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Using Intra-Cluster Elections to Reduce Computational Cost of LEACH-C Clustering Algorithm in Wireless Sensor Networks

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Abstract--Wireless Sensor Networks (WSNs) play a critical role in diverse applications, ranging from environmental monitoring to military surveillance. Clustering techniques are essential for optimizing energy consumption and improving data transmission efficiency in WSNs. This paper introduces the Intra-Cluster Election (ICE) technique, which enhances centralized clustering protocols within the LEACH-C (Low-Energy Adaptive Clustering Hierarchy-Centralized) framework. ICE improves cluster head selection by optimizing the cost function value and reducing convergence iterations. Although the improvements in energy efficiency and data delivery rates are modest compared to LEACH-C, primarily because its cost function does not account for the distance between cluster heads and the base station, ICE demonstrates significant advantages in optimization. The simulation results show that ICE substantially improves cluster head selection, leading to more efficient network operations across various WSN scenarios. It achieves approximately 12–20% improvement in the cost function compared to LEACH-C and reduces the number of required iterations by a factor ranging from 3 to 100, depending on the network conditions.

***Index Terms*--Wireless Sensor Networks (WSNs), Intra-Cluster Election (ICE), Cluster Head Selection, Centralized Clustering Protocols, Low-Energy Adaptive Clustering Hierarchy (LEACH), LEACH-Centralized (LEACH-C), Optimization Techniques, Network Efficiency.**

I. INTRODUCTION

Wireless Sensor Networks (WSNs) have emerged as a pivotal technology in various domains, including environmental monitoring, healthcare, military applications, and smart cities [1]. These networks consist of numerous sensor nodes that gather data from their surroundings and transmit it to a central processing unit or base station for analysis. Depending on the application, various types of sensors are employed in WSNs, including temperature, humidity, chemical, motion, and optical sensors, each offering specific advantages in terms of sensitivity, responsiveness, and integration capabilities [2], [3], [4]. The deployment of sensor nodes in diverse and often remote environments poses several challenges, particularly concerning energy consumption, data transmission efficiency, and network longevity. As sensor nodes are typically battery-powered, optimizing energy usage becomes critical to prolonging the network's operational lifespan.

Clustering is a widely adopted strategy in WSNs aimed at enhancing energy efficiency and optimizing data transmission [5]. By grouping sensors into clusters, where each cluster has a designated leader or cluster head, the network can reduce the number of transmissions to the base station, thus conserving energy. This architecture facilitates more organized data collection, as cluster heads can aggregate data from their members before sending it to the base station, minimizing communication overhead and extending the network's lifetime [6], [7].

Among the various clustering protocols, the Low-Energy Adaptive Clustering Hierarchy (LEACH) has been a pioneering model that significantly improves energy efficiency in WSNs [8]. LEACH employs a distributed approach, where cluster heads are selected randomly, ensuring balanced energy consumption throughout the network. This method helps prevent premature node depletion; however, it has limitations, particularly regarding scalability and energy management, especially as network density and size increase.

To address these challenges, an enhanced version of LEACH called LEACH-C (Centralized LEACH) has been

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developed [9], [10]. (LEACH-C) protocol enhances the clustering process by considering both the energy levels of nodes and their distances from the cluster heads when selecting CHs [10]. While LEACH-C effectively balances energy consumption among nodes, it still faces challenges in achieving optimal performance due to the number of iterations required for convergence [11].

In this paper, we introduce a novel technique called Intra-Cluster Election, which enhances the cost function value in the clustering process, leading to improved optimization results with fewer iterations. This approach can be applied to nearly any centralized protocol to increase optimization efficiency with lower iteration counts. We use LEACH-C to implement our technique and assess its performance with an intra-cluster election variant, LEACH-C-ICE. The comparison criteria include cost function value, remaining energy in nodes, network longevity, and overall data delivery rate. Results show that the proposed scheme delivers slightly better performance, particularly as network scale increases, while reducing the number of iterations in the optimization algorithm.

II. Related Works

Wireless Sensor Networks (WSNs) rely heavily on efficient data transmission and energy conservation due to the limited battery life of sensor nodes. Clustering has been recognized as an effective strategy to improve these factors by reducing communication overhead and extending network lifespan. This section reviews several notable clustering protocols and enhancements in WSNs.

A. LEACH Protocol

LEACH is one of the earliest and most influential clustering protocols designed for WSNs. Proposed by Heinzelman et al. (2000), this protocol employs a randomized rotation of cluster heads to evenly distribute energy consumption across the network [6]. While LEACH has demonstrated significant improvements in energy efficiency, its reliance on random selection of cluster heads can lead to inefficiencies in densely populated networks, where energy usage may not be optimally balanced.

B. LEACH-C

To address the limitations of LEACH, Heinzelman et al. (2002) introduced LEACH-C (Centralized LEACH), which determines cluster heads based on local energy levels and their distances to all other nodes. This centralized approach allows for better energy management and cluster formation but may require multiple iterations to converge on an optimal configuration. As a result, network performance can suffer with increased iteration counts, impacting real-time data transmission [10].

C. HEED Protocol

Younis and Fahmy (2004) proposed HEED (Hybrid Energy-Efficient Distributed Clustering), which balances energy consumption by considering residual energy and communication costs when electing cluster heads [7]. Unlike LEACH and LEACH-C, HEED uses a hybrid approach to cluster formation, improving scalability and robustness in network performance. It ensures that energy-efficient paths to the base station are utilized, thus enhancing network longevity.

D. Enhanced Clustering Techniques

Various enhancements to clustering protocols have been proposed to optimize energy usage and improve performance.

An extension of the original LEACH protocol, LEACH-F incorporates feedback mechanisms to provide an additional layer of energy efficiency. By allowing cluster heads to communicate their energy levels back to the nodes, the protocol can adjust the selection criteria dynamically based on real-time data [10]. This adaptation helps prolong network lifetime by preventing the premature death of nodes.

Ramesh et al. (2020) explored a fuzzy logic-based clustering approach that dynamically adjusts the criteria for selecting cluster heads based on energy levels, distance, and node mobility [12]. This method allows for a more nuanced selection process that considers multiple factors, enhancing the adaptability and efficiency of the clustering process amidst changing network conditions.

Hatamian et al. (2015) introduced a Centralized Evolutionary Clustering Protocol (CECP), utilizing a Genetic Algorithm (GA) to select optimal CHs based on residual energy, outlier nodes exclusion, and total edge weight [13]. Gupta and Jana (2015) proposed a genetic algorithm-based clustering method considering nodes' residual energy and distance from CHs [14]. Zhang et al. (2014) used SA and GA algorithms for clustering nodes. The CH selection technique is based on the average cluster energy comparison [15].

Latiff et al. (2007) implemented a distributed clustering algorithm using Particle Swarm Optimization (PSO) [16]. This method focuses on optimizing the placement of cluster heads by simulating social behavior patterns. The PSO-based approach yielded substantial improvements in both energy efficiency and network longevity, particularly in scenarios with high node densities.

Guru et al. (2005) introduced a clustering scheme using PSO that selects CHs based on distance from the BS and intra-cluster distance, but neglects nodes' residual energy [17]. Also, Singh et al. (2012) introduced PSO Semi-Distributed (PSO-SD), which considers residual energy, distance, and node density in clustering [18]. Rao et al. (2017) presented a PSO-based Energy Efficient Cluster Head Selection (PSO-ECHS) algorithm, which considers the distance to BS, intra-cluster distance, and residual energy for CH selection and cluster formation to enhance network lifetime [19]. Ali et al. (2021) introduced ARSH-FATI CH selection and novel ranked-based clustering (NRC) for cluster formation, emphasizing residual energy, distances, and workload on CHs for enhancing network lifetime [20].

E. Hybrid Memetic Algorithms

Chawda and Gupta (2020) proposed a composite cost function based on node parameters such as degree, intra-cluster communication cost, and residual energy. This approach aims to improve load balancing and prolong network lifetime, with the advantage of incorporating multiple key metrics in the cluster head selection process. However, one major drawback is its computational complexity; repeated evaluations of the cost function exhibit a time complexity of approximately $\mathcal{O}(\mathrm{N} \times K)$, which tends toward $\mathcal{O}(\mathrm{N}^2)$ in large-scale networks, posing a significant challenge for practical deployment [21].

Ahmad and Shah (2021) presented a clustering framework based on a memetic algorithm for wireless sensor networks. Their approach considers a combination of residual energy, node degree, and mobility to create stable and energy-efficient clusters. A key advantage lies in its adaptability to dynamic topology changes and its ability to prevent premature convergence. Nevertheless, evaluating the cost function and executing the local search phase, both with complexity around $\mathcal{O}(\mathrm{N} \times K)$, introduces significant computational overhead, especially in larger networks [22].

Zhang and Lan (2025) introduced an adaptive routing protocol that combines Multi-Parent Differential Evolution (MPDE) with Variable Step-Size Local Search (VSSLS). This hybrid strategy improves cluster head selection accuracy and mitigates premature convergence by leveraging both global and local search capabilities. However, the main limitation is the computational burden: complex cost function calls and nested loops in the local search phase significantly increase execution time, particularly in large-scale sensor networks [23].

Building on existing work in WSN clustering, our proposed technique, Intra-Cluster Election, enhances energy optimization within the clustering process of LEACH-C by refining the selection of cluster heads based on intra-cluster dynamics. This method reduces the number of iterations required for convergence, resulting in better performance metrics such as remaining energy in nodes, network longevity, and overall data delivery rate as evidenced in our comparative analysis with LEACH-C-ICE. In terms of complexity, the proposed method is also compared to the approach introduced by Zhang and Lan (2025) [23].

The growing body of research in clustering protocols for WSNs demonstrates the importance of developing efficient algorithms that both conserve energy and facilitate reliable data transmission. Our work aims to contribute to this field by introducing the Intra-Cluster Election technique, which improves upon traditional methods by minimizing iteration counts while maximizing network efficiency.

III. Preliminaries

This section briefly presents the network model, energy model, Leach-c, and simulated annealing used in this study.

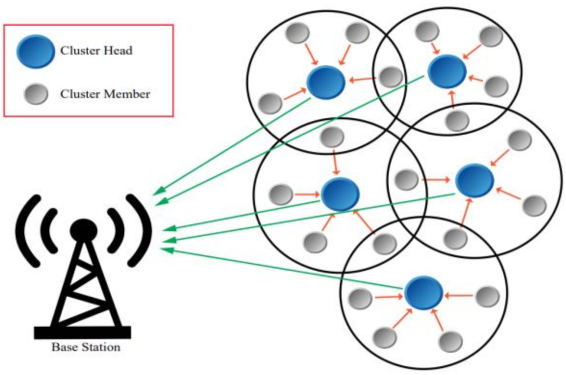

Fig. 1. A cluster based WSN model utilized in this study.

A. Network Model

The study focused on a two-hop WSN with BS and N uniformly distributed sensors. The network structure is illustrated in Fig. 1 and key assumptions are as follows:

- BS has unlimited energy and high computing power for calculations.
- Sensors know their position and BS's position and can directly communicate with BS.
- All sensors start with the same energy and can adjust transmission power based on distance.
- Sensors use TDMA (Time Division Multiple Access) to prevent collisions and decrease energy usage [24].
- No data aggregation was applied to the cluster header. But it can be considered to reduce energy consumption.
- Sensors measure surroundings within a fixed radius and then send data to their CH.

B. Energy Model

The energy model in this study is based on [6]. Sensors consume the most energy in their transmitter and receiver circuits. This energy is divided into three categories: the required energy of power amplification for the transmitter, the transmitter's electronic circuits, and the receiver's electronic circuits. The energy required during transmission includes the transmitter's electronic circuits and signal amplification, while during reception, it refers to the energy used by the receiver's electronic circuits. The corresponding equations are as follows:

$$E_{\mathrm{Tx}}(l,d) = \begin{cases} lE_{\mathrm{elec}} + l\epsilon_{\mathrm{fs}}d^2, & if \quad d < d_0 \\ lE_{\mathrm{elec}} + l\epsilon_{\mathrm{mp}}d^4, & if \quad d \geq d_0. \end{cases} \tag{1}$$

where l is the number of bits to be transmitted and E_{elec} is the energy consumed by the electronic circuits for receiving/sending one bit of information. ϵ_{fs} represents the energy required to amplify one bit of transmitted data, when the distance between the transmitter and receiver is less than d_0 and ϵ_{mp} represents the energy required to amplify one bit of transmission when the distance is greater than or equal to d_0. d_0 is the threshold diffusion distance is equal to:

$$d_0 = \sqrt{\frac{\epsilon_{\mathrm{fs}}}{\epsilon_{\mathrm{mp}}}} \tag{2}$$

The energy consumption of a sensor in the receiving mode for receiving 1 bit of data is calculated as follows:

$$E_{\mathrm{Rx}}(l) = lE_{\mathrm{elec}} \tag{3}$$

where E_{elec} is the energy required by electronic circuits to receive one bit of data.

C. Leach-c Overview

LEACH-C (Centralized LEACH) is an improved version of the LEACH protocol, specifically designed to enhance energy efficiency and extend the operational lifetime of wireless sensor networks (WSNs). Unlike its predecessor, LEACH-C employs a centralized approach for selecting cluster heads, taking into account the energy levels and distances of the sensor nodes to CH's. This section outlines the structural components of LEACH-C and its optimization algorithm (Simulated Annealing (SA)) as a method for optimizing cluster head selection.

During the setup phase of LEACH-C, each node sends information about its current location and energy level to the base station. The base station runs an optimization algorithm to determine the clusters for that round. The clusters formed by the base station will in general, be better than those formed using the distributed algorithm. [10]

Determining optimal Cluster Heads from the nodes is a problem that is known to be NP-Hard [25]. Optimization algorithms, such as tabu search [26] or simulated annealing [27], can be used to approach the optimal solution in polynomial time. LEACH-C uses simulated annealing to determine CHs [10].

In addition to determining good clusters, the base station needs to ensure that the energy load is evenly distributed among all the nodes. To do this, the base station computes the average node energy, and whichever nodes have energy below this average cannot be cluster-heads for the current round. Using the remaining nodes as possible cluster-heads, the base station runs a simulated annealing algorithm to determine the best k nodes to be cluster-heads for that round. Once the cluster heads are identified, the remaining nodes join the nearest cluster based on the total sum of squared distances between all the non-cluster-head nodes and the closest cluster-head to minimize the amount of energy the non-cluster-head nodes.

The cost function of LEACH-C $f(C)$ is as follows:

$$f(C) = \sum_{i=1}^{N} \min_{c \in C} d^2(i,c) \tag{4}$$

where $d(i,c)$ is the distance between nodes i and CH c.

Once the optimal cluster-heads and associated clusters are found, the base station transmits this information back to all the nodes in the network. This is done by broadcasting a message that contains the cluster-head ID for each node. If a node's cluster-head ID matches its own ID, that node takes on the cluster-head role; otherwise, the node determines its TDMA slot for data transmission and goes to sleep until it is time to transmit data to its cluster-head. The steady-state phase of LEACH-C is identical to LEACH.

Cluster heads are responsible for gathering data from their member nodes and aggregating it. This aggregation process effectively reduces data redundancy, and the consolidated information is subsequently transmitted in a single packet to the base station, significantly conserving energy compared to transmitting individual packets.

In the following, the simulated annealing is described.

D. Stimulated Annealing

Simulated Annealing (SA) is a probabilistic technique used for approximating the global optimum of a given function. It is particularly effective for large search spaces where traditional optimization methods may struggle.

The SA algorithm is inspired by the annealing process in metallurgy, where a material is heated and then slowly cooled to remove defects and optimize its structure. The algorithm can be summarized as follows:

- **Initialization**:
  - Start with an initial solution (C_0).
  - Set the initial temperature (T_0).
- **Iteration** (Repeat until the stopping criterion is met):
  - Generate a new candidate solution (C') by making a small random change to the current solution (C).
  - Calculate the change in the cost function ($\Delta f = f(C') - f(C)$).
  - If ($\Delta f < 0$), accept the new solution (C').
  - If ($\Delta f \geq 0$), accept the new solution (C') with a probability ($P = \exp\left(-\frac{\Delta E}{T}\right)$).
  - Decrease the temperature (T) according to a cooling schedule.
- **Cooling Schedule:**
  - A common cooling schedule is ($T = T_0 \cdot \alpha^k$), where (α) is a constant ($0 < (\alpha) < 1$) and (k) is the iteration number.

Detailed information about the SA algorithm is provided in [27].

The proposed technique aims to enhance cluster head selection in each round of the protocol by achieving more optimal values with fewer iterations. It is designed to be independent of specific clustering protocols and optimization algorithms, making it applicable to various centralized clustering protocols that utilize evolutionary optimization methods. The paper will focus on applying and comparing this scheme with the LEACH-C protocol. The proposed technique will be presented in the next section.

IV. Proposed Technique

One issue with WSN clustering algorithms is the vast search space, which often prevents the optimization algorithm from achieving the desired optimal value, despite numerous iterations and particles. For instance, consider a WSN comprising 200 nodes that need to be clustered into 15 clusters. The total number of possible states is:

$$C_K(N) = \binom{N}{K} = \frac{N!}{K!\,(N-K)!} \Rightarrow C_{15}(200) \approx 1.462 \times 10^{22}$$

A SA algorithm with 1000 iterations explores about 1000 states, and the likelihood of achieving a global optimum value is negligible.

In response to this challenge, the article introduces an innovative method termed intra-cluster election, which operates in the following subsection for each CH derived from the SA algorithm. Before explaining the proposed scheme, key terms were defined for clarity.

A. Definitions

The definitions used in this study will be defined as follows:

1. $\mathbb{S}$: is a set of sensor nodes such that $\mathbb{S} = \{s_1, s_2, \dots, s_N\}$. N represents the number of sensors, and s_i represents the sensor i witch $0 < i \leq N$.
2. $\mathbb{CH}$: is a set of cluster heads in such a way that $\mathbb{CH} = \{\mathrm{ch}_1, \mathrm{ch}_2, \dots, \mathrm{ch}_K\}$. K represents the number of clusters, and $K < N$. Also, ch_j represents the cluster head j and $0 < j < K$.
3. $\mathbb{C}$: The set of clusters in such a way that $\mathbb{C} = \{\mathrm{C}_1, \mathrm{C}_2, \dots, \mathrm{C}_\mathrm{K}\}$. Similarly, C_j also represents the cluster j, and its cluster head is ch_j.
4. d_0: The threshold distance of the sensors in the transmission energy calculation.

After defining the terms used in this study, the next section will introduce the intra-cluster election.

B. Intra-Cluster Election

In the proposed scheme, since each solution is equivalent to a selected CH and each CH of this set has several members, an additional step called intra-cluster election is considered. In this way, for each solution, after calculating a cost, an intra-cluster election is conducted. In this selection, for each cluster, the cluster cost function if any member of that cluster becomes a CH is calculated using (5), and the member with the highest value is selected as the CH of that cluster. After updating the CH, the clustering process is re-executed with the updated CH and then the best value is considered as the final solution for that iteration.

$$f(C_j)\,|c_m = \mathrm{sum}\{d^2(s_i, c_m) : \forall\, s_i \in C_j\} \tag{5}$$

The intra-cluster election causes the search space to be split into smaller spaces. This work allows the local points of the range of each particle to be checked more precisely, and the best CH is selected to achieve more optimal solutions with a lower number of iterations and particles.

C. Proposed Scheme

Similar to LEACH and LEACH-C, the proposed scheme has two phases: setup and steady-state [28]. The setup phase involves CH selection, cluster formation, and sending cluster information to CHs, which are performed at BS. Also, in the setup phase CHs store member lists, establish TDMA schedules, and share these with members. Then sensors wait for their turn to transmit data. In the steady-state phase, sensors perform sensing tasks and transmit data to CHs at predetermined intervals. CHs collect and relay data to BS without aggregation, although considering aggregation could reduce energy consumption. After data transmission, CHs switch to idle mode until the next scheduled interval. The cycle continues until the steady-state phase ends.

The proposed scheme is implemented at the start of each round during the setup phase. The full procedure of the scheme is depicted in Fig. 2 and includes the following steps:

- Setup Phase
  - **Receive nodes' information:** Sensors send their location and residual energy to BS.
  - **Calculate N_{tpr}:** BS calculates the number of transmissions per round during the initial round. This work reduces overhead by minimizing the setup phase counts and improves network QoS by adjusting transmission counts based on the nodes [10]. BS computes the number of transmissions per round (Ntpr) using (6), which is taken from [10].

$$N_{\text{tpr}} = \frac{\frac{E_{\text{Init}}}{l}}{\frac{N_0}{K}\left(E_{\text{elec}}+\epsilon_{\text{mp}} d_{\text{BS}}^4\right)+\left(\frac{N_0}{K}-1\right)\left(2E_{\text{elec}}+\epsilon_{\text{fs}}\frac{M^2}{2\pi K}\right)} \qquad (6)$$

Where E_{Init} is the initial energy of sensor nodes, N_0 is the initial number of sensors, K is the number of clusters and is calculated using (7), M is the network area, and d_{BS} is the average distance of the sensors from BS.

  - **Calculate the number of clusters (K):** Then BS calculates the number of clusters using (7) which is taken from [29].
  -

$$K = \sqrt{\frac{N}{2\pi}} \times \frac{2}{0.765} \qquad (7)$$

Where N is the number of sensors.

  - **SA:** Such as LEACH-C, BS utilizes SA to find optimal clusters. This part includes the following steps:
    - ∗ **Initialize section:** The first step is to initialize SA parameters. A random $\mathbb{CH}$ will be generated, $\mathbb{C}$ obtained by joining nodes to the nearest CH and then $f(\mathbb{C})$ will be calculated using (4). After that, a new $\mathbb{CH}'$ will be generated by randomly changing some of the CHs from $\mathbb{CH}$, then $\mathbb{C}'$ is obtained with these $\mathbb{CH}'$.
    - ∗ **Calculate Δf:** In this step, $f(\mathbb{C}')$ and $\Delta f = f(\mathbb{C}') - f(\mathbb{C})$ will be calculated and the solution stored as Fit 1.
    - ∗ **Intra-cluster election:** After cluster formation, an election is performed in each cluster to select the best CHs.
    - ∗ **Best Solution:** after updating $\mathbb{CH}'$**,** $\mathbb{C}'$ and $f(\mathbb{C}')$ are calculated again, and the solution is stored as Fit 2. The best solution for that iteration is $\arg\min(\text{Fit1}, \text{Fit2})$. Then, the next iteration begins, and upon reaching the maximum iterations, SA outputs the optimal $\mathbb{CH}$ and $\mathbb{C}$.
  - **Transmit clustering information:** After completing the clustering process, BS distributes this information across the network along with N_{tpr}. Then, the network enters the steady-state phase based on this clustering.
- **Steady-state Phase:** The steady-state phase consists of measuring and transmitting data frames to the BS at scheduled intervals through designated $\mathbb{CH}$. This phase will continue until the number of transmitted frames reaches N_{tpr}, at which point the current round ends, and a new round begins with the setup phase. This process repeats until all nodes exhaust their energy.

In the next section, the complexity of the proposed scheme will be calculated.

D. Computational Complexity

In this section, the computational complexity of LEACH-C and the proposed scheme, will be calculated.

- LEACH-C

The complexity of each iteration (I) in LEACH-C involves generating up to K points and identifying the closest nodes, which has a complexity of $\mathcal{O}(N \times K)$. Additionally, it includes forming clusters using candidate cluster heads and computing $f(C')$, with a complexity of $\mathcal{O}(N \times K)$. Therefore, the overall complexity of LEACH-C is as follows:

$$\text{Complexity of LEACH-C} = \mathcal{O}\big(I \times (N \times K)\big)$$

In this paper, since K is a function of N and calculated using (7), it can be approximated as $\sqrt{N}$, and the overall complexity can be rewritten as follows:

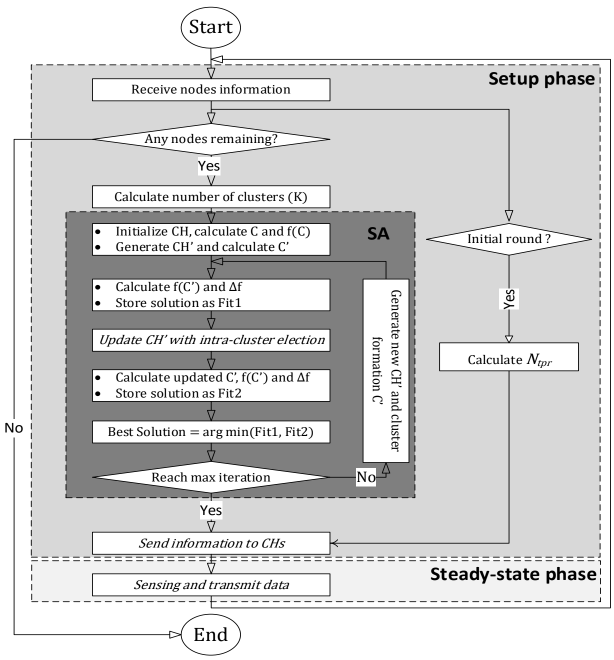

Fig. 2. Complete procedure of the proposed scheme

$$\text{Complexity of LEACH-C} = \mathcal{O}\left(I \times \left(N\sqrt{N}\right)\right)$$

Typically, the number of iterations in SA is several times greater than N. For example, in a WSN with 100 nodes, the SA algorithm may run around 500 iterations [27].

- Proposed scheme

The complexity of the proposed scheme is similar to LEACH-C, except for the intra-cluster election. The intra-cluster election occurs K times, and since there are, on average, $\frac{N}{K}$ members in each cluster, this election involves all cluster members. For each cluster head calculation, $\frac{N}{K}$ operations are required. Therefore, the complexity of the intra-cluster election is:

$$\text{complexity of intra-cluster election } = K \times \frac{N}{K} \times \frac{N}{K} = \mathcal{O}\left(\frac{N^2}{K}\right)$$

By approximating K as $\sqrt{N}$, the complexity will be:

$$\text{complexity of intra-cluster election } = \frac{N^2}{\sqrt{N}} = \mathcal{O}\left(\mathrm{N}\sqrt{\mathrm{N}}\right)$$

The overall complexity in each round involves generating CH candidates, forming clusters with these CHs, and calculating $f(C')$ with a total complexity of $\mathcal{O}\left(N\sqrt{N}\right)$; updating the CHs through intra-cluster elections, also with a complexity of $\mathcal{O}\left(N\sqrt{N}\right)$; and re-forming clusters with the updated CHs while calculating $f(C')$ again with a total complexity of $\mathcal{O}\left(N\sqrt{N}\right)$. Therefore, the overall complexity is:

$$\mathcal{O}\left(I \times \left(N\sqrt{N} + N\sqrt{N} + N\sqrt{N}\right)\right)$$

$$\text{Complexity of proposed scheme} \Rightarrow \mathcal{O}\left(I \times \left(N\sqrt{N}\right)\right)$$

In the proposed algorithm in [23], the local improvement phase is implemented using the Variable Step-Size Local Search (VSSLS) method, where one or more dimensions of the solution are randomly modified in each iteration, followed by a re-evaluation of the cost function. The time complexity of this phase is estimated as $\mathcal{O}(N \times K)$. Therefore, total complexity is:

$$\text{Complexity of VSSLS} \Rightarrow \mathcal{O}\left(N\sqrt{N}\right)$$

While the computational complexity of the local search phase in our proposed approach is similar to that of VSSLS, the incorporation of the Intra-Cluster Election mechanism substantially reduces the number of evolutionary iterations, reducing it by a factor of between 3 and 94, depending on the network size and sensor deployment, thereby accelerating convergence and reducing overall processing overhead.

In the next section, the proposed scheme will be compared with LEACH-C across various aspects.

V. Simulation Results

This section presents the performance evaluation of the proposed scheme, conducted across three different scenarios. This evaluation compares the proposed scheme with LEACH-C, and the results will be discussed.

A. Simulation Parameters

The proposed scheme and the compared protocols were simulated using Omnet++ 6.0.1 [30]. These simulations were performed on a system with an Intel Core $i3-12100$ 3.3 GHz processor, 16 GB of RAM, and the Microsoft Windows 11 operating system. The number of sensors in the simulations varied from 100 to 400, and they were distributed in simulation environments with dimensions of 100×100, 200×200, and 400×400. In all simulations, BS is positioned at the center of the simulation environment. Three scenarios are considered for various values and their parameters are detailed in Table I. The number of clusters (K) for each scenario is calculated using (7). Also, the transmission counts in each round have been calculated using (6) for each scenario.

TABLE I
Simulation Parameters

Parameter		**Scenario 1**	**Scenario 2**	**Scenario 3**
Network Environment (M)		100×100	200×200	400×400
Number of Sensors (N)		100	200	400
BS Location (x^m, y^m)		50×50	100×100	200×200
Initial Energy (J)		2	2	2
Number of clusters (K)		10	15	21
Data packet length (bit)		1000	1000	1000
Control packet length (bit)		200	200	200
Transmission rate (bps)		1×10^6	1×10^6	1×10^6
Transmissions per round (#)		1157	643	95
Iterations (#)	LEACH-C	647	564	512
	Proposed	271	6	64

In these simulations, $E_{\mathrm{elec}} = 50\,\frac{\mathrm{nJ}}{\mathrm{bit}}$, $\epsilon_{\mathrm{fs}} = 10\,\frac{\frac{\mathrm{pJ}}{\mathrm{bit}}}{m^2}$, $\epsilon_{\mathrm{mp}} = 0.0013\,\frac{\frac{\mathrm{pJ}}{\mathrm{bit}}}{m^4}$ and $d_0 = \frac{\epsilon_{\mathrm{fs}}}{\epsilon_{\mathrm{mp}}} = 87m$ are considered. Due to the using of intra-cluster election, the optimization algorithm's iterations have been reduced across all scenarios. In these scenarios, the length of the data packets is 1000 bits, the control packets 200 bits, and the data transmission rate is 1×10^6 bps. The main goal of the proposed scheme is to achieve better optimization values in less time and with fewer algorithm iterations.

The performance of the proposed scheme will be assessed based on the following metrics:

- **Optimization value:** This study aims to achieve better optimization values in less time, indicating that protocols with superior optimization are more efficient in this comparison.
- **Residual energy:** This metric evaluates the average energy remaining in the sensors after each transmission, with protocols that have higher average energy at any moment considered more efficient.
- **Number of alive nodes:** In this assessment, protocols are evaluated by the number of alive nodes in the network.
- **Number of received packets:** This metric represents the number of packets received by the BS. An increase in the number of packets received at any given moment and a steeper slope observed on the graph signifies better performance.

B. Results

Below, we will discuss the proposed scheme's performance evaluation and comparison with LEACH-C based on the mentioned criteria.

1) Comparing optimization results

Fig. 3 displays the results of evaluating and comparing the optimization values for both cases. This comparison presents the value of the cost function per iteration across all scenarios, calculated using (4). The results are based on running the algorithm 300 times and averaging the outcomes.

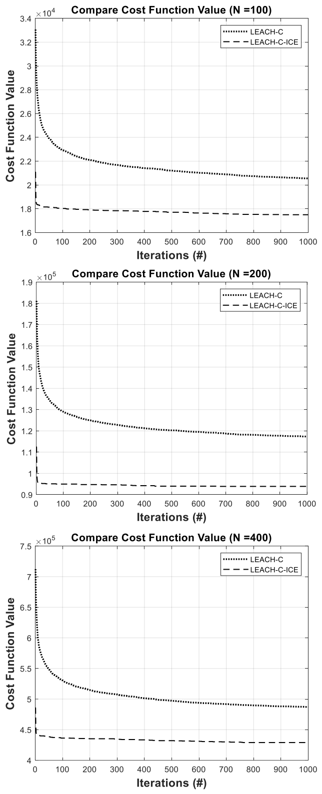

Fig. 3. Comparing optimization results of proposed scheme and LEACH-C across all scenarios.

Table II presents the optimization values after 1000 iterations for both LEACH-C and the proposed method, along with the achieved improvement. In this paper, the optimization values represent the sum of intra-cluster distances across all clusters.

TABLE II
Optimization Values After 1000 Iterations for LEACH-C and the Proposed Method

Parameter	Scenario 1	Scenario 2	Scenario 3
LEACH-C	20553	117359	487140
Proposed Method	17501	93890	428940
Improvement ratio	15%	20%	12%

The results indicate that LEACH-C-ICE achieves significantly better optimization with approximately 12–20% improvement, while also reducing the number of required iterations by 3× to 94×, depending on the network size and sensor deployment, compared to LEACH-C. All results are presented for 1,000 iterations in each scenario. This paper evaluates protocols based on the number of iterations required to reach 96% of their optimal value from the last iteration. However, the proposed scheme achieves a more optimal value than LEACH-C in the first iterations.

The number of iterations for LEACH-C in scenarios 1 to 3 is 647, 564, and 512, respectively, while the proposed scheme requires only 271, 6, and 64 iterations, as shown in Table I. This indicates that the proposed scheme significantly reduces the number of iterations compared to LEACH-C, allowing it to achieve better optimization value in a much shorter time.

2) Comparing the average residual energy in nodes

Fig. 4 shows the comparison results of the average remaining energy of all sensors in different scenarios.

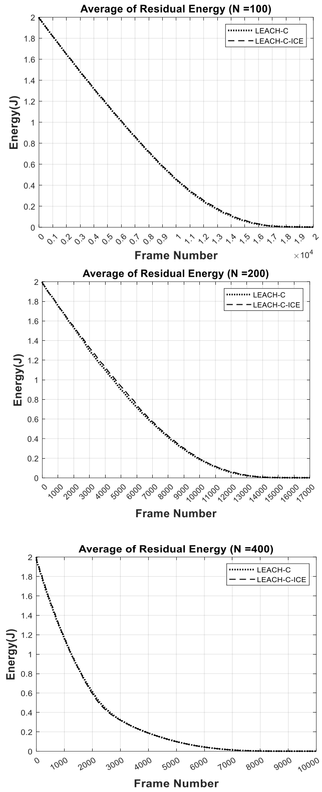

Fig. 4. Average residual energy in sensors across all scenarios

The results indicate that the proposed scheme performs similarly to LEACH-C, with only a slight improvement in average remaining energy in nodes. This minor enhancement is attributed to the cost function used in LEACH-C, which does not account for the distance of the cluster head from the base station. Consequently, even with a reduced cost function value, better outcomes cannot be achieved, as the highest energy consumption occurs in the cluster heads, leading them to be the first nodes to deplete their energy in the network.

3) Comparing alive nodes

Fig. 5 displays the number of alive nodes according to the compared protocols across all scenarios. The horizontal axis indicates the frame number, and the vertical axis denotes the number of nodes with sufficient energy for data transmission.

The results indicate that the proposed scheme shows a slight improvement in the number of alive nodes. However, it is important to note that it was implemented with significantly fewer iterations than LEACH-C, allowing it to achieve better results in a shorter time.

4) Comparing number of received packets at BS

This section analyzed the amount of data transmission to BS in LEACH-C, and the proposed scheme. A notable feature of LEACH-C is the amount of data transmitted to BS.

Fig. 6 shows packet delivery to BS. The vertical axis shows the number of packets and the Horizontal axis shows the frame number. Each node sends one data packet per frame, except during the setup phase.

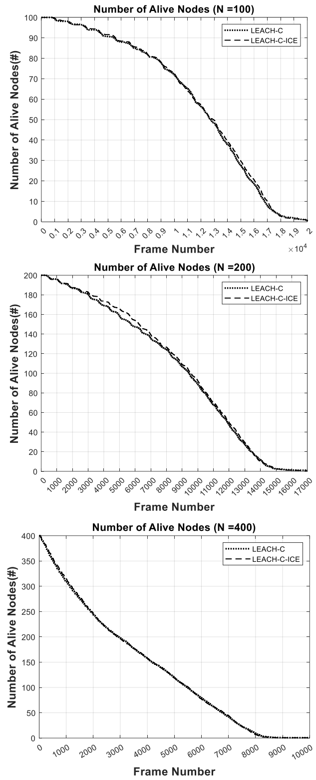

Fig. 5. Number of alive nodes per transmission for all scenarios

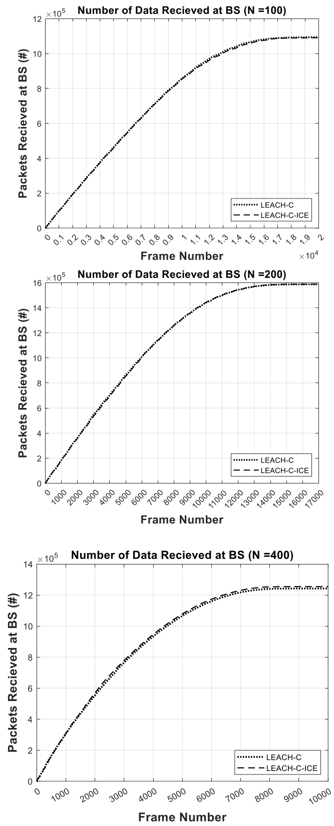

Fig. 6. Number of packets delivered to BS per frame number across different scenarios

The results indicate that the proposed scheme performs similarly, with a slight improvement as network size increases, demonstrating better performance with larger networks.

VI. CONCLUSION

In this paper, we introduced the Intra-Cluster Election (ICE) technique, which enhances the performance of centralized clustering protocols in Wireless Sensor Networks (WSNs), particularly within the LEACH-C framework. By optimizing the cluster head selection process and reducing convergence iterations, ICE demonstrates improved optimization value despite only modest gains in energy efficiency and data delivery rates compared to LEACH-C. Simulation results indicate that the implementation of ICE significantly enhances the efficiency of network operations, with an approximate $12-20\%$ improvement in the cost function compared to LEACH-C, while also reducing the number of required iterations by a factor ranging from 3 to 94, especially as the scale of the network increases. Future work can explore further refinements to the cost function and investigate the applicability of ICE in various WSN configurations and scenarios. Overall, ICE presents a promising approach for optimizing cluster head selection, thereby contributing to the advancement of effective data transmission and energy conservation in WSNs.

VII. REFERENCES

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