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RESEARCH ARTICLE

A Distributed LEACH-AHP Routing for Wireless Sensor Networks

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ABSTRACT The efficiency of routing algorithms employed plays a crucial role in determining the energy-saving potential of wireless sensor networks (WSNs). The challenge lies in developing distributed clustering algorithms that can efficiently form clusters without relying on centralized information gathering, balancing the need for cost-effectiveness, computational complexity, and flexibility within the constraints of limited resources. This study presents a novel hierarchical and distributed approach, integrating the low energy adaptive clustering hierarchy (LEACH) algorithm with the analytic hierarchy process (AHP). This approach involves maintaining a matrix within nodes, incorporating potential threshold values representing the probability of a node serving as the cluster head (CH). These values, determined through the analytic hierarchy process (AHP), consider both energy and distance conditions relative to the Sink as criteria, assigning importance levels from 1 to 9. The AHP computation, weighted with factors of 3, 5, and 7 to express preference for the energy criterion, results in threshold values that minimize energy consumption and maximize packet transmission to the Sink. This method empowers the nodes to autonomously determine their probability of becoming the CH based on their energy status and distance to the Sink, eliminating the need for centralized control. In comparison to algorithms like particle swarm optimization (PSO) and genetic algorithm (GA), the proposed method has minimal computational requirements and can be implemented in a distributed manner. The proposed approach is benchmarked against the well-established clustering algorithm LEACH. The results demonstrate that the proposed method can extend the network lifetime by up to two times and increase the number of packets sent to the Sink by approximately 50%.

INDEX TERMS AHP, leach, routing, WSN, wireless sensor networks.

NOMENCLATURE

CH	Cluster Head.
nCH	Not Cluster Head.
N	Total number of the nodes in the network.
n	The number of energy and distance states.
E	The array that contains superiority values of CH to nCH according to the energy criterion.
U	The array that contains superiority values of CH to nCH according to the distance criterion.
C	The array that contains superiority values of energy (E) to distance (U).
$E(k)$	The k^{th} element of the **E** array.
k	Index numbers for the elements of the **E** array.
$U(m)$	The m^{th} element of the **U** array.
m	Index numbers for the elements of the **U** array.
$C(q)$	The q^{th} element of the **C** array.
q	Index numbers for the elements of the **C** array.
D	The matrix that contains threshold values.
$D(e, u)$	An element of **D** matrix indexed with e and u.
e	Row index (e) signifies the ratio of nodes with lower energy than a specific node to the total remaining nodes.
u	Column index (u) denotes the ratio of remaining nodes that are closer to the base station than a specific node in the network.
P	The sequence that contains cluster head selection periods.

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p_g	The g^{th} element of $\mathbf{P}$ sequence.
$D_{(g,q)}$	One of the $\mathbf{D}$ matrices that are computed for p_g and $C(q)$.
H	Trial number for each state of n^2.
h	Index number for H .

I. INTRODUCTION

Wireless sensor networks (WSNs) encompass a multitude of sensor nodes strategically deployed for the purpose of tracking, measuring, or monitoring various physical phenomena. These sensor nodes typically operate under constrained hardware and limited energy resources. Therefore, the development of algorithms emphasizing low power consumption and minimal processing demands is paramount for the efficient functioning of WSNs [1]. The significance of energy-efficient routing is underscored by the fact that a substantial portion of energy consumption in WSNs occurs during the communication phase [2]. As a response to this challenge, employing energy-efficient routing protocols becomes imperative, contributing to reduced energy consumption and prolonged network lifespan [3].

A considerable body of literature has introduced various routing protocols designed to alleviate energy consumption in WSNs [4], [5]. These routing algorithms can be broadly categorized into flat protocols and hierarchical protocols based on their network structures [6], [7]. Hierarchical routing protocols, characterized by their scalability and resistance to overload, have demonstrated advantages in WSNs [5], [8], [9]. Clustering, a fundamental technique for hierarchical routing protocols, involves partitioning the network into clusters, thereby enhancing scalability and energy efficiency. Each cluster is overseen by a designated Cluster Head (CH), selected from the nodes through specified methods to enhance network longevity and throughput. CHs manage intra-cluster communication, with non-CH nodes transmitting data to their respective CHs. The CHs aggregate the data from their clusters and forward it to the Sink. Cluster based algorithms can be implemented in two modes: centralized and distributed [10]. The centralized clustering algorithms collect information such as node location and energy at a central point to determine optimal clusters and then report it to the nodes. In contrast, distributed clustering algorithms, executed by nodes with limited energy and computing resources, form clusters without collecting location and energy information. While distributed clustering algorithms offer cost and flexibility advantages, they must have the ability to operate within the constraints of limited resources effectively.

The low energy adaptive clustering hierarchy (LEACH) algorithm, introduced by Heinzelman et al. in [11], stands as one of the best-known and influential distributed clustering algorithms. In accordance with LEACH, CHs are selected in an alternating fashion from among the sensor nodes, strategically aiming to equitably distribute energy consumption within the network. The operational framework of LEACH unfolds in discrete rounds, each encompassing installation and steady-state phases. The installation phase encompasses pivotal processes such as CH selection, cluster formation, and the assignment of time division multiple access (TDMA) schedules for the respective cluster members.

Within the installation phase, nodes actively partake in the CH selection process. This involves the generation of a uniform random number within the range of 0 to 1 by each node. Nodes whose generated random number falls below a predefined threshold ($T(n)$) declare themselves as CHs. The threshold value, denoted as T, is computed based on the expression:

$$T = \begin{cases} \dfrac{P}{1 - P\left(r \bmod \left(\frac{1}{P}\right)\right)}, & \text{if } n \in G \\ 0, & \text{otherwise} \end{cases}, \tag{1}$$

where P signifies the percentage of CHs among the total nodes, r denotes the round number, and G represents the set of nodes not designated as CHs in the last $1/P$ rounds. Subsequently, nodes designated as CHs broadcast messages to their neighboring nodes, thereby signaling their CH status. Nodes not chosen as CHs intercept and process these broadcast messages, ultimately associating themselves with the CH exhibiting the highest received signal strength.

The threshold values in the LEACH algorithm undergo modification through the incorporation of a remaining energy factor, thereby presenting a novel deterministic approach aimed at extending the operational lifespan of the network, as proposed in [12]. Initially, the threshold value selection method expressed as

$$T = \frac{P}{1 - P\left(r \bmod \left(\frac{1}{P}\right)\right)} \left(\frac{E_n^c}{E_n^m}\right), \tag{2}$$

where E_n^c denotes the current energy level of the node, E_n^m represents the maximum energy (initial energy) of the node, P signifies the desired percentage of CHs, and r signifies the current round. However, a substantial decrease in node CH selections was observed as the energy level diminished, leading to network congestion. Consequently, the deterministic cluster-head selection method was introduced, denoted as LEACH-DCHS, by modifying the formula as

$$T_{\text{new}} = \frac{P}{1 - P\left(r \bmod \left(\frac{1}{P}\right)\right)} \times \left[\frac{E_n^c}{E_n^m} + \alpha\left(1 - \frac{E_n^c}{E_n^m}\right)\right] \tag{3}$$

where

$$\alpha = r_s \operatorname{div}(1/P) = \begin{cases} 1, & \text{if } r_s \text{ reaches } \dfrac{1}{P} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where r_s denotes consecutive rounds in which a node has not become a CH. This adjustment notably increased the probability of selecting a CH in the last $1/P$ rounds, effectively resolving the congestion issue. While LEACH-DCHS demonstrates a commendable 30% improvement in network lifetime compared to LEACH, it is not without drawbacks, including challenges such as the precise determination of the number of inactive nodes and uncontrolled overhead, as highlighted in [5].

An alternative variant integrating the genetic algorithm (GA) into the LEACH algorithm is presented in [13]. Beyond the fundamental LEACH protocol, this GA-based algorithm integrates a preparatory phase preceding the initial round. In this phase, all nodes initially perform the CH selection process, transmitting messages to the base station containing their candidate cluster, node IDs, and geographic locations. Upon receiving messages from all nodes, the base station employs a genetic algorithm to minimize the total energy consumption required for a round and explores the potential for nodes to become CHs. Subsequently, the base station disseminates an advertisement message containing the optimal T value to all nodes, facilitating the formation of clusters in the ensuing setup phase. The preparatory phase transpires only once before the setup phase in the first round, with subsequent rounds adhering to the setup and steady-state phases akin to LEACH. Despite enhancing network lifetime in comparison to LEACH across diverse base station locations, this approach exhibits limitations concerning scalability and message overhead.

Moreover, the improved LEACH (I–LEACH) algorithm incorporates considerations for remaining energy, the number of neighboring nodes, and the node's distance to the base station in the CH selection process [14]. I-LEACH demonstrates a notable enhancement, offering a 55% improvement in network lifetime compared to the baseline LEACH and a concurrent reduction in energy consumption by 59%. However, it is essential to note that this protocol, while achieving these improvements, does not account for transmission costs and exhibits heightened complexity due to increased computational load [5], [15]. Also, Vice-LEACH (V-LEACH) introduces a mechanism to prevent premature CH depletion caused by elevated energy consumption relative to other nodes [16]. In accordance with V-LEACH, when a specific node reaches the lowest energy level, the CH selects an auxiliary CH (Vice CH or VCH), transmitting the VCH ID to all other nodes within the cluster. Subsequently, normal nodes redirect their data transmission to the VCH instead of the previous CH, which assumes the role of a standard node. V–LEACH significantly extends network lifetime through the strategic selection of an auxiliary CH, conserving energy across the entire network and enhancing data transmission efficiency to the base station. Significantly, V-LEACH demonstrates a remarkable capability to ensure reliable packet delivery to the base station. However, it is noteworthy that this achievement is attained without explicit consideration for transmission costs [15].

Since most LEACH variants adopt dynamic, probabilistic, and distributed clustering approaches, ensuring an optimal number of clusters remains uncertain. In response to this challenge, the LEACH-MAC protocol is introduced with the specific aim of mitigating randomness by restricting the number of CH advertisements [17]. Demonstrating superior performance throughout its operational lifespan compared to both LEACH and LEACH-DCHS, LEACH-MAC nevertheless grapples with complexity concerns arising from energy calculations and an additional message load [5]. Beyond these variants, certain LEACH adaptations deviate by employing centralized approaches [10].

The study presented in [18] proposes a methodology leveraging the Analytic Hierarchy Process (AHP) to compute weights for three distinct factors: remaining energy, number of neighboring nodes, and distance to the Sink. Subsequently, these weights are incorporated into the modified PROMETHEE-II method to rank sensor nodes, with the highest-ranked node assuming the role of the cluster head. Notably, the proposed approach introduces Gateways with significantly higher energy levels—six times that of other nodes—that are also eligible to serve as CHs.

In addition, the ESO-LEACH algorithm, as proposed in [19], employs a hybrid approach combining particle swarm optimization (HPSO) and K-means to identify optimal cluster heads. However, it is noteworthy that this algorithm necessitates advanced nodes endowed with higher energy capacities. In the collaborative framework presented in [20], HPSO and the improved LEACH (HPSO-I-LEACH) are synergistically employed. HPSO is leveraged for CH selection, while I-LEACH is utilized for subsequent cluster formation. The FMCB-ER algorithm, introduced in [21], integrates fuzzy multi-criteria clustering and bio-inspired energy-efficient routing. This algorithm combines Fuzzy-AHP and the technique for order performance by similarity to ideal solution (TOPSIS) techniques to determine cluster heads. Additionally, the emperor penguin optimization (EPO) algorithm is incorporated to identify the most efficient routes from the CHs to the Sink. In [22], the cluster-based energy efficient routing protocol (CEER) is introduced, featuring a network comprising five distinct types of nodes with varying energy levels. The Fuzzy-AHP method is employed to ascertain threshold values (represented by parameters α, β, and σ). The proposed protocol offers five threshold-determining equations, each tailored to a specific node type, taking into account factors such as residual energy, distance to the base station, and reliability.

In this study, the primary aim was to formulate a matrix containing threshold values for diverse scenarios, predicated on the ratio of neighboring nodes' energy to their individual energy levels and their proximity to the Sink relative to a specified percentage of their neighbors. It is assumed that nodes are equipped with knowledge pertaining to the energy and distance statuses of their neighboring nodes, necessitating the selection of a threshold value commensurate with their current circumstances. The selected threshold value corresponds to the probability of a node assuming the role of a CH. To establish these threshold values in an offline setting, the AHP methodology was applied. The entire spectrum of possible values between 1 and 9 with a step size of 1, was systematically tested to assess the superiority of energy and distance criteria. For each superiority scenario, random network topologies were generated, resulting in multiple networks characterized by identical energy and distance configurations. From the multitude of obtained threshold values, those optimizing either the remaining energy or the total number of packets reaching the Sink were identified. The proposed method offers following notable advantages:

1) The proposed method adheres to a distributed structure.
2) The computational complexity of the proposed method is significantly lower in comparison to methods employing PSO, GA, or Neural Networks (NNs).
3) It is recommended to perform CH selection after a predetermined number of rounds, as opposed to repeating the process at the conclusion of each round.
4) In light of the achieved outcomes, the proposed method recommends an optimal threshold value.

II. PROPOSED METHOD

The proposed method comprises two key components: first, the offline determination of threshold values through the AHP, and second, the practical utilization of these determined threshold values. This study introduces a novel distributed clustering algorithm wherein each node within a network autonomously determines its candidacy as a CH utilizing the AHP method. The decision-making process is grounded in the respective energy levels of the nodes and their distances from the base station. To validate this conceptual framework, multiple networks are generated by randomly deploying a substantial number of nodes under identical energy and distance conditions.

The AHP method is deployed to determine the probability of a node becoming a CH, denoted as the threshold value, in each network. This determination involved an exhaustive consideration of all potential superiority relationships between the energy and distance criteria. For a given energy and distance scenario, two distinct threshold values are derived based on various superiority values between the criteria. One threshold value aimed to maximize the remaining energy in the network, while the other sought to maximize both the total number of packets and remaining energy. The study assumes an examination of N nodes randomly distributed within a $M \times M$ network area, considering a combination of n distinct energy and n distance states. n^2 threshold values obtained with AHP stored in the threshold values matrix $\mathbf{D}$. In each CH selection period p_g, the elements in the matrix $\mathbf{D}$ are computed for a specific superiority value $C(q)$ referred to as $\mathbf{D}_{g,q}$. To ensure robustness, the procedure involves iteratively generating network topologies and evaluating performances a total of H times, examining $n^2 \times H$ distinct network topologies. The final step involved calculating the average of the multiple threshold values to yield two comprehensive threshold values for a particular scenario, wherein a percentage of nodes exhibited higher energy levels than others, and another percentage of nodes were closer to the Sink.

The proposed algorithm stores an array of threshold values within the nodes, tailored for specific scenarios. Upon a node assuming the role of a CH, it continues to function as such for a predetermined number of rounds. This innovative approach aims to optimize the clustering process and enhance the overall network performance.

A. USING AHP TO DETERMINE THRESHOLD VALUES

The AHP [23] is a systematic decision-making method designed for scenarios with multiple criteria. It involves identifying crucial decision-making criteria, assessing alternatives based on these criteria, and making comparative evaluations. AHP aims to analytically choose the most suitable alternative by using predetermined criteria and their assigned importance [24]. The method employs a hierarchical structure, followed by the construction of dual comparison matrices [25], [26], [27]. Saaty's vector method is then utilized to calculate the relative importance, and the consistency of the matrices is checked through a consistency rate determination [28], [29]. If the consistency rate is deemed acceptable, the prioritization of alternatives ensues, ultimately leading to the selection of the alternative with the highest value. Table 1 outlines the assessment scale employed in this study within the framework of the AHP method.

TABLE 1. Scale of Relative Importance.

Level of Importance	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very Strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values

In the proposed approach, we used the AHP to determine the threshold values that will be used in the cluster selection phase. CHs continue to serve as cluster heads for a predetermined number of rounds. The proposed method compares two alternatives: Becoming a cluster head (CH) or not (nCH). The criteria for comparison are the percentage of neighbors that are closer to the Sink (U) and the percentage of neighbors that have less energy (E). In Table 2, the comparison between distance and remaining energy level is given. $\mathbf{C} \in \mathbb{R}^3 = \{C(q) : q = 1, 2, 3\}$ where $C(q)$ denotes

TABLE 2. Distance and remaining energy level comparison.

Criteria	E	U
E	1	$C(q)$
U	$1/C(q)$	1

q^{th} element of the $\mathbf{C}$ array, containing the superiority values of E over U. The $\mathbf{C}$ array, given in (5), indicates that E is considered superior over U in all conditions.

$$\mathbf{C} = \begin{bmatrix} 3 & 5 & 7 \end{bmatrix} \tag{5}$$

The preference is made with the help of the comparison in Table 3 and Table 4 according to E and U criteria among the alternatives CH or nCH.

TABLE 3. Comparison table according to remaining energy level criteria.

Alternatives	CH	nCH
CH	1	$E(k)$
nCH	$1/E(k)$	1

As in (6), $\mathbf{E}$ array contains the superiority values of CH to nCH in accordance with the energy criterion.

$$\mathbf{E} = \begin{bmatrix} 1 & 2 & \dots & 9 & \frac{1}{2} & \frac{1}{3} & \dots & \frac{1}{9} \end{bmatrix} \tag{6}$$

$\mathbf{E} \in \mathbb{R}^{17} = \{E(k) : k = 1, 2, 3, \dots, 17\}$ where $E(k)$ is k^{th} element of the $\mathbf{E}$ array. Similarly, the alternatives are compared to each other based on the percentage of neighboring nodes that are closer to the Sink. $\mathbf{U}$ array contains superiority values of CH to nCH according to the distance criterion as given in (7). $\mathbf{U} \in \mathbb{R}^{17} = \{U(m) : k = 1, 2, 3, \dots, 17\}$ where $U(m)$ is m^{th} element of the $\mathbf{U}$ array.

$$\mathbf{U} = \begin{bmatrix} 1 & 2 & \dots & 9 & \frac{1}{2} & \frac{1}{3} & \dots & \frac{1}{9} \end{bmatrix} \tag{7}$$

TABLE 4. Comparison table according to distance to Sink criteria.

Alternatives	CH	nCH
CH	1	$U(m)$
nCH	$1/U(m)$	1

The inputs for the AHP algorithm are the values of $E(k)$ and $U(m)$. To select cluster heads, it is necessary to know the energy levels of neighboring nodes and their distance from the Sink. Nodes should share their energy information at certain time intervals. Distance information only needs to be published once by the Sink. However, sharing energy information with other nodes will increase overall energy consumption. In the simulations, necessary energy reduction was made to send and receive energy information in cluster updates.

It is assumed that there are n^2 states representing possible energy and distance states. Threshold values obtained with AHP for the n^2 considered cases are stored in the threshold values matrix $\mathbf{D}$, as shown in (8). $\mathbf{D} = [D(e, u)]_{1 \le e,u \le n}$ where $D(e, u)$ is the $(e, u)^{th}$ element of $\mathbf{D} \in \mathbb{R}^{n \times n}$, with rows associated with energy and columns associated with distance.

$$\mathbf{D} = \begin{bmatrix} D(1,1) & \dots & D(1,n) \\ \vdots & \ddots & \vdots \\ D(n,1) & \dots & D(n,n) \end{bmatrix} \tag{8}$$

The value $D(e, u)$ serves as the threshold value for a node under the following two conditions:

Condition 1: The node possesses energy levels greater than a range of $\frac{(e-1)\times 100}{n}\%$ to $\frac{e \times 100}{n}\%$ in comparison to its neighboring nodes,

Condition 2: The node is situated at a greater distance from the base station (BS) than a range of $\frac{(u-1)\times 100}{n}\%$ to $\frac{u\times 100}{n}\%$ in relation to its neighboring nodes.

For instance, given $n = 10$, $D(1, 9)$ signifies the threshold value for scenarios where 0% to 10% of neighboring nodes have lower energy and 80% to 90% of them are closer to the base station.

In the proposed method, a node that becomes a CH will retain that role for a specific number of rounds, defined as the CH selection period. After completing this designated number of rounds, the process initiates the selection of a new cluster head. The values for CH selection period, denoted as p_g, are stored in the $\mathbf{P} \in \mathbb{R}^{\nu} = \{p_g : g = 1, 2, \dots, \nu\}$ as

$$\mathbf{P} = \begin{bmatrix} p_1 & p_2 & \cdots & p_i \end{bmatrix}. \tag{9}$$

For each p_g, the $D(e, u)$ values in the matrix $\mathbf{D}$ are computed for a specific $C(q)$ value. These calculated matrices are referred to as $\mathbf{D}_{g,q}$, and all are created for each p_g and $C(q)$ pair. Given each $\mathbf{D}_{g,q} \in \mathbb{R}^{n\times n}$, the process involves randomly generating n^2 distinct network topologies, ensuring that each topology possesses the requisite properties for $D_{g,q}\,(e, u)$.

To assess the performance of a specific $\mathbf{D}_{g,q}$ matrix, the procedure involves iteratively generating network topologies and evaluating performances a total of H times. In other words, $n^2 \times H$ distinct network topologies that satisfy the prescribed properties for $D_{g,q}\,(e, u)$ are examined. Uniformly distributed energy values in the range $[0, e_{\max}]$ are generated and assigned to $\left(\eta_e = \frac{e\times N}{n}\right)$ nodes as in (10) where $e_{\max}$ indicates the maximum energy of the nodes in the network.

$$\xi = e_{\max} \times \mathrm{rand}\,(1, \eta_e) \tag{10}$$

The energy values in the $\xi \in \mathbb{R}^{\eta_e} \sim \mathcal{U}(0, e_{\max})$ are assigned to randomly selected η_e nodes in the network. The remaining $(N - \eta_e)$ nodes are assumed to have energy equal to $e_{\max}$.

Moreover, $\psi \in \mathbb{R}^{\eta_u} \sim \mathcal{U}(0, R/2)$ is generated according to (11), with the distance values to the Sink for $\left(\eta_u = \frac{u\times N}{n}\right)$ nodes in the network. R represents the potential maximum distance to the Sink when the Sink is placed at the center of an $M \times M$ area (i.e., half of the diagonal line $(M/\sqrt{2})$).

$$\psi = (R/2) \times \mathrm{rand}\,(1, \eta_u) \tag{11}$$

Assuming the Sink coordinates as (x_s, y_s), y coordinates for η_u nodes are uniformly distributed between $(y_s - R/2)$ and $(y_s + R/2)$ using (12). The $(\mathbf{x_r}, \mathbf{y_r})$ coordinates are computed with (12) and (13), where $\odot$ denotes the Hadamard product. These coordinates are assigned to η_u nodes from a pool of N. The remaining $(N - \eta_u)$ nodes are randomly placed within an area of dimensions $M \times M$ such that their distance from the Sink exceeds $R/2$. Consequently, all nodes are created based on the values of e and u.

$$\mathbf{y_r} = (y_s - (R/2)) + (R \times \text{rand}(1, \eta_u)) \tag{12}$$

$$\mathbf{x_r} = |x_s - \sqrt{(\psi \odot \psi) - (\mathbf{y_r} - y_s) \odot (\mathbf{y_r} - y_s)}| \tag{13}$$

The threshold values, computed using the AHP, are derived for all combinations of $E(k)$, $U(m)$, and $C(q)$ values, stored in arrays $\mathbf{E} \in \mathbb{R}^{17}$, $\mathbf{U} \in \mathbb{R}^{17}$, and $\mathbf{C} \in \mathbb{R}^{3}$. Then, all possible threshold values are denoted as $T(k, m, q)$ and are calculated as

$$T(k, m, q) = \mu_e \cdot W + \mu_u \cdot (1-W) \tag{14}$$

where μ_e $\forall k \in \{1, 2, \ldots, 17\}$, μ_u $\forall m \in \{m = 1, 2, \ldots, 17\}$, and W $\forall q \in \{q = 1, 2, 3\}$ are calculated as given (15), (16), and (17), respectively.

$$\mu_e = \frac{1}{2}\left(\frac{1}{1 + \frac{1}{E(k)}} + \frac{E(k)}{1 + E(k)}\right) \tag{15}$$

$$\mu_u = \frac{1}{2}\left(\frac{1}{1 + \frac{1}{U(m)}} + \frac{U(m)}{1 + U(m)}\right) \tag{16}$$

$$W = \frac{1}{2}\left(\frac{1}{1 + \frac{1}{C(q)}} + \frac{C(q)}{1 + C(q)}\right) \tag{17}$$

After obtaining all possible threshold values, the threshold values are tried one by one using the CH selection periods specified in (9) in a network where the nodes are randomly located in accordance with the desired energy and distance characteristics. The threshold value $T(k, m, q)$ is used by the nodes to decide to become a CH. Each node makes its decision as follows:

$$a = \text{rand}; \begin{cases} \text{become cluster head,} & \text{if } a \leq T(k, m, q) \\ \text{do not become cluster head,} & \text{if } a > T(k, m, q) \end{cases} \tag{18}$$

where $a \sim \mathcal{U}(0, 1)$.

The nodes that decide not to become CH assign themselves to the clusters with the closest CH. After clusters are created, normal nodes send their packets to their CHs, and the CHs send their packets and the packets of their members to the Sink during p_g rounds. After completing p_g rounds, the CH selection period starts again.

The threshold values, stored as $D_{g,q}(e, u)$ in $\mathbf{D}_{g,q}$ matrices, are calculated by the proposed method as follows: For each of the (e, u) pairs, H different networks are created. The energy and location of the nodes in the created networks are determined as in (10), (12), and (13). All possible threshold values $T(k, m, q)$ are used in the created networks. The sum of the remaining energy of the nodes, $\Gamma_{g,q,e,u,h}(k, m)$, and the total number of packets that reached the Sink, $\Lambda_{g,q,e,u,h}(k, m)$, after p_g loops are calculated for each of the H networks. $E_{g,q,e,u,h}(k, m)$ and $P_{g,q,e,u,h}(k, m)$ are the normalized values of remaining energy and total packets that reached the Sink.

$$E_{g,q,e,u,h}(k, m) = \frac{\Gamma_{g,q,e,u,h}(k, m)}{\max_{1 \leq h \leq H}\left(\Gamma_{g,q,e,u,h}(k, m)\right)} \tag{19}$$

$$P_{g,q,e,u,h}(k, m) = \frac{\Lambda_{g,q,e,u,h}(k, m)}{\max_{1 \leq h \leq H}\left(\Lambda_{g,q,e,u,h}(k, m)\right)} \tag{20}$$

For each of the H trials, the index numbers of $(k_h^\dagger) \in \{1, 2, \ldots, 17\}$ and $(m_h^\dagger) \in \{1, 2, \ldots, 17\}$ are determined using (21) or (22).

$$(k_h^\dagger, m_h^\dagger) = \max_{(k,m)}\left(E_{g,q,e,u,h}(k, m)\right) \tag{21}$$

$$(k_h^\dagger, m_h^\dagger) = \max_{(k,m)}\left(E_{g,q,e,u,h}(k, m) + P_{g,q,e,u,h}(k, m)\right) \tag{22}$$

The mean value of the total H threshold values $T(k_h^\dagger, m_h^\dagger, q)$ corresponding to $k_h^\dagger$ and $m_h^\dagger$ is stored as $D_{g,q}(e, u)$ in the $\mathbf{D}_{g,q}$ matrix.

$$D_{(g,q)}(e, u) = \frac{1}{H}\sum_{h=1}^{H} T(k_h^\dagger, m_h^\dagger, q) \tag{23}$$

The $\mathbf{D}_{g,q}$ matrices are calculated offline and stored in the memory of the nodes. The nodes can use the threshold value $D_{g,q}(e, u)$ to become CH according to g, q, e and u values without any centralized control. The Algorithm 1 shows determining all possible threshold values by the proposed method.

Algorithm 1 Threshold Value Calculation Algorithm

Input: H, $\mathbf{C}$ (5), $\mathbf{E}$ (6), $\mathbf{U}$ (7), $\mathbf{D}$ (8), and $\mathbf{P}$ (9)
Output: $\mathbf{D}_{g,q}$
Use AHP to calculate possible threshold values for $\mathbf{C}$, $\mathbf{E}$, and $\mathbf{U}$
Store the threshold values $T(k, m, q)$ in $\mathbf{T}$ (14)
for $e = 1$ to n **do**
  for $u = 1$ to n **do**
    for $g = 1$ to ν **do**
      for $q = 1$ to 3 **do**
        for $h = 1$ to H **do**
          Create a network according to (e, u)
          Use $T(k, m, q)$ threshold values.
          Obtain $\Gamma_{g,q,e,u,h}(k, m)$ and $\Lambda_{g,q,e,u,h}(k, m)$
          Obtain $\mathrm{E}_{g,q,e,u,h}(k, m)$ and $\mathrm{P}_{g,q,e,u,h}(k, m)$
          Find $k_h^\dagger$ and $m_h^\dagger$ using ((21) or (22))
          Store $T(k_h^\dagger, m_h^\dagger, q)$ value.
        end for
        Calculate and store $D_{g,q}(e, u)$ using (23)
      end for
    end for
  end for
end for

B. USING DETERMINED THRESHOLD VALUES AND SIMULATION SCENARIO

The nodes are required to acquire information regarding the energy levels and distances from the Sink of their neighboring nodes after the CH selection period p_g. According to energy and distance information of the neighbors, the nodes can determine e and u index numbers of $D_{g,q}(e, u)$. It is assumed

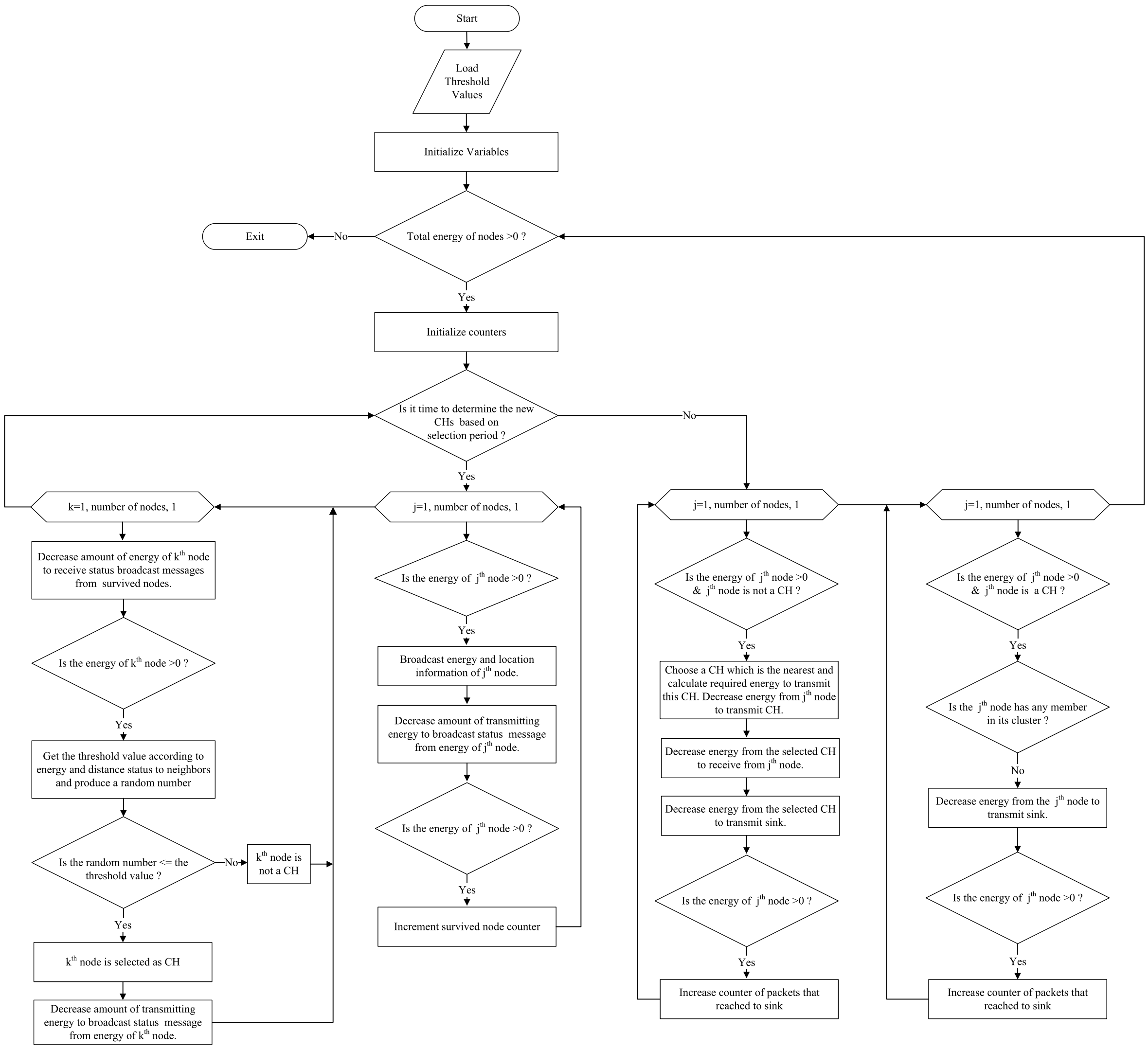

FIGURE 1. The flowchart for the simulation of the proposed method.

that g and q values are fixed and determined before the network installation.

The nodes declare themselves as CH if the uniformly distributed number they produce between (0, 1] is less than $D_{g,q}(e, u)$ in the CH selection phase. The CH selection phase starts after each p_g rounds. The nodes broadcast their energy and distance from the Sink in the CH selection phase. The nodes choose the appropriate threshold value $D_{g,q}(e, u)$ stored in their memory. After the CH selection phase finishes, the normal nodes transmit their data to CHs which are the closest to them. CHs transmit the data that reached them to the Sink. The normal nodes and CHs stay as normal and CH during p_g rounds.

The simulation flowchart is depicted in Fig. 1. Energy calculations were conducted using a first-order radio model [11]. The energy required for transmitting B bits over a distance of d meters, denoted as $E_{\mathrm{Tx}}(B, d)$, and the energy required for receiving B bits, denoted as $E_{\mathrm{Rx}}(B)$, are expressed by (24) and (25), respectively, where E_{elec} represents the energy required for the receiver and transmitter circuits to process one bit, and ϵ_{amp} represents the energy coefficient for the amplifier.

$$E_{\mathrm{Tx}}(B, d) = E_{\mathrm{elec}} \times B + \epsilon_{\mathrm{amp}} \times B \times d^2 \tag{24}$$

$$E_{\mathrm{Rx}}(B) = E_{\mathrm{elec}} \times B \tag{25}$$

Assuming the energy requirement of 50 nJ/bit for receiver and transmitter electronic circuits (E_{elec} = 50 nJ/bit) and the amplifier energy coefficient of 100 pJ/bit/m^2 (ϵ_{amp} = 100 pJ/bit/m^2), simulations consider a packet size of 250 bytes. As a practical scenario, consider an application employed for monitoring and surveillance within a battery-powered WSN system, where the positions of the nodes are fixed.

III. NUMERICAL RESULTS

The numerical studies are conducted in two phases: initially, Algorithm 1 is utilized to acquire $D_{g,q}(e, u)$ values, and subsequently, the performance of a certain network is assessed

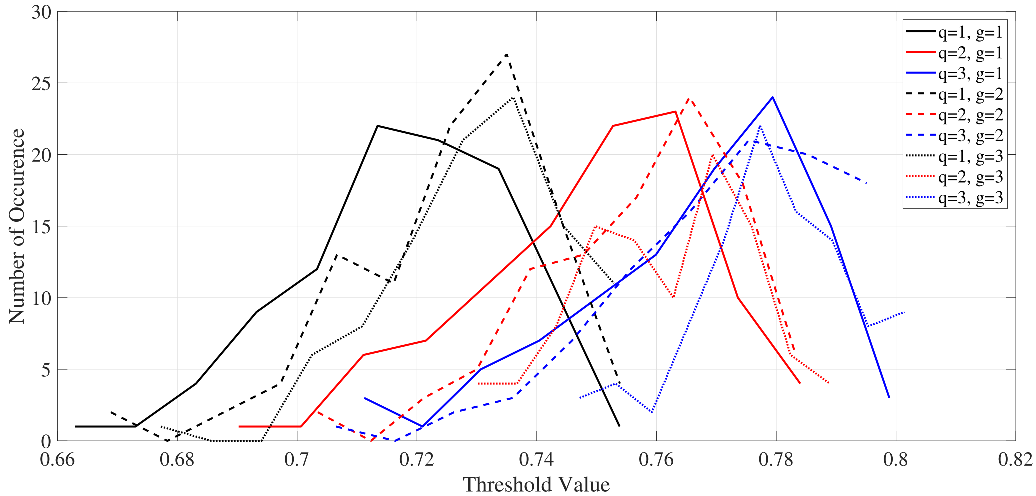

FIGURE 2. Variation of threshold values which are obtained by (21) with the Sink located at the coordinates (50, 50) (i.e. center of 100 × 100 network area).

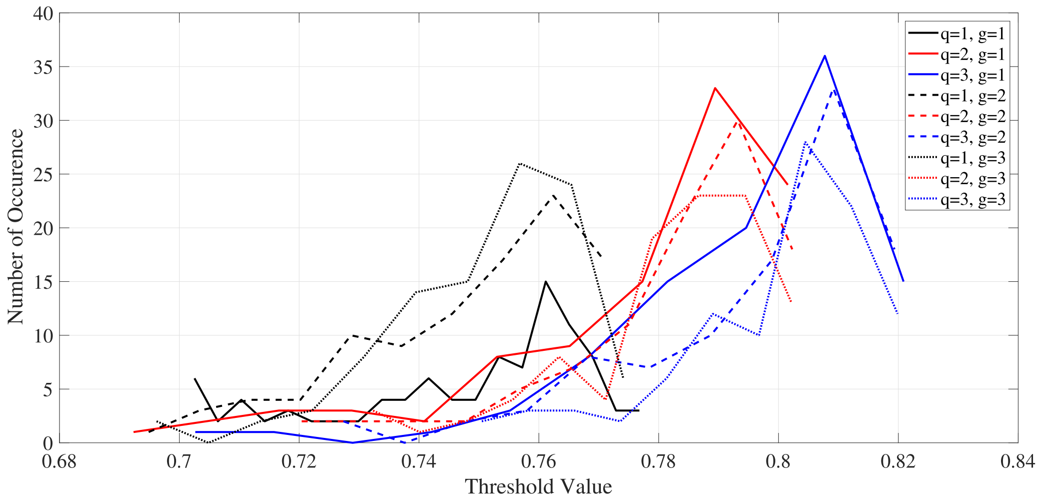

FIGURE 3. Variation of threshold values obtained through (21) with the Sink located at the coordinates (200, 200) (i.e. far from 100 × 100 network area).

using these threshold values. The parameters employed in this study are detailed in Table 5, and a total of 9 (i.e., size($\mathbf{C}$) × size($\mathbf{P}$)) simulation cases given in Table 6, are examined. According to the results obtained with Algorithm 1, the number of occurrences of threshold values stored in $\mathbf{D}_{g,q}$ matrices is shown in Fig. 2 and Fig. 3.

TABLE 5. Parameters Used for Numerical Results.

Parameter	Value
Size of network	100×100 (i.e. $M = 100$)
Number of nodes	$N = 100$
Number of states	$n = 10$ (i.e. $\mathbf{D} \in \mathbb{R}^{10\times 10}$)
Cluster head selection periods	$\mathbf{P} = [100, 150, 200]$
Importance values of energy	$\mathbf{C} = [3, 5, 7]$
Maximum energy of nodes	$e_{\max} = 0.5$ J
Sink coordinates	$(50, 50), (200, 200)$
Trial number for each state	$H = 100$
Location of the nodes	Random x and y coordinates (0-100)

Fig. 2 shows variations in $D_{(g,q)}(e, u)$ values when considering the total energy of the network as per (21). According to the results presented in Fig. 2, if the Sink is located at the center of a 100×100 area, the threshold values range from 0.66 to 0.80. On the other hand, with an increase in the importance of energy to the distance of the base station (q), the threshold values also increase. The variation in the cluster head selection period (p_g) does not lead to a significant change in threshold values.

Fig. 3 shows the variation in threshold values when the Sink is located at $(200, 200)$. As depicted in Fig. 3, the threshold values obtained from (21) slightly increase and range between 0.69 and 0.82. Higher threshold values indicate that a greater number of nodes are willing to become cluster heads. Having a higher number of cluster heads offers other nodes the opportunity to find a nearer cluster head. However, cluster heads are expected to consume more energy than the other nodes. For instance, in Fig. 2, the mean threshold value for $p_g = 100$ and $C(q) = 7$ is 0.766, signifying that 76.6% of the nodes are willing to become cluster heads. Consequently, each node may become a cluster

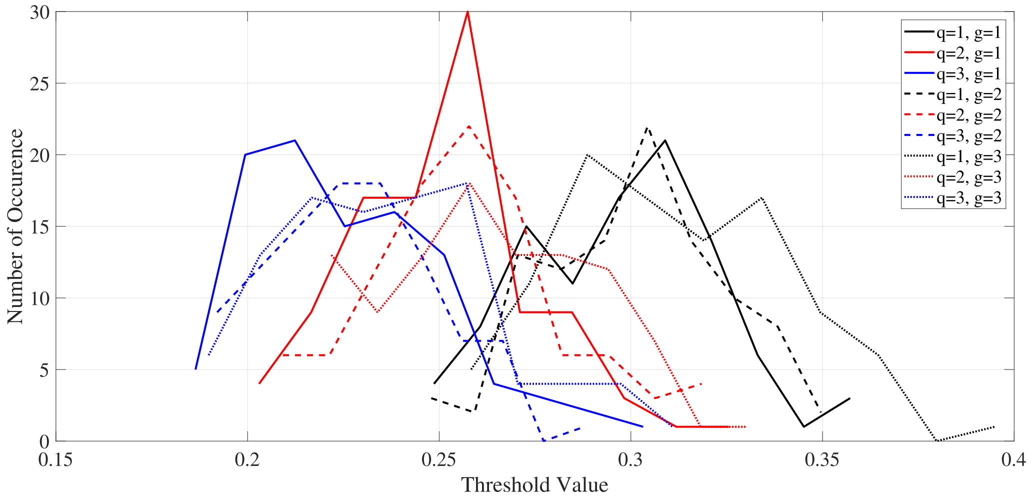

FIGURE 4. Variation of threshold values which are obtained by (22) with the Sink located at the coordinates (50, 50) (i.e. center of 100 × 100 network area).

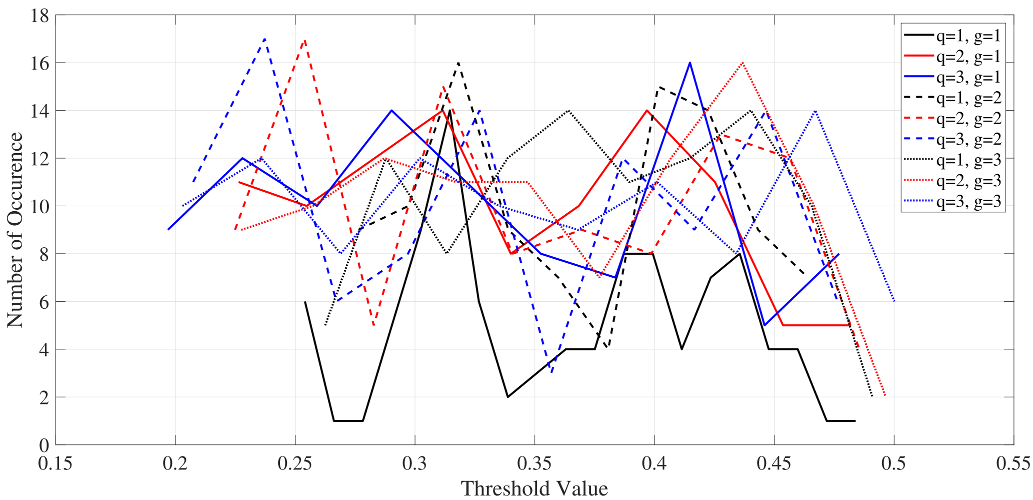

FIGURE 5. Variation of threshold values obtained through (22) with the Sink located at the coordinates (200, 200) (i.e. far from 100 × 100 network area).

head about 8 times and a normal node 2 times over the course of 10 cluster head selection periods. A node may consume more energy during the eight cluster head selection periods and less energy during the other two cluster head selection periods. Even when the Sink is located far from the nodes, as shown in Fig. 3, there is no significant change in the mean value of the thresholds. For $p_g = 100$ and $C(q) = 7$, the mean value of the thresholds in Fig. 3 is found to be 0.796.

Based on the results illustrated in Fig. 2 and Fig. 3, it is evident that the threshold values exhibit only slight variation within a limited range. The mean threshold value, as determined from these results, can effectively serve as a single threshold value. This single threshold value can be employed to mitigate the communication overhead necessitated for acquiring information about the status of neighboring nodes at the conclusion of each cluster selection period.

Fig. 4 and Fig. 5 illustrate the variation in $D_{g,q}(e, u)$ values, considering the summation of energy and total packets delivered to the Sink, as per (22). The threshold values depicted range from 0.18 to 0.39 in Fig. 4 and from 0.19 to 0.5 in Fig. 5. As illustrated in Fig. 4, the results indicate a decrease in threshold values as the superiority (q) of energy over distance from the base station increases. This is in contrast to the observed increase in threshold values under the same circumstances, as shown in Fig. 2 and Fig. 3. The threshold values observed in Fig. 4 and Fig. 5 are lower than those in Fig. 2 and Fig. 3. Lower threshold values imply a reduced number of CHs, leading to larger clusters with a greater number of member nodes. Larger clusters can accumulate more packets for transmission to the Sink. The increased transmission of packets by CHs results in higher energy consumption, potentially causing CHs to be situated at a greater distance from their members in subsequent rounds.

In this study, a comparative analysis is conducted between the CH selection process utilizing the K-means and HPSO algorithm (KMHPSO) and the proposed method. The KMH-PSO algorithm operates as a centralized approach, employing

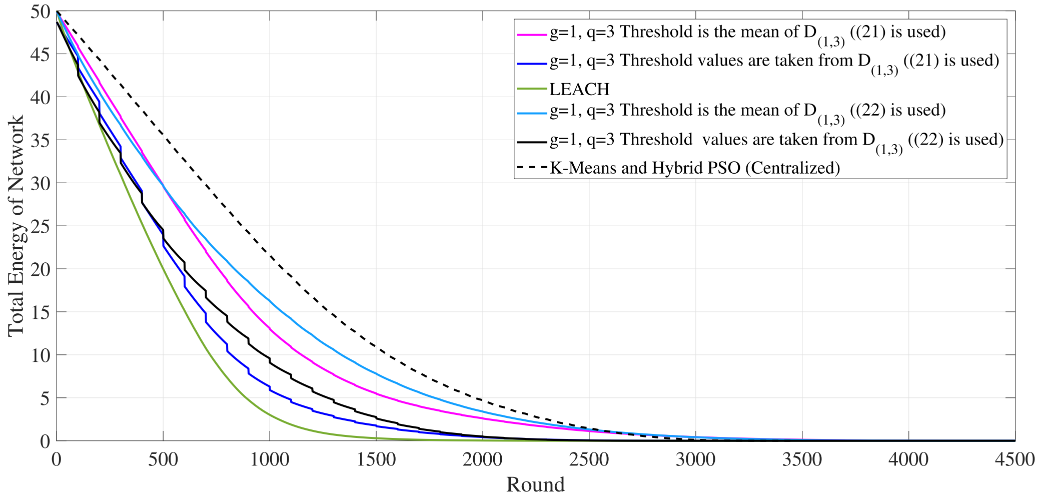

FIGURE 6. Variation of the total energy with the Sink located at the coordinates (50, 50) (i.e. center of 100 × 100 network area).

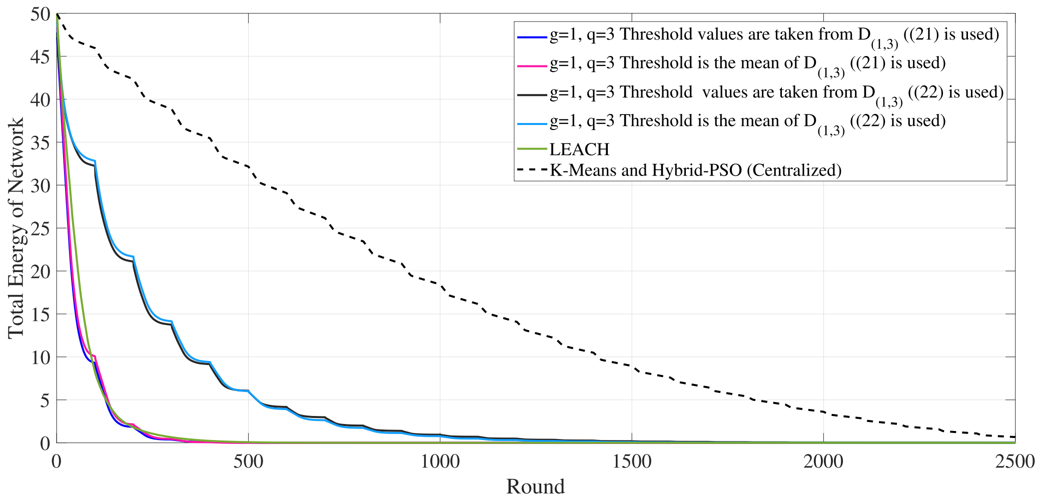

FIGURE 7. Variation of the total energy with the Sink located at the coordinates (200, 200) (i.e. far from 100 × 100 network area).

the K-Means algorithm for spatial clustering and the HPSO algorithm for CH selection. This approach utilizes the Sink as a central entity to determine the CHs after a specific number of rounds. Once the Sink identifies the CHs, it announces the selected nodes to the network. The CH selection period and CH ratio are set to 100 and 0.05, respectively. The results indicate that KMHPSO outperforms in terms of the total number of packets reaching the Sink. However, it is noteworthy that the proposed method, which does not necessitate centralized control, demonstrates a substantially lower computational cost compared to KMHPSO, which involves 50 iterations of the Hybrid PSO and K-Means algorithm in our simulations. Specifically, the mean number of total packets reaching the Sink is observed to be 132920 and 31414 when the Sink is located at the center and at coordinates (200, 200) with KMHPSO. Furthermore, the maximum lifetimes are determined to be 3444 and 2504 when the Sink is located at the center and at coordinates (200, 200), respectively.

Fig. 6 displays the variation in the total energy of the network with the Sink located at the center. All simulation results pertaining to the performance of the network are based on the average outcomes from 100 simulation runs. Comprehensive results, incorporating all possible values of g and q, are presented in Tables 7 and 8, with select outcomes visualized in figures. The findings from Fig. 6 indicate that lower threshold values contribute to maintaining the total energy slightly higher, attributed to the reduced number of CHs with elevated energy consumption. However, as the energy consumption of CHs exerts a more pronounced influence on the overall network energy at lower energy levels, the lifetime of the network exhibits negligible variations compared to the utilization of lower or higher threshold levels.

Fig. 7 illustrates the variation in the total energy of the network when the Sink is positioned at a considerable distance from the network. Notably, the threshold values determined through (22) contribute to an extended network

TABLE 6. The simulation cases.

Case	1	2	3	4	5	6	7	8	9
CH Selection Periods (p_g)	100	100	100	150	150	150	200	200	200
Level of Importance ($C(q)$)	7	5	3	7	5	3	7	5	3
Mean of Threshold Values (Eq. 22, (200,200))	0.3287	0.3405	0.3631	0.3337	0.3478	0.3673	0.3466	0.3551	0.3758
Mean of Threshold Values (Eq. 21, (200,200))	0.796	0.7775	0.7469	0.7974	0.7822	0.7483	0.7966	0.7828	0.7508
Mean of Threshold Values (Eq. 22, (50,50))	0.2269	0.2512	0.2976	0.2281	0.2572	0.3007	0.2366	0.2638	0.3111
Mean of Threshold Values (Eq. 21, (50,50))	0.7660	0.7486	0.7178	0.7721	0.7564	0.7254	0.7795	0.7616	0.7303

TABLE 7. Corresponding Network Lifetimes and Packets Reaching Sink Located at (50, 50).

	Eq. (21)		Eq. (22)		Fixed Threshold ($p_g = 100; g = 1$)		
Case	Network Lifetime	# Packets	Network Lifetime	# Packets	Threshold	Network Lifetime	# Packets
1	3016	91769.16	3006	58711.71	0.1	4525	58898.47
2	3025	89991.56	3142	58822.77	0.2	4548	71830.54
3	3000	88228.63	3050	61468.4	0.3	4771	79521.55
4	3505	101252.98	3280	60951.56	0.4	4619	86521.47
5	3450	99214.21	3423	63046.93	0.5	4520	95326.53
6	3542	96425.57	3385	65919.37	0.6	4539	103224.5
7	3821	107523.29	3712	62399.49	0.7	4525	115338.39
8	3800	105223.16	3785	64647.32	0.8	4535	123963.6
9	3818	102940.18	3713	67850.22	0.9	4504	136264.65
Mean	3441.889	98063.19333	3388.444	62646.41889		4565.111	96765.52222
Std	329.6366	6499.655506	279.2431	2913.173971		78.9957	23913.31383

lifetime, as depicted in Fig. 7. On the other hand, utilizing a single threshold value yields comparable results to employing the threshold values derived from the AHP method, as seen in Fig. 7. It becomes conceivable to consider this mean threshold value as an optimal threshold for the network. To further explore the optimal threshold, derived by averaging the threshold values obtained through the AHP method based on conceivable energy and location information, a comparison is conducted with potential threshold values ranging in increments of 0.1 between 0.1 and 0.9. The results of this comparative analysis are presented in Tables 7 and 8.

In the scenario where the BS is situated at the center of the network, the utilization of (21) in simulation reveals a slightly higher average network lifetime compared to the usage of (22). However, there is a notable increase in the average number of packets reaching the BS when employing (21). On the other hand, for the LEACH with $P = 0.05$, the mean network lifetime is found to be 1778, and the total number of packets reaching the Sink is 50321. According to the results depicted in Table 7, the proposed methodology attains an approximately twofold improvement in both network lifetime and packets reached to the Sink when compared with the LEACH protocol.

Utilizing (21) results in higher threshold values, leading to an increased number of CHs. In this scenario, member nodes are more likely to find CHs in close proximity. Additionally, some CHs are situated relatively close to the Sink, preventing premature depletion of their battery and conserving energy. This conservation, in turn, enables member nodes to transmit more packets through these CHs. In contrast, the use of (22) generates lower threshold values, resulting in a decreased count of CHs. As a consequence, some member nodes associated with CHs find themselves positioned at greater distances. This spatial separation contributes to premature depletion of energy resources, leading to a reduction in the quantity of transmitted packets.

Positioning the Sink far from the network results in an elevated number of CHs when (21) is employed. However, these CHs are relatively distant from the Sink, leading to their early depletion. Conversely, employing (22) yields a reduced number of CHs, thereby contributing to the extension of the network's lifetime. Despite the shorter network lifetime observed for (21) compared to (22), the latter results in fewer CHs positioned away from member nodes. Consequently, member nodes deplete rapidly, resulting in a lower total number of packets sent to the BS. For the LEACH with $P = 0.05$, the mean network lifetime and packets sent to the Sink are calculated as 711.43 and 4166.6, respectively. As indicated in Table 8, the proposed methodology attains approximately 50% more network lifetime and a 25% increase in packets sent to the Sink compared to LEACH.

When the Sink is positioned at the center of the network, and (21) is used, Case 7 with a CH selection period (p_g) of 200, a level of importance ($C(q)$) of 7, and a mean threshold value of 0.7795 emerges as the optimal configuration as given in Table 6. This case delivers the best network lifetime of 3821 rounds and achieves the maximum number of packets reaching the Sink at 107523.29 as given in Table 7. In contrast, the least favorable outcome is observed in Case 3, characterized by p_g of 100, $C(q)$ of 3, and a mean threshold value of 0.7178 as given in Table 6. This case provides a network lifetime of only 3000 rounds and a number of packets reaching the Sink at 88228.63 as given in Table 7. When utilizing (22) with the Sink at the center of the network, Case 8, featuring p_g of 200 and $C(q)$ of 5, and a mean threshold value of 0.2638 yields the longest network lifetime as in Table 6, allowing the network to operate for 3785 rounds as in Table 7.

TABLE 8. Corresponding Network Lifetimes and Number of Packets Sink Located at (200, 200).

	Eq. (21)		Eq. (22)		Fixed Threshold ($p_g = 100$; g=1)		
Case	Network Lifetime	# Packets	Network Lifetime	# Packets	Threshold	Network Lifetime	# Packets
1	549	5384.27	3004	4951.78	0.1	4824	3895.43
2	557	5357.29	2509	4954.54	0.2	3721	4870.46
3	633	5327.84	2010	5009.7	0.3	2618	5171.54
4	792	5333.2	3796	4820.51	0.4	1644	5320.4
5	933	5358.57	3604	4854.12	0.5	1239	5380.11
6	1255	5326.66	3601	4874.78	0.6	1080	5431.01
7	855	5323.97	4148	4742.83	0.7	728	5452.81
8	1032	5325.03	4279	4722.7	0.8	851	5498
9	1253	5308.59	3938	4837.22	0.9	446	5547.81
Mean	873.2222	5338.38	3432.111	4863.131111		1905.667	5174.174444
Std	255.7172	22.16030836	725.2539	91.04012881		1419.86	492.0813978

For the same Sink location, when the fixed threshold is used, the best network lifetime is achieved with a threshold value of 0.3, allowing the network to operate for 4771 rounds. However, with a fixed threshold value of 0.9, the maximum number of packets reaching the BS is observed (136264.65).

In the scenario where the Sink is positioned away from the network, the impact of parameters p_g and $C(q)$ on the network lifetime is found to be insignificant when utilizing threshold values obtained from (21). Nevertheless, Cases 6 ($p_g = 150, C(q) = 3$) and Case 9 ($p_g = 200, C(q) = 3$) outperform other configurations, in terms of the number of packets reaching the Sink. When employing threshold values derived from (22) under the same conditions, a notable improvement is observed compared to both fixed threshold values and those obtained via (21). Specifically, Case 8 ($p_g = 200, C(q) = 5$) stands out, showcasing improved network lifetime. Additionally, Case 8 demonstrates a commendable level of packets reaching the Sink.

When the energy consumption of CHs is considerably high, it is seen that the use of the threshold values matrix obtained by the AHP method has a better mean network lifetime. In addition, in cases where the energy consumption of CHs is high, it is seen that the performance obtained with (22) is better than the performance obtained with (21).

Based on the obtained results, the implementation of a hierarchical WSN following the outlined procedure yields enhanced performance in terms of both packet number and network lifetime compared to LEACH. The network operates according to the following principles:

- Nodes within the network autonomously declare themselves as CHs based on a predetermined threshold value, maintaining this threshold value until the subsequent CH selection period.
- A node assuming the role of a CH retains this designation for a specified number of consecutive periods.

Notably, when the Sink is centrally located within the network, employing a fixed threshold leads to an improved network lifetime. Furthermore, a direct correlation is observed between the threshold level and the number of packets reaching the Sink, with higher thresholds corresponding to increased packet delivery. The fixed threshold consistently outperforms both (21) and (22). Conversely, in scenarios where the Sink is distant from the network and CHs exhibit heightened energy consumption, a lower threshold level is associated with a prolonged network lifetime.

Table 8 highlights the favourable performance achieved when the Sink is distanced from the network, particularly with a fixed threshold value of 0.1. Subsequently, an in-depth analysis of the case with a fixed threshold of 0.1 is conducted, providing mean results for one hundred distinct networks with randomly located nodes, as presented in Table 9. This comparison involved assessing values above and below 0.1 in relation to the 0.1 threshold. Although a higher threshold value of 0.15 results in more packets reaching the Sink, the network lifetime is 673 for this threshold compared to 815 for a threshold value of 0.1, when rounds that are unable to communicate with the Sink are disregarded due to the CH being inactive. Consequently, it is evident that a fixed threshold of 0.1 yields commendable outcomes for the location of Sink at coordinates (200, 200).

TABLE 9. Network lifetime and packet numbers comparison of fixed thresholds (BS away: 200, 200).

	T=0.05	T=0.1	T=0.15
Lifetime	2854	4562	4477
Packets To BS	1139	3474	4327
Rounds Nodes Can Send Packets	51	815	673

IV. CONCLUSION

In this study, a distributed hierarchical clustering algorithm is introduced, aiming to determine optimal threshold values based on energy and distance levels to the Sink for nodes through the application of the AHP method. The determination of the probability for a node to become a CH involves the consideration of energy and distance as criteria with assigned specific importance levels.

The primary objective is to pre-calculate threshold values (i.e., the probability of nodes becoming CHs) for various scenarios offline and subsequently apply these values in corresponding situations. The proposed algorithm is assessed against the well-established LEACH algorithm to ascertain its effectiveness. The results reveal a significant outperformance of the proposed algorithm, surpassing LEACH with a network lifetime exceeding two times and an additional 50% increase in packets sent to the Sink. Additionally, a comparative analysis is conducted between the proposed algorithm and the centralized KMHPSO algorithm, known for its higher processing power. The findings suggest that superior CHs can be selected in a distributed manner through the integration of artificial intelligence.

The proposed method aims to leverage a threshold values matrix obtained offline through the AHP method, resulting in a computationally efficient algorithm. However, potential avenues for future research may explore the determination of threshold values using an artificial NN in a distributed manner, albeit with an associated increase in computational load.

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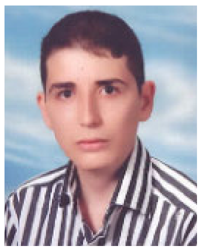

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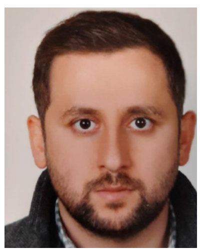

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