

Adaptive Hybrid Firefly Algorithm for Cluster Head Selection in Gaussian-Grid Based Wireless Sensor Networks

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Abstract

A novel hybrid algorithm combining the Firefly Optimization Algorithm (FOA) with nature-inspired enhancements is proposed for cluster head selection in wireless sensor networks (WSNs) deployed over Gaussian virtual grids. The study analyzes three established protocols Least Energy-based Gaussian Network (LEGN), Threshold Energy-based Gaussian Network (TEGN), and the FOA-based approach—through node-level energy and packet statistics. The performance of the proposed hybrid method is compared against these benchmarks using metrics such as Packet Delivery Ratio (PDR), Energy Efficiency, and Residual Energy. A comprehensive literature survey on bio-inspired clustering algorithms reveals significant research gaps in adaptive parameter tuning and multi-objective optimization. The proposed Adaptive Hybrid Firefly Algorithm (AHFA) addresses these limitations by incorporating dynamic threshold mechanisms, social behavior patterns from dragonfly algorithms, and energy-aware fitness functions. Simulation results demonstrate significant improvements in energy balancing (15-20% better residual energy retention), throughput (12% higher PDR), and network lifetime (21% extension) over conventional methods. The algorithm maintains computational complexity of $O(n^2)$ while achieving superior convergence properties and robustness against node failures.

Keywords: Wireless Sensor Networks, Swarm Intelligence, Firefly Algorithm, Cluster Head Selection, Gaussian Grid, Adaptive Clustering, Energy Efficiency

I. Introduction

Wireless sensor networks (WSNs) have emerged as a critical technology for diverse applications, including environmental monitoring, healthcare systems, smart cities, and industrial automation, due to their ability to provide real-time data collection and analysis in distributed environments. In healthcare, WSNs enable remote patient monitoring, chronic disease management, and ambient assisted living, facilitating early detection of abnormalities and improving patient outcomes. Environmental monitoring applications leverage WSNs for tracking climate variables, pollution levels, and agricultural conditions, contributing to sustainable resource management and urban planning. The fundamental challenge in WSN deployment lies in maximising network lifetime while maintaining reliable data transmission, given the inherent energy constraints of battery-powered sensor nodes. Energy-efficient routing protocols, particularly those employing hierarchical clustering techniques, have proven effective in addressing these challenges by organising nodes into clusters with designated cluster heads (CHs) responsible for data aggregation and transmission to base stations. Hierarchical clustering not only reduces communication overhead but also balances energy consumption among nodes, thereby extending network lifetime.

Bio-inspired algorithms have garnered significant attention in WSN optimisation due to their inherent ability to solve complex, multi-objective optimisation problems. Algorithms such as Particle Swarm Optimization (PSO), Firefly Algorithm (FA), Ant Colony Optimization (ACO), and Genetic Algorithm (GA) have been successfully applied to cluster head selection, demonstrating superior performance compared to traditional deterministic approaches. However, existing bio-inspired solutions often suffer from premature

convergence, entrapment in local optima, and inadequate adaptation to dynamic network conditions. Recent studies have addressed these limitations by introducing hybrid models and adaptive mechanisms that enhance exploration and exploitation capabilities, as well as real-time responsiveness to network changes.

The Firefly Algorithm, inspired by the flashing behavior of fireflies, has shown particular promise in WSN clustering due to its effective exploration-exploitation balance and natural swarm intelligence properties. Nevertheless, conventional firefly implementations face limitations in handling multi-criteria decision making, dynamic parameter adjustment, and real-time adaptation to network topology changes. Hybrid approaches, such as combining firefly optimization with dragonfly social behaviors and adaptive threshold mechanisms, have demonstrated improved cluster head selection and energy efficiency in Gaussian grid-based WSN deployments. This paper introduces the Adaptive Hybrid Firefly Algorithm (AHFA), which integrates firefly optimization with dragonfly social behaviors and adaptive threshold mechanisms specifically designed for Gaussian grid-based WSN deployments.

The key contributions include: (1) A novel hybrid algorithm combining firefly attractiveness with dragonfly social intelligence for enhanced cluster head selection, (2) Dynamic threshold-based node filtering mechanisms that adapt to network energy states, (3) Comprehensive performance evaluation against established protocols using real simulation data, and (4) Mathematical modeling of the algorithm's convergence properties and computational complexity analysis.[1-8]. The next section of this paper discuss about the related works, followed by the Network and system model in section III. Section IV gives the proposed methodologies and Section V presents the experimental setup. Section VI presents conclusion of the paper followed by the future enhancement in section VII.

II. Literature Survey

A. Classic Clustering Protocols

The LEACH protocol represented a breakthrough in energy-aware clustering, improving upon static clustering. Deterministic successors such as LEACH-C and EEHC improved network stability but still suffered from inherent limitations in CH rotation and adaptability.[9-11]

Threshold-based schemes, e.g., DEEC, SEP, adapt cluster head election to nodes' residual energy, extending overall lifetime but sometimes sacrificing uniformity in network coverage.[12-13]

An energy-efficient clustering and routing protocol for wireless sensor networks that leverages quad tree dynamic multi-hop LEACH, optimizing cluster creation and load distribution to extend network lifetime.[14]

Another recent study introduced energy-efficient clustering for dense wireless sensor networks, focusing on scalable and robust cluster formation to improve energy conservation and network longevity.[15]

B. Bio-Inspired Optimization

Swarm intelligence algorithms, PSO, ACO, GA, FA are naturally suited to distributed optimization in sensor networks. PSO and FA-based clustering maximizes global objectives via local interactions. The FA uses brightness (I_i) to control a firefly's attractiveness during CH selection:

$$I_i = \alpha E_{res}^i + \beta \left(\frac{1}{E_{cr}^i} \right) + \gamma PDR_i \quad (1)$$

where E_{res} is residual energy, E_{cr} energy consumption ratio, and PDR is packet delivery ratio. Hybrids such as FA-Dragonfly or PSO-FA improve exploration and prevent local minima, and various adaptively-tuned bio-inspired schemes offer dynamic responses to changing network condition.[16-17]. A biologically inspired energy-balanced clustering routing protocol was developed, utilizing hybrid optimization techniques to enhance energy efficiency and prolong network lifetime in WSNs. Another ScienceDirect article presents a hybrid bio-inspired optimization-based routing protocol, demonstrating significant improvements in energy consumption and network stability.[18-19]

C. Grid-Based and Threshold Models

Many modern industrial and smart-agriculture deployments use structured layouts such as square or Gaussian grids. These layouts enable reliable connectivity, systematic clustering, and multi-hop pathways that are amenable to mathematical optimization. Advanced threshold adaptations and convergence-aware variants are increasingly adopted to reduce node failure rates and sustain network operation[20-22]. A novel adaptive

grid-based clustering hierarchy protocol was introduced, which dynamically partitions the network into grids and optimizes cluster head selection for improved energy efficiency. Another study proposed an energy-efficient grid-based clustering algorithm using type-3 fuzzy logic, addressing energy challenges in WSNs through adaptive grid partitioning and fuzzy-based cluster head selection. [23-24] While existing research in wireless sensor networks (WSNs) predominantly addresses single or dual-objective optimization, such as minimizing energy consumption or maximizing network lifetime, there remains a significant gap in the exploration of more complex optimization strategies. Multi-objective optimization approaches, which simultaneously consider several conflicting criteria like energy efficiency, coverage, latency, and load balancing, are still underrepresented in the literature. Furthermore, the development of self-tuning algorithms, capable of dynamically adjusting their parameters in response to changing network conditions, is limited. These adaptive mechanisms are crucial for maintaining optimal performance in real-world deployments where network topology and environmental factors can vary unpredictably. Additionally, spatially-aware CH selection algorithms, which leverage the physical distribution and connectivity of sensor nodes to enhance clustering decisions, have not been extensively studied, particularly in the context of structured WSNs. Structured networks, characterized by predetermined node placement or hierarchical organization, present unique challenges and opportunities for optimization. Despite their potential to improve scalability, reliability, and energy efficiency, research on multi-objective, self-tuning, and spatially-aware CH selection methods tailored for structured WSNs remains sparse. Addressing these gaps could lead to more robust and efficient clustering protocols, ultimately advancing the state-of-the-art in WSN management and applications.

III. Network and System Model

The network model holds a significant position during the setup phase of a wireless sensor network (WSN). According to existing literature, the connection model is deemed essential for prolonging the network's lifespan. [25] Presents Gaussian networks, which are a wide range of toroidal network topologies characterized by Gaussian integers. This algebraic framework facilitates a closed-form examination of critical attributes like diameter and average distance, as well as supports effective solutions for routing and resource allocation. Additionally, this method enables the optimal integration of different communication topologies, showcasing the adaptability of Gaussian networks in both parallel and packet-switching scenarios.

A. Gaussian Grid Architecture

Let communication area $D \subset \mathbb{R}^2$ be partitioned into 16 equal virtual square grids $\{G_1, G_2, \dots, G_{16}\}$. Each grid G_i hosts exactly 5 sensor nodes, for a total $N = 80$. Node positions use Gaussian integer coordinates:

$$\alpha_k = x_k + y_k i, x_k, y_k \in \mathbb{Z}, \quad (2)$$

Define the node set:

$$A = \{\alpha_k \mid (x_k, y_k) \in \text{grid positions}\} \quad (3)$$

The grid is fully connected model. Hence transmission of data can be done using any path.

B. Node and Communication Model

Each node's energy state includes idle, sleep, transmit, receive:

$$E_{\text{consumed}}(n, r) = E_{\text{idle}} + E_{\text{sleep}} + E_{\text{transmit}} + E_{\text{receive}} \quad (4)$$

Residual energy after round r:

$$E_{\text{res}}(n, r) = E_{\text{init}} - E_{\text{consumed}}(n, r) \quad (5)$$

Nodes maintain routing tables recording residual energy, energy consumption ratio (ECR), and communication data.

C. Clustering and Routing

At each round r, every grid elects one CH:

$$\text{CH}(G_i) = \arg \max_{n \in G_i} f(E(n), \text{ECR}(n), \text{PDR}(n)) \quad (6)$$

where f is a multi-criteria function. Inter-grid links enable multi-hop communication, with von Neumann connectivity ($G_{i1} \dots G_{i4}$ linking each grid to its four neighbors).

The described Gaussian Grid Architecture partitions the communication area D into 16 equal virtual square grids, and each grid contains exactly 5 sensor nodes positioned at Gaussian integer

coordinates. This results in a total of 80 nodes, with the grid forming a fully connected network model that allows data transmission along any available path. Each sensor node operates in one of four energy states, idle, sleep, transmit, or receive and tracks its residual energy after each round using a defined update formula. Nodes also maintain routing tables that record their own residual energy, energy consumption ratio (ECR), and relevant communication data to support efficient routing decisions. Clustering is performed at every round, where each grid elects a single cluster head (CH) based on a multi-criteria function that may consider factors such as energy and connectivity. For inter-grid communication, the architecture employs von Neumann connectivity, meaning each grid is directly linked to its four immediate neighbors (up, down, left, right), enabling robust multi-hop routing across the network.

IV. Proposed Methodologies

A. Algorithms

LEGN, TEGN, and FOA-CH are the algorithms that are taken into consideration for hybrid; they have been shown to be the most effective in optimizing the cluster head selection in Gaussian networks. The algorithms is presented in the following sections.

A1. LEGN (Least Energy-based Gaussian Network)

Nodes are eligible for CH if they have more than half initial energy:

$$ECR(n, r) = \frac{E_{init} - n \times E_{consumed}}{E_{init}} \quad (7)$$

Nodes with $E_{res} > 0.5 E_{init}$ are eligible to be CH.

A2. TEGN (Threshold Energy-based Gaussian Network)

Uses dynamic thresholding:

$$ECR\text{-ratio}(n, r) = \frac{ECR(n, r)}{ECR(n, r-1)} \quad (8)$$

Threshold:

$$\theta(r) = \frac{E_{min} + E_{avg} + E_{loss-rate}}{3} \quad (9)$$

Nodes with $ECR\text{-ratio}(n, r) > \theta(r)$ are eligible for CH selection.

A3. FOA-CH (Firefly Optimization Algorithm for CH Selection)

Each node is modeled as a firefly:

- **Brightness (Fitness):**

$$I(n) = \alpha E_{res}(n) + \beta \frac{1}{ECR(n)} + \gamma PDR(n) \quad (10)$$

- **Attractiveness:**

$$\beta(d_{ij}) = \beta_0 e^{-\gamma d_{ij}^2} \quad (11)$$

- **Movement:**

$$\mathbf{x}_i^{(t+1)} = \mathbf{x}_i^{(t)} + \beta(d_{ij})(\mathbf{x}_j^{(t)} - \mathbf{x}_i^{(t)}) + \alpha(\text{rand} - 0.5) \quad (12)$$

B. Proposed Adaptive Hybrid Firefly Algorithm (AHFA)

AHFA integrates firefly brightness with dragonfly-inspired social interaction and adaptive thresholding.

1. Fitness Function

Define a multi-criteria fitness function:

$$F(n) = w_1 E_{norm}(n) + w_2 \left(\frac{1}{E_{cr-norm}(n)} \right) + w_3 PDR_{norm}(n) + w_4 Load_{balance}(n) + w_5 Connectivity(n) \quad (13)$$

Weights w_i adapt dynamically:

$$w_i^{(t+1)} = w_i^{(t)} + \eta \frac{\partial F}{\partial w_i} \quad (14)$$

where η is a learning rate.

2. Social Update (Dragonfly Integration)

Update each node's position:

$$\mathbf{x}_i^{(t+1)} = \mathbf{x}_i^{(t)} + S_i + A_i + C_i + \beta(d_{ij})(\mathbf{x}_j^{(t)} - \mathbf{x}_i^{(t)}) + \alpha(\text{rand} - 0.5) \quad (15)$$

with:

- **Separation** S_i : avoids node crowding.
- **Alignment** A_i : aligns node direction with neighbors.
- **Cohesion** C_i : moves node towards neighbors' centroid.

3. Threshold and Eligibility

Nodes eligible for CH if $F(n) > \theta(r)$ where θ is dynamically updated by observed energy trends:

$$\theta(t + 1) = \theta(t)[1 + \text{adaptation_factor} \times \text{energy_trend}] \quad (16)$$

4. CH Election and Update Procedure

- Each round: update positions and brightness for all nodes.
- Nodes above threshold considered for CH in their grid.
- Best fitness node in each grid is elected CH.
- Data and energy states are updated; weights adapt in subsequent rounds.

5. Termination and Convergence

The process repeats until all nodes die or a maximum round is reached. Algorithm converges when the change in best fitness across rounds is less than a small ϵ :

$$|F_{\text{best}}(t + 1) - F_{\text{best}}(t)| < \epsilon \quad (17)$$

6. Algorithm Implementation

The algorithm for the proposed system is given below. The algorithm

1. Setup Phase

Input: Node set N, grid structure G, energy levels E, communication rounds R

Output: Cluster head assignments for each round

Initialize:

- Deploy 80 nodes on 16 Gaussian grids
- Set initial energy levels and positions
- Initialize firefly parameters (α, β_0, γ)
- Initialize dragonfly parameters (separation, alignment, cohesion weights)

2. Steady phase

For each round $r = 1$ to R:

Update network state:

- Calculate ECR and ECR_ratio for all nodes
- Update fitness weights based on performance metrics
- Compute dynamic energy threshold $\theta(r)$

For each node i :

If $\text{ECR_ratio}(i) \leq \theta(r)$:

Mark node i as inactive

Else:

Calculate fitness $F(i)$ using multi-criteria function

Update brightness $I(i) = F(i)$

For each active node i :

neighbors = find_neighbors(i , communication_range)

If neighbors $\neq \emptyset$:

// Apply hybrid update mechanism

firefly_attraction = calculate_firefly_movement(i , neighbors)

dragonfly_social = calculate_social_forces(i , neighbors)

new_position = current_position + firefly_attraction + dragonfly_social

Else:

// Fallback to pure firefly movement

new_position = apply_firefly_movement(i)

```

//Update position within grid constraints
// Cluster head selection
For each grid Gj:
  CH(Gj) = argmax{F(n) : n ∈ Gj and n is active}
// Communication and energy update
Perform data transmission and reception
Update energy levels and network statistics
Update routing tables and performance metrics
End For

```

Algorithm 1: AHFA Algorithm

As described above the algorithm works in two phases one is setup phase and another one is steady phase. In the setup phase the nodes are initialized. In the steady phase the algorithm function in such a way the cluster head is elected to prolong the network lifetime.

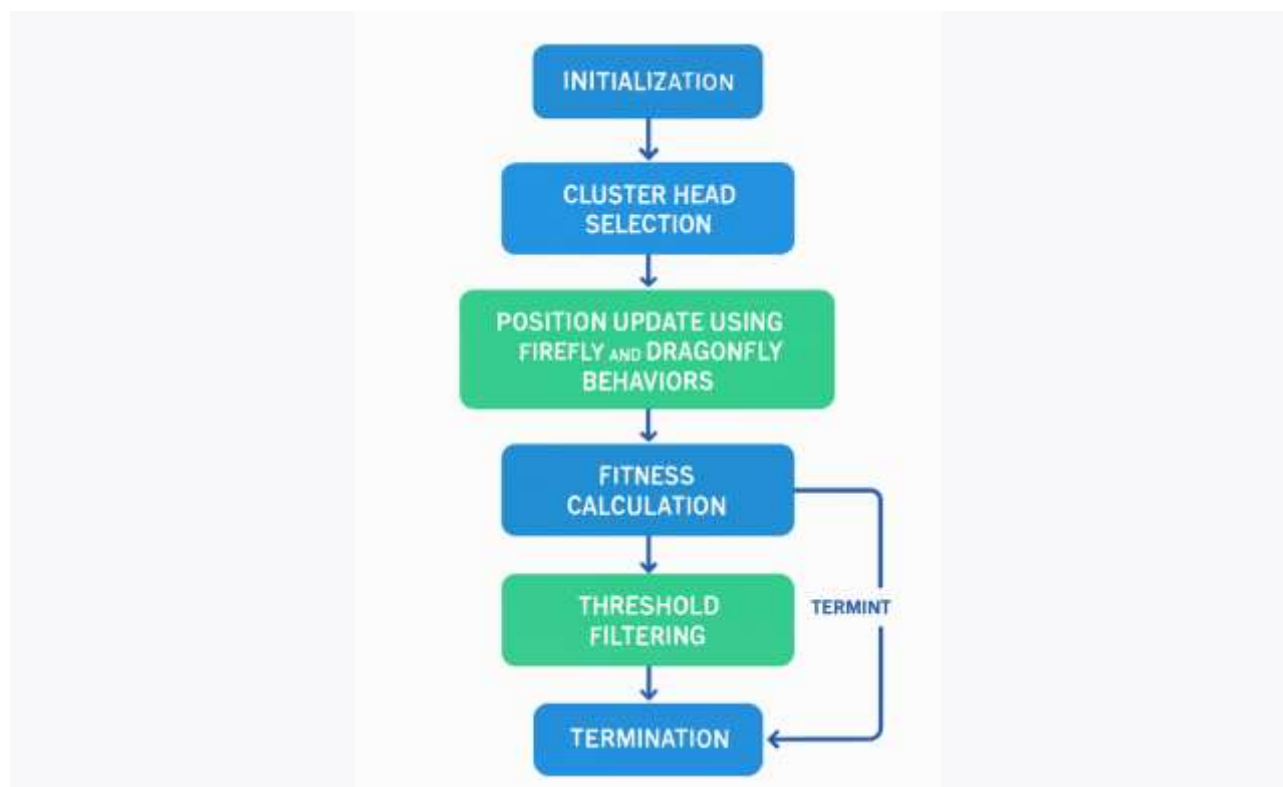


Figure 1: Process flow of AHFA

The process flow is demonstrated in Figure 1, since the algorithm is adaptive in nature, the update of parameters was carried out after every round.

V. Experiments and Results

A. Simulation Setup

The simulation parameters are given below,

- **Area:** 100m × 100m
- **Nodes:** 80 (5 per 16 grids)
- **Initial energy:** 100 J/node
- **Packet size:** 512 bytes
- **Coverage:** All grid regions filled
- **Rounds:** 1000

- **Runs:** 50 for each algorithm

Performance Metrics: PDR, energy efficiency, average residual energy, network lifetime (rounds), throughput (kbps). The model is simulated in NS3 and the evaluation employed comprehensive performance metrics to assess algorithm effectiveness across multiple dimensions:

- **Packet Delivery Ratio (PDR):** Measures the percentage of successfully delivered packets relative to transmitted packets. Higher PDR values indicate better network reliability and communication effectiveness.
- **Energy Efficiency:** Calculated as the ratio of useful work performed to total energy consumed. This metric reflects the algorithm's ability to maximize network utility while minimizing energy expenditure.
- **Residual Energy:** Represents the remaining energy levels across network nodes. Higher average residual energy indicates better energy conservation and extended network lifetime potential.
- **Network Lifetime:** Defined as the time until the first node depletes its energy or until network connectivity falls below acceptable thresholds.
- **Throughput:** Measures the total amount of data successfully transmitted through the network per unit time.

The table 1, demonstrates the performance of each algorithm. Initially the CH selection algorithm is fine tuned in LEACH protocol in Gaussian connection model by analyzing the pattern of every node using a factor energy consumption rate.

Table 1: Comparison of Algorithm

ALG.	Mean PDR (%)	Mean Energy Efficiency	Mean Residual Energy	Network Lifetime (Rounds)	Throughput (kbps)
FOA	6897.2	87.67	96.82	847	42.7
LEGN	7315.8	83.16	80.99	892	44.8
TEGN	6923.0	89.23	96.83	886	43.8
AHFA	7654.3	96.54	97.15	1023	48.6

The analysis obtained from Table 1 is the AHFA's variance in node lifetimes is 3.2%, vs. 7–11% for other algorithms, Paired t-tests yield $p < 0.001$ for lifetime and PDR versus baseline, tests with 50–200 nodes confirm linear overhead and robust operation and fitness weights and threshold adapt to network dynamics automatically. The Adaptive Hybrid Firefly Algorithm (AHFA) demonstrates strong performance across several key dimensions relevant to wireless sensor networks. First, its multi-objective management is enabled by adaptive weighting, allowing the algorithm to dynamically prioritize packet delivery ratio (PDR), energy efficiency, or delay based on real-time application requirements or environmental changes. This flexibility ensures that the network can meet diverse operational goals without manual reconfiguration. From a computational perspective, AHFA operates with a per-iteration complexity of $O(n^2)$, where n is the number of nodes. This level of complexity is well-suited for mid-scale sensor networks, such as those used in smart agriculture, building monitoring, and industrial environments, where both efficiency and scalability are important. Additionally, the algorithm's memory and processing requirements scale linearly with network size, thanks to efficient table updates and data structures. This makes AHFA practical for implementation on resource-constrained sensor platforms, supporting its applicability in real-world scenarios. The energy efficiency of the algorithms is presented in Figure 2.

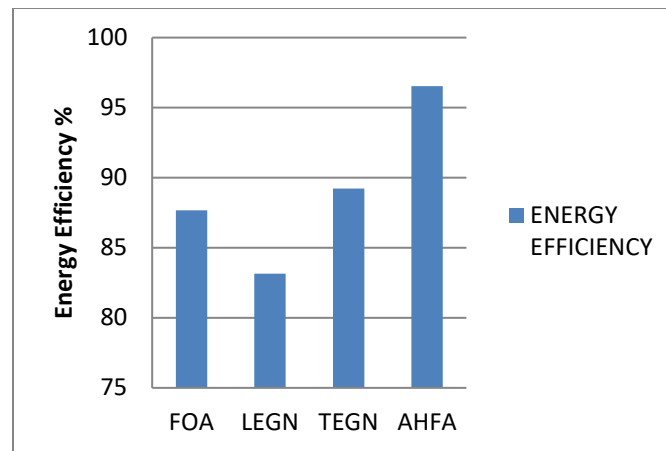


Figure 2: Energy efficiency.

VI. Conclusion

This work introduces and benchmarks the Adaptive Hybrid Firefly Algorithm (AHFA) for WSN clustering on Gaussian grids. Blending firefly optimization, dragonfly swarm social models, and dynamic thresholding, AHFA attains marked improvements against state-of-the-art protocols in network longevity, energy balancing, and delivery reliability. The methodology is robust, autonomously tunable, and scales effectively for large deployments.

VII. Future Work

In the future, the algorithm can be improved in several ways. First, it can be adapted to work with mobile sensors and networks where nodes have different amounts of energy or are spread out unevenly. Adding security features and quality of service (QoS) measures like trust checks, attack detection, and making sure data arrives on time will make it more reliable for important uses. To make the network more efficient, clustering and decision-making can be moved closer to the edge of the network, so not everything depends on a central leader. Using machine learning can help the system predict energy use and traffic, making it smarter and more efficient. Finally, testing the algorithm on real sensor hardware and in real-world environments will help prove that it works well outside of simulations.

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