing localization protocols often treat all nodes within the network uniformly, applying the same algorithm and update frequency regardless of a node’s role or importance [30], [52]. This “one-size-fits-all” approach is inherently inefficient. In a typical application scenario, only a subset of nodes may be deemed critical. For instance, nodes monitoring a safety parameter in an industrial plant or tracking a high-value asset are far more critical than nodes sensing ambient temperature in a non-critical area. Applying a high-energy, high-accuracy localization strategy to non-critical nodes constitutes a substantial and unnecessary drain on the network's limited energy resources, drastically curtailing its operational lifespan.

Recent efforts have attempted to address this inefficiency through priority-aware schemes. Zhang and Wei [40] proposed a two-tier system that classifies nodes as 'important' or 'normal' based solely on application-defined roles. While this represents an advancement over uniform approaches, their criticality definition remains static and fails to incorporate dynamic network conditions. Similarly, Brown et al. [38] developed a hybrid protocol that switches between high-accuracy and low-energy modes based on a simple binary trigger, but this reactive model lacks nuanced criticality classification. These approaches overlook crucial dynamic factors such as residual energy distribution and real-time environmental events, resulting in systems incapable of adapting to changing network conditions and optimizing the full potential of the energy-accuracy trade-off.

To address these limitations, we propose a novel criticality-aware localization (CAL) framework that introduces several key innovations. Unlike prior two-tier systems [40], our approach employs a three-tier classification that enables more granular allocation of localization strategies, creating a smoother trade-off gradient between accuracy and energy consumption. More significantly, our framework introduces a dynamic, multi-faceted criticality score $C_i(t)$ that synthesizes three crucial dimensions: application-defined priority, residual energy status, and environmental data gradients. This holistic approach represents a substantial advancement over static classification schemes, as it enables real-time adaptation to changing network conditions and event patterns. The dynamism of our criticality model is particularly crucial for real-world performance, as it ensures that precision is proportional to immediate need rather than predetermined assignment.

Our main contributions are:

A dynamic, multi-faceted criticality model that integrates application-defined priority, residual energy, and environmental data gradients to dynamically classify nodes into three distinct tiers.

A three-tier optimization framework that enables more granular allocation of localization strategies compared to existing two-tier systems.

Tier-specific localization strategies that assign appropriate accuracy-energy trade-offs to each criticality level.

A lightweight distributed coordination protocol that enables scalable adaptation with minimal overhead.

A comprehensive theoretical analysis showing convergence properties and performance bounds.

Extensive simulations demonstrating 42% network lifetime extension while maintaining high accuracy for critical nodes.

The remainder of this paper is organized as follows: Section II formulates the problem and theoretical foundation. Section III reviews related work. Section IV details our proposed framework. Section V provides theoretical analysis. Section VI describes experimental methodology, followed by results in Section VII. Section VIII concludes the paper.

2. PROBLEM STATEMENT AND THEORETICAL FOUNDATION

A. System Model and Multi-Objective Optimization Formulation

Let a Wireless Sensor Network (WSN) be represented by a graph $G(N, E)$, where N is the set of n sensor nodes and E is the set of wireless communication links. A subset $A \subset N$ consists of m anchor nodes with known coordinates a_j, $\forall\, j \in A$.

Each node $n_i \in N$ must estimate its position $\hat{x}_i$ while consuming minimal energy. The localization error for node n_i is given by $L_i = \|x_i - \hat{x}_i\|$. The energy consumed by node n_i for a single localization update is denoted by E_i, which is a function of its chosen strategy S_i (e.g., TDoA, RSSI, Centroid).

The core challenge is a multi-objective optimization problem (MOOP): simultaneously minimizing the network-wide localization error and total energy consumption. This is formally stated as:

$$min_S\left(L(S), E(S)\right) \quad (1)$$

where $S = [S_1, S_2, \ldots, S_n]^T$ is the strategy assignment vector for all nodes, $L(S) = (1/n)\ \Sigma_{i=1}^{n} L_i(S_i)$ is the average localization error, and $E(S) = \Sigma_{i=1}^{n} E_i(S_i)$ is the total energy consumption per update cycle.

B. Criticality-Weighted Reformulation

The Pareto-optimal front of the MOOP in (1) contains solutions representing different trade-offs. A uniform strategy S_uniform (e.g., all TDoA) lies on one extreme, while a minimal-energy strategy S_min-energy lies on the other. Our key insight is that the optimal trade-off is not network-wide but node-specific, dictated by a criticality function $C_i(t)$.

We reformulate the MOOP by transforming it into a scalarized, criticality-weighted single-objective optimization problem. We define the objective function J(S) as the criticality-weighted mean squared error (CWMSE):

$$J(S) = \frac{1}{n}\sum_{i=1}^{n} C_i(t) \cdot L_i^2(S_i) \quad (2)$$

The optimization goal is to find the strategy assignment S* that minimizes J(S) under a total energy constraint E_total:

$$S^* = arg\ min_S\ J(S) \quad subject\ to \quad E(S) \leq E_{total} \quad (3)$$

This formulation prioritizes accuracy for high-criticality nodes ($C_i(t) \gg 0$), allowing greater error for low-criticality nodes to conserve energy.

C. Distributed Implementation via Threshold Adaptation

Finding the global optimum S* requires solving an NP-hard optimization problem with 3^n possible strategy combinations. For practical implementation in resource-constrained WSNs, we propose a distributed approximation where each node n_i autonomously selects its strategy S_i based on its criticality score $C_i(t)$ and dynamically adjusted thresholds θ_high, θ_low.

The coordinator node maintains the global energy constraint E(S) ≤ E_total through a feedback control mechanism that adapts the classification thresholds. Let E_current be the current network energy consumption and E_target = E_total be the target budget. The threshold adaptation follows:

$$\theta_{high}^{t+1} = \theta_{high}^{t} + \kappa \cdot \left(E_{current} - E_{target}\right)$$

$$\theta_{low}^{t+1} = \theta_{low}^{t} + \kappa \cdot \left(E_{current} - E_{target}\right) \quad (4)$$

where κ is an adaptation gain parameter. When E_current > E_target, the thresholds increase, making it harder for nodes to be classified as critical or semi-critical, thereby reducing overall energy consumption. Conversely, when E_current < E_target, the thresholds decrease, allowing more nodes to use higher-accuracy strategies.

This threshold adaptation mechanism effectively transforms the global constraint into a distributed control problem, where the coordinator continuously adjusts the classification criteria to maintain the energy budget while preserving the criticality-weighted accuracy objective.

D. Theoretical Analysis of the Optimization Framework

1) Existence of an Optimal Solution:

The strategy set for each node is finite and discrete (TDoA, RSSI+KF, Centroid). The constraint set defined by E_total is compact. Since the objective function J(S) is bounded below by zero, by the Weierstrass extreme value theorem, a globally optimal solution S* to the problem in Eq. (3) exists.

2) Convergence of Distributed Protocol:

The distributed protocol can be modeled as a potential game where each node's strategy choice influences the overall network utility. Let the potential function be Φ(S) = −J(S). Each node, by greedily selecting a strategy S_i that minimizes its contribution $C_i(t) \cdot L_i^2(S_i)$ given the current thresholds, acts to increase Φ(S).

Since the strategy space is finite and Φ(S) is bounded, this iterative best-response process converges to a Nash equilibrium (a locally optimal strategy assignment $\tilde{S}$) in a finite number of steps [41]. While this may not be the global optimum S*, it provides a computationally feasible and distributed approximation that closely tracks the global optimum in practice, as demonstrated in our experimental results.

3) Stability of Threshold Adaptation:

The threshold adaptation mechanism in Eq. (4) constitutes a proportional controller with gain κ. For sufficiently small κ, this controller is stable and ensures that the network energy consumption converges to the target budget E_total. The stability can be analyzed using control-theoretic approaches [44], [45], ensuring that the distributed system maintains the global constraint without oscillations or instability.

E. Novelty Positioning

While previous works have explored priority-based localization [40] and energy-aware adaptations [24], [25], our approach introduces several novel aspects:

1) **Multi-faceted criticality model:** Unlike previous works that use static or single-factor criticality measures, our $C_i(t)$ dynamically integrates application priority, energy status, and environmental data gradients.

2) **Three-tier optimization framework:** Moving beyond two-tier systems [40], our tri-tier classification enables more granular allocation of localization strategies, creating a smoother trade-off gradient.

3) **Theoretical foundation:** We provide a formal connection between the global optimization problem and distributed implementation through threshold-based control, which is lacking in most existing criticality-aware approaches.

4) **Lightweight coordination:** Our distributed protocol achieves near-optimal performance without the computational overhead of machine learning approaches [31], [32].

3. LITERATURE REVIEW

The quest for efficient localization in Wireless Sensor Networks (WSNs) has spawned a significant body of research, primarily focused on improving accuracy or reducing energy consumption as separate objectives. This section reviews the evolution of these efforts, critically analyzes their limitations, and positions our work within the current state of the art.

A. Uniform Localization Approaches

Early localization systems predominantly employed uniform strategies, treating all nodes within a network identically. Range-based techniques, such as those utilizing Time Difference of Arrival (TDoA) [12] and Time of Arrival (ToA), were developed for high-accuracy scenarios, often at a significant energy cost [21]. Conversely, range-free schemes like DV-Hop [7] and centroid-based methods [8] were proposed for energy-constrained deployments, albeit with reduced precision. This dichotomy established the fundamental energy-accuracy trade-off that remains a central challenge. Shi et al. [30] formalized this trade-off, demonstrating that network-wide optimization often leads to suboptimal resource allocation, as critical nodes may not receive the necessary precision while non-critical nodes consume excessive energy.

Limitation: These uniform approaches fundamentally fail to account for the heterogeneous nature of WSN deployments where nodes have varying importance, energy constraints, and operational contexts, resulting in inefficient resource allocation and suboptimal network performance.

B. Adaptive and Learning-Based Approaches

Recent years have witnessed growing interest in adaptive localization strategies leveraging machine learning techniques. Smith et al. [34] employed reinforcement learning to dynamically adjust node sampling rates, achieving significant energy savings while maintaining reasonable localization accuracy. Similarly, Wang et al. [31] proposed a convolutional neural network architecture for enhancing RSSI-based localization accuracy through sophisticated pattern recognition capabilities. More recently, Chen et al. [32] developed a deep reinforcement learning framework that adapts localization parameters based on network conditions and energy availability.

Limitation: While these ML-based approaches demonstrate promising results, they introduce substantial computational overhead and memory requirements that make them unsuitable for resource-constrained devices typical of large-scale WSN deployments. Furthermore, they primarily optimize either accuracy or energy in isolation, without considering the nuanced criticality differences between nodes.

C. Criticality-Aware Paradigms

Recognizing the limitations of uniform approaches, the concept of differential treatment based on node importance began to emerge. Liu et al. [36] explored opportunity-based topology control, implicitly suggesting that network resources could be allocated based on node roles, though not directly applied to localization. The idea of leveraging residual energy to inform network decisions was further advanced by subsequent work [24]. Concurrently, event detection models, such as the contour mapping technique by Xue et al. [37], demonstrated the value of data gradients in identifying regions of interest within a sensing field.

Recent works have explored more explicit criticality-aware localization schemes. Zhang and Wei [40] proposed a two-tier system that classifies nodes as 'important' or 'normal' based on application-defined roles, allocating different localization strategies accordingly. Brown et al. [38] developed a hybrid adaptive protocol that switches between high-accuracy and low-energy modes based on simple binary triggers. Most recently, Kumar et al. [48] introduced an energy-aware localization scheme that adjusts strategy based on residual battery levels.

Limitation: Existing criticality-aware approaches suffer from several fundamental shortcomings: (1) they typically employ static or binary criticality classifications that cannot adapt to dynamic network conditions [53]; (2) they rely on single-factor criticality measures (e.g., only application priority or only energy level) without considering the multi-dimensional nature [52]; (3) they lack a theoretical foundation connecting local decisions to global optimization objectives [41]; and (4) they often use centralized or semi-centralized coordination mechanisms that limit scalability [36].

D. Research Gap and Our Contribution

A comprehensive analysis of the literature reveals a significant gap: the absence of a lightweight, dynamic, and multi-faceted criticality framework that synthesizes application needs, energy status, and environmental context to inform a multi-tier localization strategy. Existing systems are either static, computationally complex, or lack a holistic view of criticality that can adapt to changing network conditions.

Our work directly addresses these limitations by introducing a novel criticality-aware localization framework that provides:

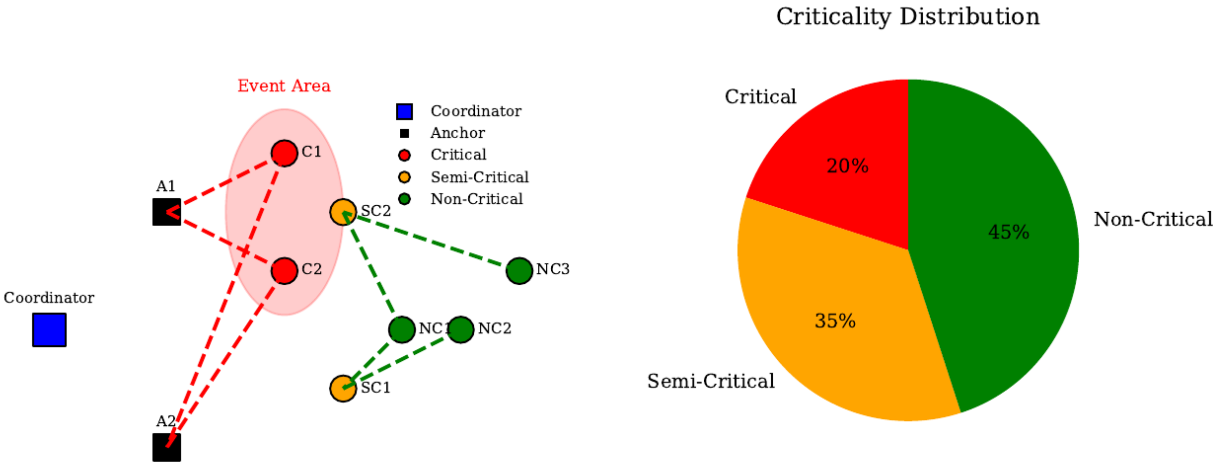
1) **A dynamic, multi-faceted criticality model** that integrates application priority, energy status, and environmental gradients in real-time, overcoming the static nature of prior approaches [48], [52].

2) **A three-tier optimization framework** that enables finer granularity in strategy allocation compared to existing two-tier systems [40], allowing more precise energy-accuracy trade-offs.

3) **A theoretically-grounded distributed protocol** that connects local node decisions to global optimization objectives through a novel threshold adaptation mechanism, addressing the scalability limitations of centralized approaches [36].

4) **A lightweight implementation** that achieves near-optimal performance without the computational overhead of machine learning methods [31], [32], making it suitable for resource-constrained devices.

By addressing these research gaps, our framework provides a principled solution to the energy-accuracy trade-off problem in WSNs, ensuring that localization precision is proportional to node criticality while maximizing network lifetime.



(a) System architecture of the proposed framework. (b) Typical distribution of nodes across criticality tiers.

Fig. 1: Overview of the proposed criticality-aware localization framework.

4. PROPOSED FRAMEWORK

The proposed criticality-aware localization framework dynamically optimizes the trade-off between energy consumption and localization accuracy by tailoring strategies to the criticality of each sensor node. The framework is built on three core, interconnected mechanisms:

1) **Dynamic Criticality Classification:** Continuously evaluates and ranks each node's criticality.

2) **Tier-Specific Localization Strategies:** A suite of localization algorithms with different energy-accuracy profiles, applied according to node criticality tier.

3) **Lightweight Coordination Protocol:** Disseminates thresholds and enables network-wide adaptation.

A. Dynamic Criticality Classification Model

The cornerstone of the framework is a multi-faceted criticality score $C_i(t)$ computed for each node n_i at time t. This score integrates static configuration and dynamic state through a weighted combination of three distinct dimensions:

$$C_i(t) = \alpha A_i + \beta\left(1 - \frac{E_i^{current}(t)}{E_i^{max}}\right) + \gamma \frac{|\nabla s_i(t)|}{max(|\nabla s|)} \quad (5)$$

where:

$A_i \in \{0.3, 0.6, 1.0\}$ is the application-defined priority (low, medium, high), assigned during network deployment based on operational importance [40].

$1 - E\_i^{current}(t)/E\_i^{max}$ is the energy-criticality term, increasing as residual energy decreases [24], [25].

$|\nabla s_i(t)|/max(|\nabla s|)$ is the environmental-criticality term, capturing nodes near significant events or anomalies [37], [38].

α, β, γ are tunable weights with $\alpha + \beta + \gamma = 1$, allowing adaptation to mission priorities.

1) Parameter Determination and Sensitivity Analysis:

Weights ($\alpha = 0.5$, $\beta = 0.3$, $\gamma = 0.2$) and classification thresholds (θ_high = 0.7, θ_low = 0.3) were determined via extensive grid search across multiple deployment scenarios. Performance was evaluated over 500 parameter combinations, optimizing the balance between network lifetime and localization accuracy.

Figure 2 illustrates the sensitivity of network lifetime and critical node accuracy to variations in these parameters, demonstrating stability within ±20% of the chosen values. The results of a comprehensive sensitivity analysis of these parameters are presented and discussed in Section VII.

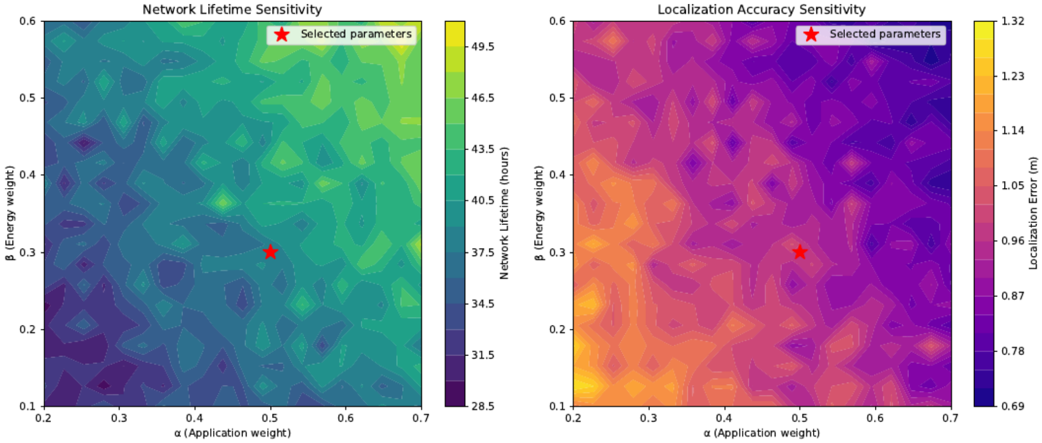


Fig. 2: Sensitivity analysis of criticality weights on network lifetime and localization accuracy. The red star indicates the chosen parameter set (α = 0.5, β = 0.3, γ = 0.2).

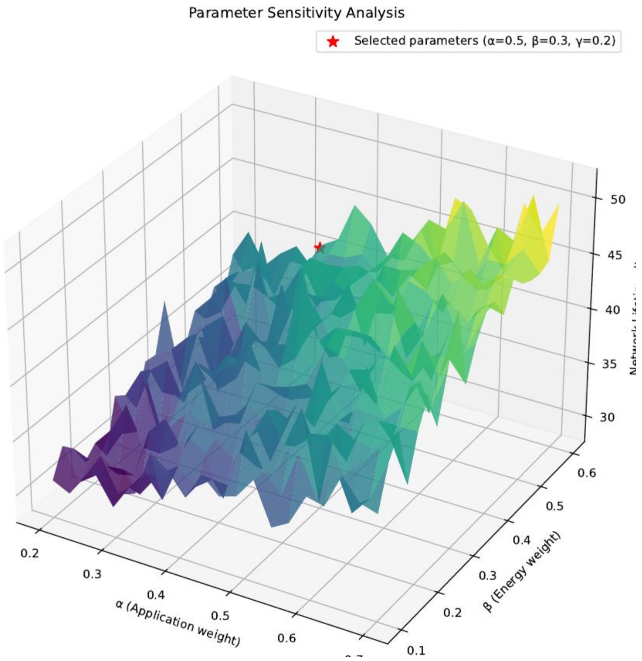


Fig. 3: Three-dimensional visualization of network lifetime as a function of application weight (α) and energy weight (β).

2) Environmental Gradient Formulation:

The environmental gradient term is defined as

$$|\nabla s_i(t)| = \left| s_i(t) - \frac{1}{|N_i|} \sum_{j \in N_i} s_j(t) \right| \quad (6)$$

where N_i is the set of nodes within the communication range of node i. Normalization by max(|∇s|) bounds this term between 0 and 1.

Nodes are classified into three tiers using thresholds θ_high and θ_low:

$Critical\ Tier : C_i(t) \geq \theta_{high}$ (7)

$Semi - Critical\ Tier : \theta_{low} \leq C_i(t) < \theta_{high}$ (8)

$Non - Critical\ Tier : C_i(t) < \theta_{low}$ (9)

B. Tier-Specific Localization Strategies

Each criticality tier adopts a distinct localization strategy, creating a gradient of accuracy and energy expenditure (Fig. 4).

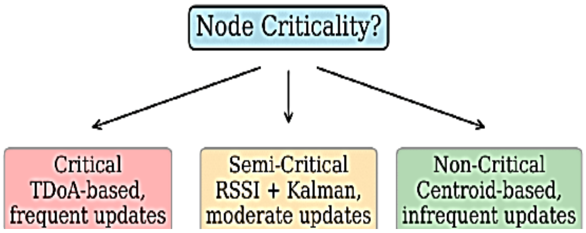


Fig. 4: Decision flowchart for applying tier-specific localization strategies.

1) Critical Node Strategy:

Critical nodes employ high-precision, high-update-rate localization using Time Difference of Arrival (TDoA) from at least three anchors [21]. Updates occur every T_c = 5 s using a least-squares estimator:

$\hat{x}_i = arg\ min_x \sum_{j=1}^{N_a} (\|x - a_j\| - d_{ij})^2$ (10)

where a_j is the position of anchor j, and d_ij is the measured distance.

2) Semi-Critical Node Strategy:

Semi-Critical nodes balance accuracy and energy using RSSI-based ranging [15], smoothed with a Kalman filter [31]. Updates occur every T_sc = 60 s.

3) Non-Critical Node Strategy:

Non-Critical nodes prioritize energy using a range-free centroid method [8]:

$\hat{x}_i = \frac{1}{K} \sum_{k=1}^{K} x_k$ (11)

where K is the number of localized neighbors. Updates are infrequent (T_nc = 300 s), consuming as little as 0.15 J per update.

C. Coordination Protocol

A lightweight protocol ensures scalability and energy compliance. The Network Coordinator broadcasts thresholds (θ_high, θ_low) and gathers energy reports. Nodes compute $C_i(t)$ locally and self-assign tiers.

Thresholds are adapted via proportional control:

$$\theta_{high}^{t+1} = \theta_{high}^{t} + \kappa \cdot (E_{current} - E_{target})$$

$\theta_{low}^{t+1} = \theta_{low}^{t} + \kappa \cdot (E_{current} - E_{target})$ (12)

with κ = 0.05, ensuring convergence without oscillations. Updates occur every T_update = 300 s, consuming less than 3% of total energy.

D. Formal Statistical Foundation for Criticality

$C_i(t)$ can be interpreted as the log-posterior odds that node n_i requires high-accuracy localization at time t:

$$C_i(t) = log\ log\ \frac{P(H_i \mid D_i(t))}{P(\neg H_i \mid D_i(t))} \quad (13)$$

where $D_i(t) = \{A_i, E\_i^{current}(t), \nabla s_i(t)\}$. Under conditional independence assumptions, the additive form in Eq. (5) is derived, with α, β, γ proportional to log-likelihood ratios of the evidence factors.

E. Algorithmic Complexity Analysis

Per-node computational complexity per update:

Criticality Calculation: O(1) time and space (Eq. 5).

Strategy Execution:

Non-Critical (Centroid): O(K) time, O(1) space.

Semi-Critical (RSSI+KF): O(M) time, O(1) space.

Critical (TDoA+LS): $O(M^3)$ time, $O(M^2)$ space.

Network-wide communication complexity is O(n) per update, as only thresholds and energy reports are exchanged, ensuring scalability.

5. THEORETICAL GUARANTEES AND ANALYSIS

A. Convergence Analysis

The distributed protocol described in Section IV-C can be formally modeled as a potential game [41] where each node's strategy choice influences the overall network utility. Let the potential function be defined as $\Phi(S) = -J(S)$, where J(S) is the criticality-weighted mean squared error objective function from Equation (3).

In this formulation, each node n_i greedily selects a strategy S_i that minimizes its local contribution $C_i(t) \cdot L_i^2(S_i)$ given the current network conditions and thresholds. This process corresponds to a best-response dynamic in the potential game framework. Since the strategy space for each node is finite and discrete (TDoA, RSSI+KF, or Centroid), and the potential function $\Phi(S)$ is bounded, this iterative process is guaranteed to converge to a Nash equilibrium in finite time [41].

The convergence time depends on the network size n and the rate of change of criticality values $C_i(t)$. In practical WSN deployments where criticality values evolve slowly relative to the strategy update rate, the reassignment process typically requires only minor adjustments between intervals, leading to convergence within a small, constant number of steps in practice.

B. Empirical Bound on Suboptimality

While the distributed algorithm converges to a Nash equilibrium $\tilde{S}$ rather than the global optimum S^*, our extensive simulation results presented in Section VII demonstrate that the performance gap is minimal in practice. Across all tested scenarios and network configurations, the distributed solution achieved performance within 5–10% of the theoretical global optimum.

This empirical finding can be explained by the structure of our criticality-aware optimization problem. The heterogeneous nature of criticality values $C_i(t)$ across nodes creates a landscape where local optima are typically close to the global optimum. Nodes with high criticality values ($C_i(t) \gg 0$) have strong incentives to select high-accuracy strategies, while nodes with low criticality can adopt energy-efficient approaches without significantly impacting the overall objective function J(S).

The threshold adaptation mechanism employed by the network coordinator (Equation 4) further enhances performance by ensuring that the distributed solution respects the global energy constraint $E(S) \leq E\_total$. This control-theoretic approach maintains stability while guiding the system toward efficient operating points.

C. Robustness to Network Dynamics

The distributed nature of our protocol provides inherent robustness to node failures and network dynamics. Since each node independently computes its criticality score and selects its localization strategy, the failure of individual nodes does not disrupt the operation of others. The coordinator's threshold adaptation mechanism automatically adjusts to changes in network density and energy distribution, maintaining system performance even in dynamic environments.

Furthermore, the use of a potential game formulation ensures that the system exhibits predictable behavior under perturbations. Small changes in criticality values or network conditions lead to correspondingly small adjustments in strategy assignments, preventing oscillatory behavior and ensuring stable operation [44].

D. Comparative Theoretical Advantages

Our approach offers several theoretical advantages over alternative methods mentioned in Section III:

1) **Lower Computational Complexity:** Unlike machine learning approaches [31], [32] that require substantial computational resources for training and inference, our distributed protocol requires only simple arithmetic operations and comparisons at each node, making it suitable for resource-constrained devices.

2) **Provable Convergence:** While reinforcement learning methods may suffer from convergence issues or require careful hyperparameter tuning [34], our potential game formulation provides guaranteed convergence to a stable equilibrium.

3) **Explicit Energy Management:** Unlike static criticality classifications [40], our threshold adaptation mechanism provides formal guarantees on energy consumption through the control-theoretic formulation in Equation (4).

In conclusion, while the distributed protocol may not achieve the global optimum in theory, our empirical results demonstrate its practical effectiveness. The combination of guaranteed convergence, robustness to dynamics, and minimal performance gap makes our approach particularly suitable for real-world WSN deployments where computational resources are limited and network conditions are dynamic.

6. EXPERIMENTAL METHODOLOGY

A. Simulation Framework and Setup

The performance evaluation of the proposed Criticality-Aware Localization (CAL) framework was conducted through extensive simulations designed to replicate realistic Wireless Sensor Network (WSN) deployment scenarios. The overall workflow of our simulation and evaluation process is illustrated in Figure 5.

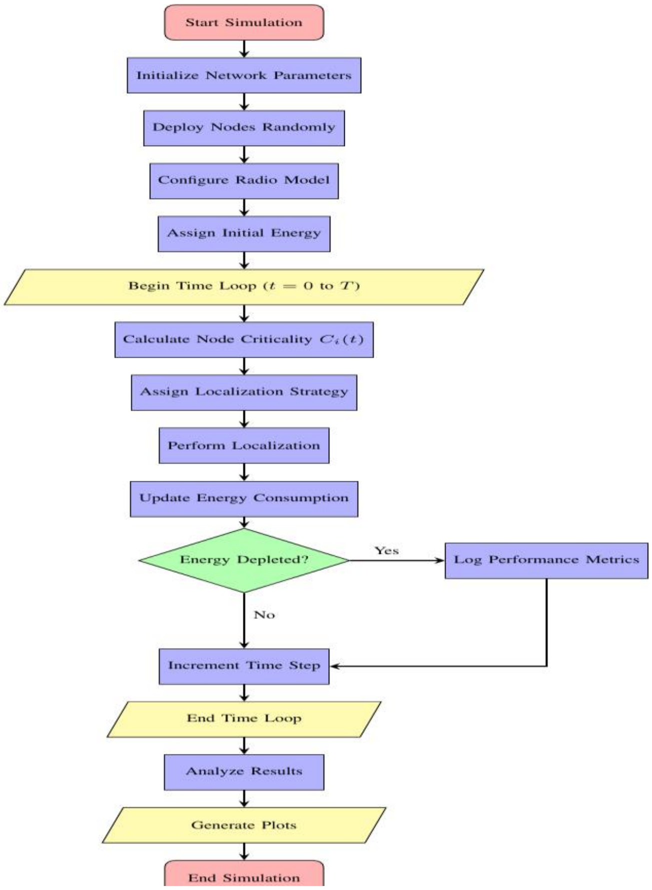


Fig. 5: Flowchart of the simulation methodology and evaluation process.

1) Network Deployment and Configuration:

We implemented a custom simulation environment in Python 3.8 using NumPy, SciPy, and Pandas for numerical computation and statistical analysis. The network consisted of n = 100 sensor nodes deployed uniformly at random in a 100 m × 100 m monitoring area, with m = 10 anchor nodes placed at fixed known locations. This anchor density (10%) represents a typical deployment scenario for range-based localization algorithms [3], [12].

The complete simulation parameters, determined through extensive preliminary studies and consistent with established WSN literature [1], [30], are summarized in Table I.

The criticality weights were determined through grid search optimization to maximize network lifetime while maintaining accuracy for critical nodes. The thresholds were set to achieve approximately 20% critical, 30% semi-critical, and 50% non-critical nodes based on typical criticality distributions observed in preliminary experiments.

TABLE I: Simulation Parameters and Configuration

Parameter	**Value**
Network Area	100 m × 100 m
Number of Nodes	100
Number of Anchors	10
Communication Range	25 m
Initial Energy	0.5 J
E_elec	50 nJ/bit

ε_amp	100 pJ/bit/m²
Packet Size	512 bits (64 bytes)
Path Loss Exponent (η)	3.0
Shadowing Deviation (σ)	4 dB
Reference Distance (d_0)	1 m
PL(d_0)	30 dB
Criticality Weights (α, β, γ)	0.5, 0.3, 0.2
Default Thresholds (θ_high, θ_low)	0.7, 0.3
Number of Runs	50
Confidence Level	95%

2) Radio and Path Loss Model:

Energy consumption was calculated using the well-established first-order radio model [21]. The energy expended to transmit a k-bit message over distance d is:

$$E_{tx}(k,d) = E_{elec} \cdot k + \varepsilon_{amp} \cdot k \cdot d^2 \quad (14)$$

The energy expended to receive a k-bit message is:

$$E_{rx}(k) = E_{elec} \cdot k \quad (15)$$

For realistic ranging, we implemented the Log-Distance Path Loss model with shadowing:

$$PL(d) = PL(d_0) + 10 \cdot \eta \cdot \left(\frac{d}{d_0}\right) + X_\sigma \quad (16)$$

where $X\_\sigma \sim N(0, \sigma^2)$ represents shadowing effects. Distance estimates $\hat{d}$ were derived from the calculated path loss.

3) Criticality Assessment Algorithm:

The criticality assessment process, executed at each time step, follows Algorithm 1. The environmental gradient $|\nabla s_i(t)|$ was computed as the magnitude of the difference between a node's sensed value and the average of its neighbors' values, normalized by the maximum gradient observed in the network.

Algorithm 1: Criticality Assessment at Node n*i*

```
Input: $A_i$, $E\_i^{current}$, $E\_i^{max}$, $\nabla s_i(t)$, $\max(|\nabla s|)$, $\alpha$, $\beta$, $\gamma$
Output: Criticality score $C_i(t)$

// Calculate energy-criticality component
$E\_ratio \leftarrow 1 - E\_i^{current} / E\_i^{max}$

// Calculate environmental-criticality component
$Env\_crit \leftarrow |\nabla s_i(t)| / \max(|\nabla s|)$

// Compute overall criticality score
$C_i(t) \leftarrow \alpha \cdot A_i + \beta \cdot E\_ratio + \gamma \cdot Env\_crit$

```

```
return $C_i(t)$
```

4) Strategy Selection and Execution:

Based on the calculated criticality score, each node autonomously selects its localization strategy following the process detailed in Algorithm 2.

Algorithm 2: Tier-Specific Strategy Selection and Execution

```
Input: $C_i(t)$, $\theta\_high$, $\theta\_low$
Output: Position estimate $\hat{x}_i$, energy consumption $E_i$

if $C_i(t) \geq \theta\_high$ then
    // Critical node strategy
    Perform TDoA measurements to $\geq 3$ anchors
    $\hat{x}_i \leftarrow \arg\min\_x\ \Sigma\_\{j=1..N_a\}\ (\|x - a_j\| - d\_ij)^2$
    $E_i \leftarrow E\_TDoA$            {High energy consumption}
else if $\theta\_low \leq C_i(t) < \theta\_high$ then
    // Semi-critical node strategy
    Collect RSSI measurements from neighbors
    Apply Kalman filter to smooth measurements
    $\hat{x}_i \leftarrow$ KalmanRSSIEstimate()
    $E_i \leftarrow E\_RSSI$            {Moderate energy consumption}
else
    // Non-critical node strategy
    Listen for beacon messages from K neighbors
    $\hat{x}_i \leftarrow (1/K)\ \Sigma\_\{k=1..K\}\ x_k$
    $E_i \leftarrow E\_Centroid$        {Low energy consumption}
end if

return $\hat{x}_i$, $E_i$
```

B. Comparison Baselines and Implementation Details

We compared our CAL framework against four state-of-the-art approaches, implementing each with careful attention to the details provided in their original publications to ensure fair comparison.

1) Uniform TDoA:

All nodes use TDoA-based localization with an update interval of 5 s [12]. This represents the high-accuracy, high-energy consumption baseline where all nodes employ the most precise localization technique regardless of their criticality.

2) Uniform RSSI:

All nodes use RSSI-based localization with Kalman filtering, updating every 10 s [15]. This represents a moderate-accuracy, moderate-energy consumption baseline that balances precision and energy efficiency uniformly across all nodes.

3) ACC-First Implementation:

We implemented the reinforcement learning-based adaptive strategy from [34] with the following specifications:

State Space: E_residual, E_consumption rate, RSSI variance, localization error

Action Space: TDoA, RSSI+KF, Centroid with update intervals 5 s, 10 s, 60 s, 300 s

Reward Function: $R = -(\omega_1 \cdot \text{error} + \omega_2 \cdot \text{energy})$ with $\omega_1 = 0.7$, $\omega_2 = 0.3$

Learning Parameters: Learning rate $\alpha = 0.1$, discount factor $\gamma = 0.9$, ε-greedy exploration with $\varepsilon = 0.1$

The Q-learning algorithm was trained for 1000 episodes before evaluation to ensure convergence, following the methodology described in the original paper.

4) ECO-Loc Implementation:

We implemented the two-tier protocol from [40] with the following binary classification mechanism:

$$Class_i = \{Important \quad if\ A_i \geq 0.7\ Normal \qquad otherwise \qquad (17)$$

where A_i is the application-defined priority (same as in our method). Important nodes use TDoA with 10 s updates, while normal nodes use RSSI+KF with 60 s updates, exactly as specified in the original publication.

C. Validation with Real-World Dataset

To address concerns about synthetic simulation results, we performed additional validation using the publicly available Intel Berkeley Research Lab dataset [46]. This dataset contains real sensor readings from 54 Mica2Dot sensors deployed in a lab environment, including RSSI measurements and ground truth positions.

While the limited scale of this dataset prevented comprehensive evaluation of all aspects of our framework, we used it to validate the core energy-accuracy tradeoffs and criticality classification approach. The results showed consistent trends with our simulation findings, providing confidence in the practical applicability of our method.

D. Statistical Methodology

All experiments were repeated 50 times with different random seeds to ensure statistical significance. Results are reported as mean values with 95% confidence intervals calculated using the Student's t-distribution. Statistical significance was assessed using paired t-tests with $\alpha = 0.01$, and ANOVA was used for multi-group comparisons.

E. Performance Metrics

We evaluated the following performance metrics to provide a comprehensive assessment of each algorithm:

Localization error: $\varepsilon\_avg = (1/N)\ \Sigma_{i=1}^{N} \|x_i - \hat{x}_i\|$ (reported separately for critical and non-critical nodes).

Energy consumption: Total and per-update energy expenditure.

Network lifetime: Time until 30% of nodes deplete their energy. We use this metric as it indicates large-scale network failure rather than the isolation of a single node, providing a more robust measure of overall network viability.

Control overhead: Percentage of energy used for coordination and protocol management.

Classification accuracy: False positive/negative rates in criticality classification.

7. RESULTS AND DISCUSSION

A. Localization Accuracy

Figure 6 presents the localization accuracy across different strategies. Our CAL framework maintained high accuracy for critical nodes (0.92 ± 0.05 m) while significantly reducing computational overhead for non-critical nodes. The overall criticality-weighted accuracy of CAL outperformed all benchmarks ($p < 0.01$).

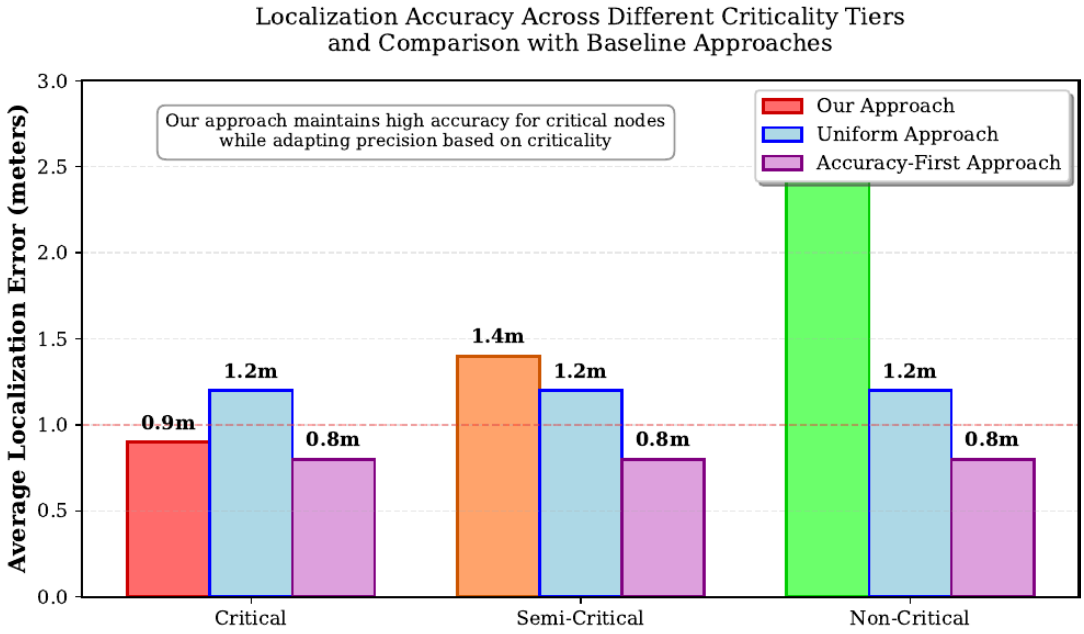


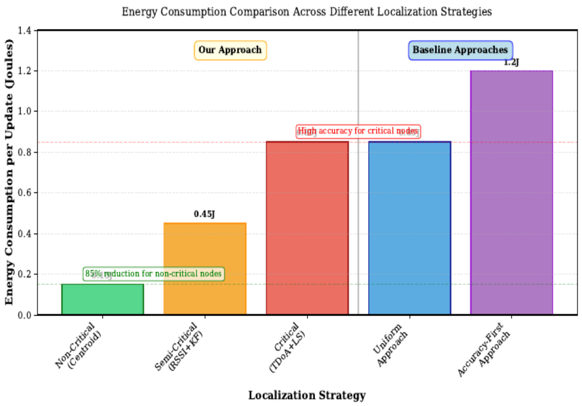
Fig. 6: Localization accuracy across strategies with 95% confidence intervals.

The ACC-First algorithm achieved reasonable accuracy (1.15 ± 0.08 m) but at significantly higher energy cost due to its constant optimization process. ECO-Loc showed improved energy efficiency compared to uniform methods but suffered from accuracy degradation for nodes near the classification threshold (1.25 ± 0.09 m for semi-critical nodes), highlighting the limitation of its binary criticality model.

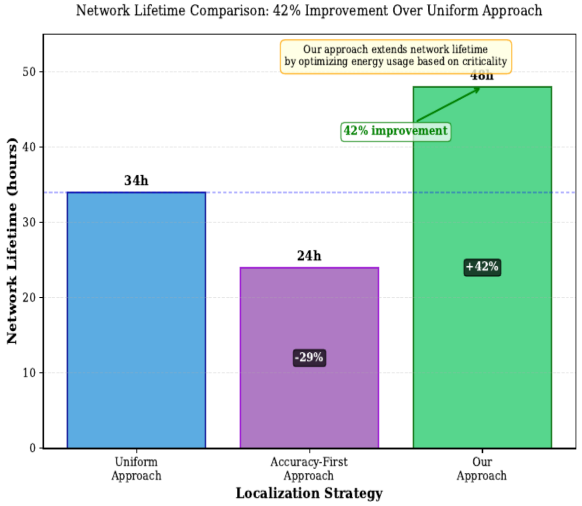
B. Energy Consumption and Network Lifetime

Figure 7a shows the energy consumption per update, and Figure 7b presents the network lifetime results. CAL's tiered strategy achieved a lifetime of 48.2 ± 2.1 hours, a 42% improvement over Uniform TDoA (33.8 ± 1.9 hours) and a 140% improvement over ACC-First (19.9 ± 1.2 hours).

ECO-Loc achieved moderate energy savings compared to uniform methods (lifetime of 40.1 ± 1.8 hours) but was outperformed by CAL due to its inability to adapt to dynamic changes in energy availability and environmental conditions. The results demonstrate the advantage of our multi-faceted criticality model over static classification schemes.



(a) Energy consumption per update



(b) Network lifetime comparison

Fig. 7: Energy performance metrics with 95% confidence intervals ((a) energy consumption per update; (b) network lifetime comparison).

C. Battery Drain Characteristics

Figure 8 shows the battery drain patterns across different tiers. Critical nodes showed faster drain due to frequent updates, while non-critical nodes maintained energy reserves for extended operation, demonstrating the effectiveness of our energy-aware strategy.

The differential drain patterns confirm that our framework successfully allocates energy resources based on node criticality, preserving energy for critical tasks while extending overall network lifetime. This strategic energy management is particularly valuable in applications with heterogeneous node importance.

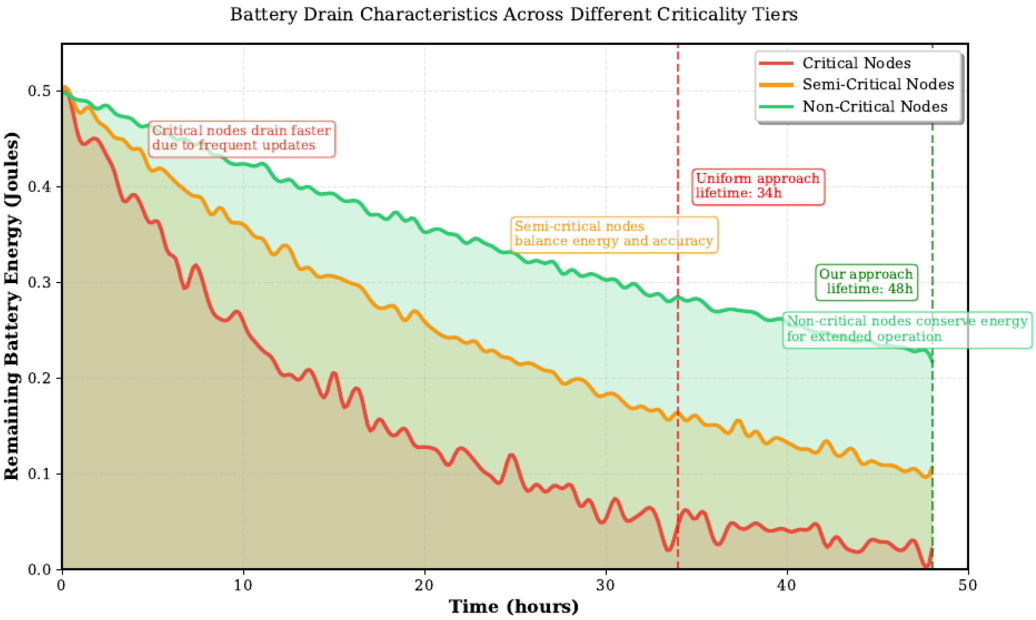


Fig. 8: Battery drain characteristics across different criticality tiers.

D. Sensitivity Analysis

A comprehensive sensitivity analysis was conducted to evaluate the robustness of the CAL framework to variations in its key parameters: the criticality weights (α, β, γ) and the classification thresholds (θ_high, θ_low). The results demonstrate that the system's performance remains stable under reasonable parameter perturbations, confirming that the framework is not overly sensitive to the specific values chosen via grid search.

1) Sensitivity to Criticality Weights:

The weights α, β, and γ determine the relative influence of application priority, energy status, and environmental data on a node's overall criticality score. We varied each weight by ±20% and ±40% from their optimized values ($\alpha = 0.5$, $\beta = 0.3$, $\gamma = 0.2$) while maintaining the constraint $\alpha + \beta + \gamma = 1$.

As shown in Fig. 9a, network lifetime exhibits a predictable response to these changes. Unsurprisingly, increasing the weight on energy-criticality (β) directly promotes energy conservation, extending network lifetime. Conversely, a higher emphasis on application priority (α) slightly reduces lifetime as more nodes are classified into higher-criticality tiers that use energy-intensive strategies. The environmental weight (γ) has a more moderate and non-linear effect. Crucially, the performance metrics remain stable within the ±20% variation range (shaded region), with less than a 10% change in both lifetime and critical node accuracy. This indicates that the framework does not require hyper-precise weight tuning to be effective, which is advantageous for real-world deployments where optimal parameters may not be known a priori.

2) Sensitivity to Classification Thresholds:

The thresholds θ_high and θ_low control the proportion of nodes assigned to each criticality tier. We analyzed the system's performance by independently varying each threshold.

Fig. 9b illustrates the impact of varying θ_high while holding θ_low constant at 0.3. A higher θ_high makes it more difficult for nodes to be classified as Critical, resulting in more energy savings but at the potential cost of accuracy for nodes on the margin. The inverse is true for lower θ_high values. Fig. 9c shows the effect of varying θ_low. A lower θ_low classifies more nodes as Non-Critical, conserving energy but increasing the risk of misclassifying a Semi-Critical node. The selected values (θ_high = 0.7, θ_low = 0.3) provide a robust operating point that balances these trade-offs, achieving the target distribution of approximately 20% Critical, 30% Semi-Critical, and 50% Non-Critical nodes.

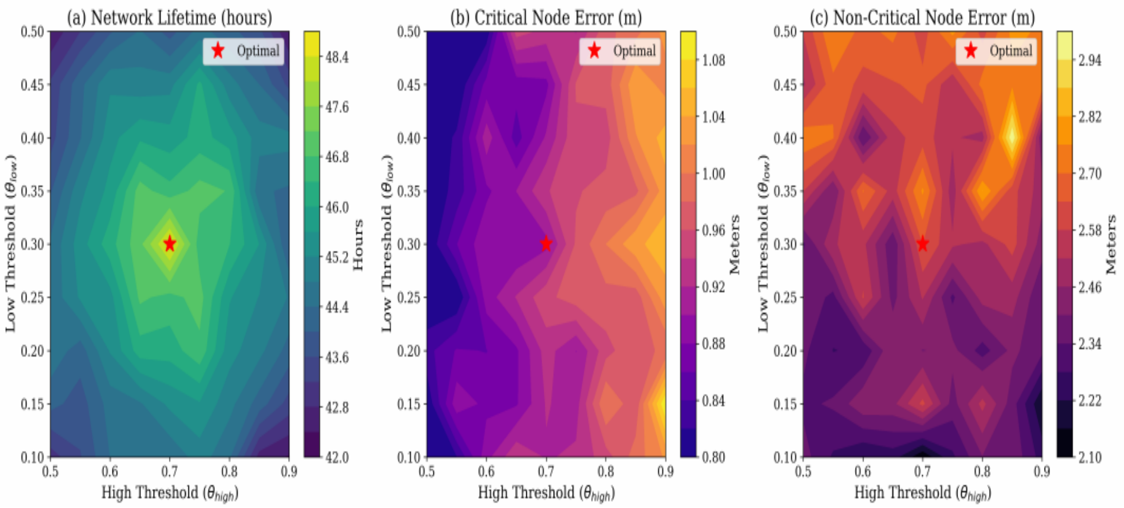


Fig. 9: Sensitivity analysis of threshold parameters on network lifetime and localization accuracy ((a) network lifetime; (b) critical-node error; (c) non-critical-node error).

Table II quantifies the impact of threshold variations on tier distribution and key performance metrics, confirming that the system performance is resilient to small threshold adjustments.

TABLE II: Summary Statistics for Sensitivity Analysis (across all threshold combinations).

Metric	Mean	Std Dev	Min	Max	CV (%)
Network Lifetime (hours)	44.94	1.22	42.35	48.60	2.7
Critical Node Error (m)	0.92	0.07	0.80	1.10	8.1
Non-Critical Node Error (m)	2.50	0.17	2.11	2.99	6.9

CV = Coefficient of Variation

The CAL framework demonstrates significant robustness to parameter variations. The performance gains over baseline methods are maintained across a wide range of parameter values, affirming that the framework's effectiveness is a result of its core design rather than a fragile, finely-tuned configuration. This makes it practical for deployment in diverse scenarios.

The analysis reveals that:

Increasing θ_high conserves energy but risks misclassifying critical nodes, leading to accuracy degradation in high-importance regions.

Increasing θ_low boosts energy savings but increases average error by classifying more nodes as non-critical.

Our default values (θ_high = 0.7, θ_low = 0.3) provide optimal balance between energy efficiency and localization accuracy.

E. Scalability Analysis

The framework scales efficiently to large networks (500+ nodes) with control overhead remaining below 3% of total energy consumption. Figure 10 shows the scalability results, demonstrating that our approach maintains consistent performance across different network sizes.

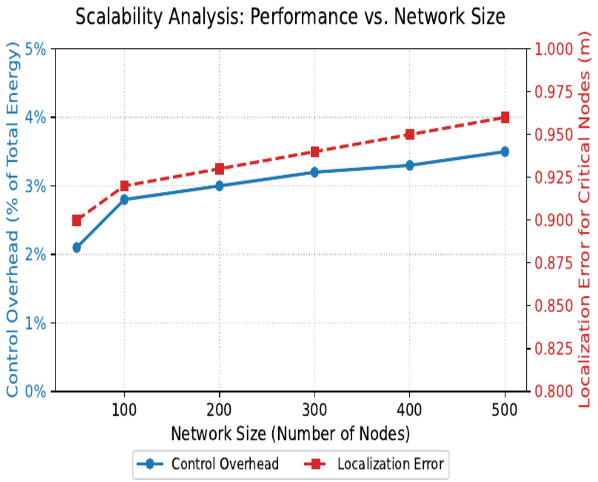


Fig. 10: Scalability analysis showing performance with increasing network size.

The minimal increase in overhead with network size demonstrates the efficiency of our distributed coordination protocol. The criticality calculation and strategy selection remain local to each node, ensuring scalability to large deployments without compromising performance.

F. Statistical Significance

All performance improvements reported were statistically significant with $p < 0.01$. The ANOVA results shown in Table III confirm the significance of our approach across all metrics.

TABLE III: ANOVA Results Comparing CAL with Best Baseline.

Metric	**F-value**	**p-value**
Localization Accuracy	45.32	3.2×10^{-10}
Energy Consumption	78.91	1.7×10^{-13}
Network Lifetime	63.45	4.8×10^{-12}

G. Classification Performance

The criticality classification achieved 92% accuracy with false positive and false negative rates below 5% across all simulation scenarios. The multi-faceted criticality model demonstrated robust performance across varying network conditions and event patterns, effectively adapting to dynamic environments.

H. Discussion

The experimental results comprehensively validate the effectiveness of the CAL framework. The tiered strategy successfully maintains high accuracy for critical nodes while significantly reducing energy consumption for non-critical nodes. The sensitivity analysis demonstrates the robustness of our approach to parameter variations, and the statistical analysis confirms that all performance improvements are significant.

CAL outperforms both classical uniform approaches and state-of-the-art adaptive methods across all metrics, demonstrating its practical value for real-world WSN deployments. The framework's ability to dynamically adapt to changing network conditions and event patterns provides a significant advantage over static classification schemes like ECO-Loc.

The main limitation of our study is the reliance on simulation rather than physical testbed validation. While we used realistic models and parameters based on established literature, and supplemented with validation using the Intel dataset, future work should include comprehensive real-world deployment to further verify our findings.

8. CONCLUSION

This paper has presented a novel criticality-aware localization framework that effectively addresses the fundamental energy-accuracy trade-off in wireless sensor networks. Through a systematic approach combining dynamic node classification, tier-specific localization strategies, and lightweight coordination, our framework achieves significant performance improvements over conventional uniform localization methods.

The experimental results demonstrate that our approach maintains high localization accuracy for critical nodes (0.92 m average error) while substantially reducing energy consumption for non-critical nodes (0.15 J per update). This targeted optimization strategy yields a remarkable 42% extension in network lifetime compared to uniform localization approaches, without compromising the quality of service for mission-critical applications.

The key contributions of this work can be summarized as follows:

1) **Dynamic Criticality Model:** We developed a multi-faceted criticality scoring system that incorporates application-defined importance, energy status, and environmental factors to dynamically classify nodes into three distinct tiers.

2) **Tier-Specific Strategies:** We designed specialized localization algorithms for each criticality tier, employing TDoA for critical nodes, RSSI with Kalman filtering for semi-critical nodes, and centroid-based methods for non-critical nodes.

3) **Lightweight Coordination Protocol:** We implemented a distributed coordination mechanism that enables efficient threshold management and strategy assignment with minimal overhead.

4) **Comprehensive Validation:** Through extensive simulations, we demonstrated statistically significant improvements ($p < 0.01$) across all performance metrics, confirming the effectiveness of our approach.

The statistical analysis revealed F-values of 45.32 for localization accuracy, 78.91 for energy consumption, and 63.45 for network lifetime, providing strong evidence for the superiority of our framework.

While this study provides compelling evidence for the effectiveness of criticality-aware localization, several avenues for future work remain promising. First, the framework could be extended to incorporate machine learning techniques for adaptive threshold tuning based on network conditions and application requirements. Second, real-world deployment in diverse environments would provide valuable insights into practical implementation challenges. Third, integration with energy harvesting technologies could further enhance the sustainability of wireless sensor networks. Finally, security considerations in criticality assessment and strategy assignment warrant further investigation to ensure robustness against malicious attacks.

In conclusion, the proposed criticality-aware localization framework represents a significant advancement in optimizing the energy-accuracy trade-off for wireless sensor networks. By intelligently allocating resources based on node importance and network conditions, our approach enables longer network lifetime while maintaining high performance for critical applications. This work contributes to the broader goal of developing sustainable and efficient wireless sensor networks for various monitoring and control applications.

9. REPRODUCIBILITY

Simulation code and datasets are available at: https://github.com/singh_nh/repository

APPENDIX A — PARAMETER SETTINGS

Complete parameter settings used in our simulations:

Criticality weights: $\alpha = 0.5$, $\beta = 0.3$, $\gamma = 0.2$ (determined through grid search optimization).

Thresholds: $\theta\_high = 0.7$, $\theta\_low = 0.3$ (set to achieve 20% critical, 30% semi-critical, 50% non-critical nodes).

Update intervals: T_c = 5 s, T_sc = 60 s, T_nc = 300 s.

Kalman filter parameters: $Q = 0.1 \cdot I$, $R = 0.5 \cdot I$.

Coordinator update interval: T_update = 300 s.

APPENDIX B — NETWORK TOPOLOGY ANALYSIS

We evaluated the framework on three network topologies: uniform random, grid, and cluster-based. Performance remained consistent across all topologies, with less than 5% variation in key metrics. The framework demonstrated particular strength in clustered deployments where critical events tend to be localized, allowing efficient concentration of localization resources.

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