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Research Article

Energy Efficient Routing Protocol and Cluster Head Selection Using Modified Spider Monkey Optimization

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Abstract: Wireless sensor networks (WSNs) offer advantages in deployment flexibility and affordability due to their compact size and low cost. However, real-world WSN implementations face challenges, particularly regarding energy consumption. The limited battery capacity of sensor nodes restricts their operational lifespan, often resulting in; it is difficult to periodically replace the batteries in sensor nodes or recharge them, which reduces the system's overall operating time. To address the energy consumption challenge, WSNs are often divided into clusters. This clustering approach reduces communication costs and the energy required for routing data packets. Consequently, selecting the most efficient cluster head (CH) is crucial for maximizing the network's overall lifespan. This paper proposes a protocol that prioritizes energy efficiency, proximity to the base station, and even distribution within clusters when selecting CHs for intra-cluster communication. For inter-cluster communication, the protocol draws inspiration from the SMO protocol to identify the optimal next-hop CH based on remaining energy and distance to the base station. The performance of this proposed protocol is then compared against LEACH routing protocols. The simulation results indicate that the network becomes more optimized and energy efficient by using the proposed protocol.

***Keywords*:** cluster head selection, WSN, SMO, intra-cluster communication

1. Introduction

Wireless Sensor Networks (WSNs) consist of small, self-organizing sensor nodes distributed over large areas to monitor environmental conditions without needing existing infrastructure. These nodes work together to wirelessly send collected data to a base station (sink), which then connects to other networks, such as the Internet, for local or remote access. Each node has a sensing unit with one or more sensors and an Analog-to-Digital Converter (ADC). The sensors measure variables like temperature, humidity, pressure, and speed, while the ADC converts these analog signals into digital data for processing. The processing unit, usually a microcontroller with on-chip and flash memory, handles data processing, storage, and regulates other components, performing the necessary computations for the node's operations. Nodes communicate wirelessly via a transceiver that acts as both transmitter and receiver, using media such as radio frequency, optical (laser), or infrared. This integration enables WSNs to efficiently monitor and transmit environmental data across large areas, supporting various applications with minimal infrastructure.

In a WSN, batteries are the primary power source for sensor nodes. These batteries can either be recharged or cannot. The sensing unit uses energy to sense the environment, the processor unit uses energy to process data, and the transceiver

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unit uses energy to communicate. In a network of nodes with limited computation capacity, the maximum energy is consumed during the transmission of data, whereas sensing and data processing use much less energy. Location awareness is helpful or perhaps required in many of these applications. The localization of sensors [1] can be implemented by adding a location-finding system (like GPS) to each sensor node. Sensor node placement and network design in WSNs can be dynamic, adapting to environmental conditions and usage patterns. This flexibility is often achieved through mobile elements that can adjust sensor positions as needed. To extend network lifespan beyond battery limitations, various energy harvesting techniques are employed. WSNs find application in diverse real-world scenarios. Sensor nodes within these networks perform crucial tasks like data collection, transmission, reception, and even on-the-fly processing [2]. To efficiently execute these functions, they must manage their resources effectively. Due to the often harsh deployment environments, replacing depleted batteries in sensor nodes is impractical and costly. Sensor node failure, signified by the breakdown of the communication link with the central hub (sink), ultimately leads to network collapse. Since a sensor node's lifespan is directly tied to its energy consumption, maximizing remaining energy [3] across the network translates to a longer overall network lifetime. Therefore, minimizing energy usage is paramount for extending the operational lifespan of a WSN. In response to this challenge, many types of research have been performed to minimize energy consumption using various newly developed algorithms and approaches in different layers of WSN.

2. Spider monkey optimization (SMO)

One of the most intelligent monkeys in the new world is the spider monkey. When these monkeys are hanged by their tails, they resemble spiders. As a result, this species of monkey is referred to as a spider monkey. They always choose to live with their parents. Approximately 40–50 spider monkeys make constitute a group. This group's leader is a female spider monkey. All spider monkeys forage in tiny groups during the day in various directions, and at night they all congregate in their environment to share their foraging experiences with one another. Based on their prior experience, the leader female spider monkey chooses the foraging path. The leader splits the group into smaller groups if there is not enough food for everyone, and each of these groups forages independently in a different direction. Spider monkeys communicate across great distances by making a distinctive sound. Every spider monkey has a distinctive audible sound that helps other group monkeys recognize it.

The behaviours of spider monkeys served as the inspiration for the population-based meta-heuristic algorithm known as SMO. Inspired by the social dynamics of spider monkeys, which exhibit fission-fusion behaviour, this protocol mimics their intelligent foraging patterns, created by Bansal et al (2014) [4]. Global leader refers to the group's overall leader and local leader to the leaders of smaller organizations. Based on the availability of food sources, the global leader decides to fragment the groups into tinnier groups. Food scarcity is defined in the SMO algorithm as a lack of improvement in the solution, which indicates that the algorithm has reached the local optimal point. Each small group should be divided into an appropriate number of individuals. The global leader decides whether to fuse the group if additional fission results in a group with fewer members than the required minimum.

The proposed protocol leverages the Sequential Minimal Optimization (SMO) algorithm, inspired by the problem-solving behaviour of spider monkeys. The SMO algorithm operates in a series of distinct stages: Local Leader Selection (LLS), Local Leader Learning (LLL), Local Leader Decision (LLD), Global Leader Selection (GLS), Global Leader Learning (GLL), and Global Leader Decision (GLD).

2.1 *Initialization of the population*

An initial population of N spider monkeys are initialized in initialization phase which are uniformly distributed over the search space. Each SM_i is initialized as follows:

$$SM_{ij} = SM_{min\ j} + U(0,1) \times (SM_{max\ j} - SM_{min\ j}) \tag{1}$$

where,

$$SM_{ij} = \ i^{th} \text{ Spider Monkey in } \ j^{th} \text{ dimension}$$

$$SM_{min\ j} = \text{lower bound of the search space in } j^{th} \text{ dimension}$$

$$SM_{max\ j} = \text{upper bound of the search space in } \ j^{th} \text{ dimension}$$

$$U(0,1) = \ \text{random number uniformly distributed in the range } (0,\ 1)$$

2.2 *Local leader phase (LLP)*

During the local leader phase, each spider monkey can adjust its position based on the information from its local leader and group members as shown in Figure 1. The position is updated if the fitness value of the new position is higher than the previous one; otherwise, it remains unchanged. The equation for updating a position is as follows:

$$SM_{new\ ij} = SM_{ij} + U(0,1) \times (LL_{kj} - SM_{ij}) + U(-1,1) \times (SM_{rj} - SM_{ij}) \tag{2}$$

where,

$$SM_{ij} = \ \text{current position of } i^{th} \ SM \text{ in } j^{th} \text{ dimension}$$

$$LL_{kj} = \ \text{Local Leader of } k^{th} \text{ group in } j^{th} \text{ dimension}$$

$$SM_{rj} = \ \text{randomly selected } SM \text{ from the } k^{th} \text{ group in } j^{th} \text{ dimension such that } r \neq i$$

$$U(-1,1) = \ \text{uniformly distributed random number in the range } (-1,\ 1)$$

The second part is the influence of the local leader, where i^{th} SM is persuaded by and drawn to the local leader of the k^{th} group while still remaining persistent. Social impact is the last part, and i^{th} SM is learning from society (other individuals). Pr (Perturbation rate), which aids in maintaining the stochastic aspect of the algorithm, introduces fluctuations into the search process to prevent premature stagnation.

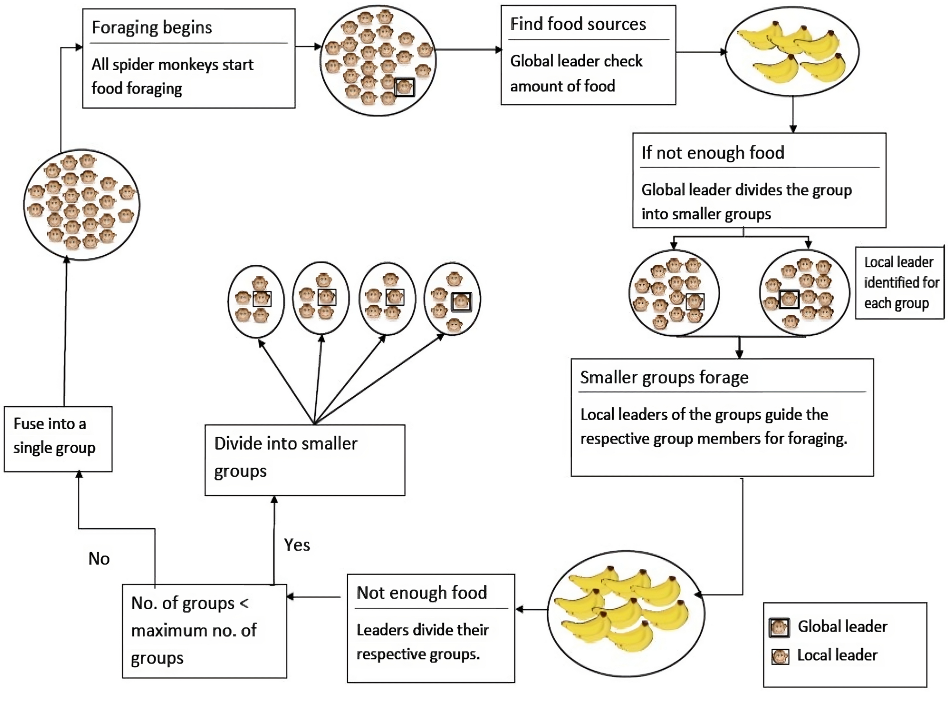

Figure 1. Foraging behaviour of spider monkeys

2.3 *Global leader phase (GLP)*

Some SMs are chosen based on their selection probability value ($prob_i$) during the global leader phase, with each monkey (SM) dynamically adapting its location based on insights gleaned from the leading member of the entire group and its immediate neighbors within the network. The algorithm provides more opportunity to better fitness solutions to change their position. One of the two formulas shown below can be used to determine whether $fitness_i$, the fitness of the i^{th} SM has a chance of being chosen for the global leader phase:

$$prob_i = \frac{(fitness_i)}{(\sum_{i=1}^{N} fitness_i)} \ (or)$$

$$prob_i = 0.9 \times \frac{(fitness_i)}{\max\_fit} + 0.1 \tag{3}$$

Equation for position update is:

$$SM_{new\ ij} = SM_{ij} + U(0,1) \times (GL_j - SM_{ij}) + U(-1,1) \times (SM_{rj} - SM_{ij}) \tag{4}$$

where, $GL_j =$ position of global leader in the j^{th} dimension

The position update equation for SMs incorporates three key factors. The first term reflects the inertia of the individual SM, representing its tendency to stay in its current location. The second term represents the attraction of the SM towards the global leader, guiding the search towards promising areas. This term helps to exploit the best regions of the search space identified so far. Finally, the third term, representing the social influence, encourages exploration and helps to avoid getting stuck in local optima.

2.4 *Global leader learning phase (GLLP)*

During the Global Leader Learning Phase (GLLP), the SM with the highest fitness value (best overall solution) is chosen as the new Global Leader using a greedy selection process. A "global limit counter," which counts the number of iterations since the last update, is used to keep an eye on this leader position. Should the leader's position stay the same, the counter advances by one. A successful update, on the other hand, resets the counter to 0 (zero).

2.5 *Local leader learning phase (LLLP)*

Like the global leader selection process, the Local Leader Learning Phase (LLLP) finds the most promising member of each group by using a greedy strategy. As the best answer, the SM with the highest fitness value is designated as the Local Leader. The number of iterations that the Local Leader's position stays unaltered is tracked by a counter that functions similarly to the global limit counter. When an update is successful, this counter resets to zero and increases by 1 for each iteration that passes without an update. This process is used by each group to choose its own Local Leader.

2.6 *Local leader decision phase (LLDP)*

Both local and global leaders have been identified after the learning phase. When the $LocalLimitCount$ exceeds the $LocalLeaderLimit$, which occurs when a Local Leader's position is not updated up to the $LocalLeaderLimit$, all group members either update their positions randomly using Equation (1) or using the experience of the global leader using Equation (5).

$$SM_{new\ ij} = SM_{ij} + U(0,1) \times (GL_j - SM_{ij}) + U(0,1) \times \left(SM_{rj} - LL_{kj}\right) \tag{5}$$

The position update equation for SMs incorporates three key influences. The second term reflects the attraction towards the global leader, guiding individual SMs to adjust their search based on the global leader's experience. This helps them explore promising areas of the search space. The third term introduces repulsion from the local leader, particularly if the group seems stuck in a sub-optimal region (like a food scarcity zone).

To prevent the local leader from getting trapped in such local optima, a pre-defined local leader limit (LLL) is employed. If the local leader counter (LLC) exceeds this limit, indicating stagnation, the LLC is reset to zero. This triggers the SM initialization process mentioned earlier, promoting broader exploration of the search space.

2.7 *Global leader decision phase (GLDP)*

The Global Leader Decision phase (GLD) modifies the swarm structure in accordance with the global leader's update state, just like the local leader decision phase does. The swarm goes through a fission or fusion process if the global leader's position remains unchanged for a set amount of time (known as the Global Leader Limit). After setting the Global Leader Counter (GLC) to zero, the number of groups in existence at the time is contrasted with the maximum limit (MG). The global leader further divides existing groups to diversify exploration if GLC exceeds the limit, suggesting that the entire swarm may be stranded. On the other hand, groups combine to form a single unit if the number of groups is less than the maximum, which may help them arrive at a better solution.

3. Literature survey

Authors of the research article [5] discuss recent developments and potential synergies in wireless sensor networks, emphasizing their importance in various applications and the advancements that have been made in the field. This work [6] proposes a hybrid approach to energy-efficient clustering and routing in WSNs, aiming to enhance network longevity and efficiency through innovative clustering and routing techniques. This paper [7] introduces a Boolean spider monkey optimization (BSMO) for energy-efficient clustering in WSNs, demonstrating significant improvements in network lifetime and energy consumption. Authors of this paper [8] describe an energy-efficient cluster-head selection method using sampling-based spider monkey optimization, highlighting its effectiveness in reducing energy usage and prolonging network lifespan. This research [9] explores a multi-objective spider monkey optimization for energy-efficient clustering and routing in WSNs, addressing multiple network performance metrics simultaneously. Authors of this paper [10] review various routing protocols in WSNs, discussing their design principles, performance metrics, and application scenarios. This article [11] surveys clustering objectives in WSNs, analyzing current research directions and proposing future research avenues to enhance network performance. The authors of this article [12] examine modern clustering techniques in WSNs, emphasizing the latest innovations and their impact on network efficiency and reliability.

This work [13] evaluates and compares the LEACH and PEGASIS algorithms based on energy consumption, providing insights into their efficiency and practical applicability in WSNs. In this paper authors [14] analyze clustering in WSNs, focusing on performance metrics and taxonomy of clustering schemes, contributing to the understanding of their effectiveness. This research article [15] investigates cluster head selection in WSNs under a fuzzy environment, proposing a method that enhances decision-making processes in network management. Authors of this paper [16] provide a survey of spider monkey optimization (SMO) techniques, discussing their applications and effectiveness in various optimization problems, including WSNs. The authors of this work [17] discuss a genetic algorithm (GA) enabled distributed zone approach for green communication in WSNs, aiming to reduce energy consumption and improve network sustainability. In this paper authors [18] propose an energy-efficient clustering and routing optimization model for maximizing the lifetime of WSNs, emphasizing its practical implications and performance benefits. Authors [19] survey clustering algorithms in WSNs, identifying challenges, current research trends, and future directions to improve clustering efficiency and network performance. Authors of this work [20] conduct a contemporary survey on clustering techniques for WSNs, presenting an overview of the latest methodologies and their impact on network design. Authors [21] applies discrete spider monkey optimization to the traveling salesman problem, demonstrating its potential for solving complex optimization problems beyond WSNs. This work [22] presents an energy-efficient routing protocol based on SMO optimization in WSNs, showcasing its ability to enhance network longevity and efficiency.

In this work authors [23] develop a traffic-aware routing protocol for WSNs, addressing the need for efficient data transmission and reduced congestion in network traffic. Here [24] introduces a smart spider monkey optimization (SSMO) for energy-based cluster-head selection, adapted for biomedical engineering applications, demonstrating its versatility and efficiency. This research [25] proposes spider monkey optimization for energy-efficient clustering in heterogeneous underwater WSNs, highlighting its effectiveness in challenging environments. Authors of the article [26] introduce a fuzzy-gossip routing protocol for energy-efficient WSNs, showcasing its ability to improve data transmission and reduce energy usage. Authors [27] propose a spider monkey optimization routing protocol for WSNs, highlighting its potential to enhance network efficiency and reduce energy consumption. This article [28] introduces a genetic spider monkey-based routing protocol to increase the network lifetime and manage energy in WSNs, showcasing significant improvements in network performance. Authors [29] introduce a hyperbolic spider monkey optimization algorithm, discussing its innovative approach and potential applications in various optimization scenarios. Authors of this work [30] examine cluster head selection in monkey-inspired optimization-based routing protocol for WSNs, demonstrating its efficiency and effectiveness in network management. This study [31] presents a centralized control approach to optimize energy consumption in UASNs, balancing energy use among nodes and extending network lifetime. Hierarchical management and consideration of nodes' remaining energy during CH selection improve efficiency. Simulations show the proposed CCCS outperforms GTC, EULC, cDBR, and LEACH schemes. This article [32] proposes a PSO-based unequal clustering method for UASNs to address their short life cycle. Considering nodes' residual energy and distance, it balances energy consumption and extends network life. However, it overlooks network connectivity and information transmission reliability. This article [33] addresses the limited energy capacity of acoustic sensor nodes by applying game theory to UASNs. A game-theory-based clustering (GTC) scheme is developed, where nodes make decisions based on the Nash equilibrium, incentivized for collective benefit. Non uniform sectors ensure balanced CH energy consumption. Simulations show the GTC scheme effectively balances energy use and extends network lifetime.

These literature surveys cover a broad spectrum of topics related to WSNs, focusing on energy efficiency, clustering techniques, optimization algorithms, and routing protocols, providing a comprehensive overview of recent advancements and research directions in the field. Metaheuristic algorithms like Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) have inspired novel strategies for solving complex optimization problems. The Colony Search Optimization Algorithm (CSOA) [34] builds on these concepts, simulating early human social behaviors to achieve competitive optimization results. Traditional optimization algorithms often struggle with complex, multi-objective problems like those involving transportation uncertainties. The Hybrid Beetle Swarm Optimization (HBSO) algorithm [35], enhanced by Dijkstra's algorithm, effectively addresses these challenges, outperforming GA, PSO, and BAS in efficiency and reliability.

3.1 *Problem statement*

WSNs are organized into clusters to reduce energy consumption and lower the cost of routing communication. The entire network lifetime is significantly impacted by the choice of cluster heads. In-efficient cluster head selection can lead to network partition and early death of nodes as the cluster heads are the nodes that consume high energy within a cluster. Hence, the life of the WSN is over even though so many nodes have enough energy to communicate. Cluster head performs the aggregation of the data packets and transmits it to sink through inter-cluster routing. Therefore, the election of the cluster head as the next forwarder node has a significant effect on the network lifetime.

To enhance the routing path, decrease energy usage, and prolong WSN lifespan, a protocol is needed to choose the optimal cluster head for intra-cluster routing and the next forwarder cluster head for inter-cluster routing.

4. Objectives

The key goal in addressing this issue is to enhance cluster head selection in order to acquire an energy-efficient routing in WSN. This is accomplished by choosing the best and most suitable node to serve as the cluster head, one that has a high remaining energy and consume less energy in terms of transmission, aggregation and reception within the cluster for intra-cluster communication and best next forwarder cluster head for inter-cluster communication.

5. Proposed work

This methodology aims to decrease energy consumption, increase overall network efficiency, and prolong the network's operating life. A cluster head (CH) is designated in a clustering hierarchy and given the responsibility of gathering data from nearby non-CH nodes and transmitting it to the base station. The suggested approach chooses the CH for intra-cluster routing as shown in Figure 2, based on the remaining energy of the sensor node, the CH's distance from the base station, and the distance between all non-CH nodes and the CH. One way to think about this selecting process is like a troop of spider monkeys. Typically, the leader of such a group is always a female, chosen based on the monkeys' fitness and fertility. The most suitable female monkey is elected as the local leader of the group. For inter-cluster routing, the optimal node is chosen as the next forwarder among all CHs. When a CH needs to send aggregated data to the base station, it selects a CH from the existing CHs to forward the data packet, considering the next forwarder CH's remaining energy and its distance to the base station.

All sensor nodes share their positions with neighbouring nodes and the base station, in both both intra-cluster routing and inter-cluster routing as Figures 3 and 4 respectively. Our method assumes uniform initial energy and transmission range for all nodes. The base station monitors each node's status, including battery life; GPS coordinates, and cluster head (CH) information.

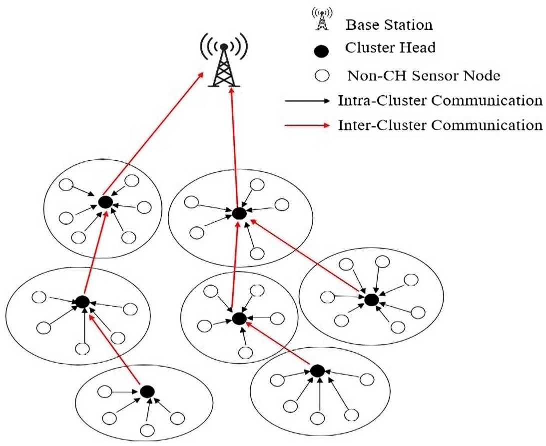

Figure 2. Routing path for WSN

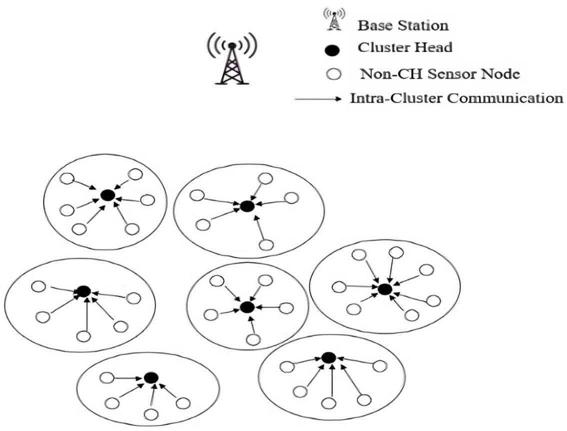

Figure 3. Intra-cluster routing

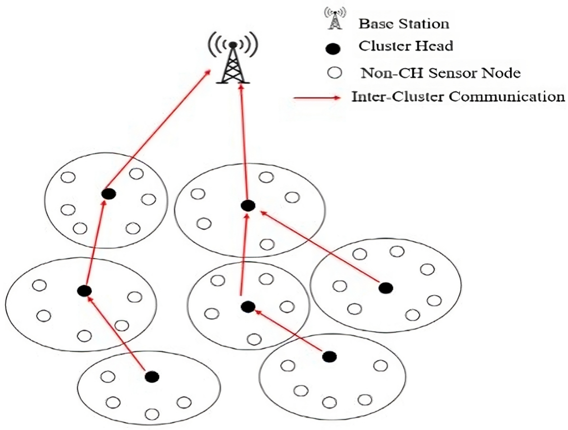

Figure 4. Inter-cluster routing

The proposed protocol is divided into 4 phases. We can implement distinct optimization technique to individual phases.

The proposed algorithm's steps are as follows:

Phase 1:

i. For each round, Find the number of clusters to be formed

$$K_{opt} = \frac{\sqrt{N_s}}{\sqrt{2\pi}} \times \frac{\sqrt{\varepsilon_{fs}}}{\sqrt{\varepsilon_{mp}}} \times \frac{M}{{d_{toBS}}^2} \tag{6}$$

where,

K_{opt} = Optimal number of clusters
N_s = No. of nodes alive
ε_{fs} = Amplification Co-efficient of Free Space Signal
ε_{mp} = Amplification Co-efficient of Multi-path Fading Signal
d_{toBS} = Average distance between all nodes and base station

$$d_{toBS} = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(x_i - x_s)^2 + (y_i - y_s)^2} \tag{7}$$

where,

Co-ordinate of Base station is (x_s, y_s) and co-ordinate of i^{th} node is (x_i, y_i).

Phase 2:

ii. Perform K-means clustering based on Euclidean Distance taking $K = K_{opt}$.

Phase 3:

iii. For a cluster, initialize all the nodes as individual spider monkey. Calculate fitness value of all SMs (nodes) present in the cluster.

$$fitness_i = (a \times RE_i) + \left(b \times \frac{1}{d_{BSi}}\right) + \left(c \times \frac{1}{d_{CNi}}\right) \tag{8}$$

where,

$$RE_i = \text{ residual energy of } i^{th}\text{node}$$

$$d_{BSi} = \text{ distance of } i^{th} \text{ node to the base station}$$

$$d_{CNi} = \text{ distance of } i^{th} \text{ node to the centroid of the cluster}$$

Let (x_i, y_i) is coordinate of i^{th} sensor node and (x_s, y_s) is the coordinate of sink
d_{BSi} can be calculated as

$$d_{BSi} = \sqrt{(x_s - x_i)^2 + (y_s - y_i)^2} \tag{9}$$

Let a cluster contains '**n**' nodes,
Co-ordinates of Centroid of a cluster

$$(x_c, y_c) = \left(\frac{1}{n}\sum_{i=1}^{n} x_i, \frac{1}{n}\sum_{i=1}^{n} y_i\right) \tag{10}$$

d_{CNi} can be calculated as

$$d_{CNi} = \sqrt{(x_c - x_i)^2 + (y_c - y_i)^2} \tag{11}$$

a, b, and c are three integral constants which controls the effectiveness of each parameter. These three constants are user specified.

iv. Then calculate probability value of each node that belongs to the population

$$prob_i = \frac{(fitness_i)}{(\sum_{i=1}^{n} fitness_i)} \tag{12}$$

where,

$$prob_i = \text{ probability value of } i^{th} \text{ node}$$

$$fitness_i = \text{ fitness value of } i^{th}\text{node}$$

$$n = \text{ Number of nodes present in the cluster}$$

v. Some nodes are selected from the population based on their probability values. Then select the best node with highest probability value as Local Leader Spider Monkey. The selected LLSM is the Cluster Head for that cluster. In similar way, find CH of all the clusters.

vi. All non-CH nodes of a cluster will transmit data packet to respective CH. CH will aggregate the packets and will forward it for Base Station.

Phase 4:

vii. Select the source CH node as Local Leader Spider Monkey (LLSM). Find all the neighbor CH nodes of LLSM that are in the range of LLSM. Take these neighbor CH nodes as the initial population.

viii. If the sink node is found in the range of LLSM (if the sink belongs to the initial population), then LLSM can send the data directly to the sink without any hops.

ix. Otherwise, calculate the fitness value of all neighbor CH nodes that are found(initial population)

$$fitness_i = (d \times RE_i) + \left(e \times \frac{1}{d_{BsChi}}\right) \tag{13}$$

where,

$$RE_i = \text{residual energy of } i^{th} \text{ neighbour CH node}$$

$$d_{BsChi} = \text{distance of } i^{th} \text{ CH node to the base station}$$

d and e are two integral constants which controls the effectiveness of each parameter.

x. Then select the best CH node with highest fitness value as Global Leader Spider Monkey. The selected GLSM is the next CH node in the forwarding path.

xi. Now the LLSM is updated taking information from the GLSM (GLSM becomes new LLSM) and the same process continues. In the process of expansions, set of CH nodes are discovered which are successors to the source node.

6. Simulation

6.1 *Simulation setup*

Following simulations are done by using PYTHON. We are assuming that all nodes are homogeneous and have the same energy resources. Network parameter settings for simulation is consider as per Table 1. All nodes are assigned with a distinctive identification (ID) and the same initial energy. The location of nodes and BS are fixed. Their mobility is not allowed, i.e., they do not move after deployment. After data aggregation, CH produces a data of length equal to the data sent by normal nodes.

A 100 m × 100 m field is used for the experiment, with 100 nodes randomly deployed within it. The sink is located at (90 m, 90 m). Each node has a transmission range of 20 m and an initial energy of 0.005J.

Table 1. Network parameter settings for simulation

Parameters	Parameters Meaning	Values
x_m	Length of the field (in meters)	100 m
y_m	Breadth of the field (in meters)	100 m
$sink_x$	X—coordinate of the sink (in meters)	90 m
$sink_y$	Y—coordinate of the sink (in meters)	90 m
n	No. nodes in the network	100
node_range	Transmission range (in meters)	20 m
E_o	Initial energy of a node (in Joules)	0.005 J
E_{elec}	Energy dissipated in receiving or transmitting circuit (in Joules/bit)	50 nJ/bit
E_{fs}	Amplification Coefficient of Free Space Signal (in Joules/bit/m^2)	10 pJ/bit/m^2
E_{mp}	Amplification Coefficient of Multi-Path Fading Signal (in Joules/bit/m^2)	0.00013 pJ/bit/m^2
d_o	Distance Threshold	$\left(\frac{\sqrt{\varepsilon_{fs}}}{\sqrt{\varepsilon_{mp}}}\right)$ m $\approx$ 200 m
E_{DA}	Amount of energy spent by the node to perform data aggregation (in Joules/bit)	5 nJ/bit
L	Size of the data packet (in bits)	2000 bits
a	Constant to control remaining energy factor in fitness function for intra-cluster communication	300
b	Constant to control distance factor (node to base station) in fitness function for intra-cluster communication	100
c	Constant to control distance factor (node to centroid) in fitness function for intra-cluster communication	200
d	Constant to control remaining energy factor in fitness function for inter-cluster communication	200
e	Constant to control distance factor (node to base station) in fitness function for inter-cluster communication	100

In the WSN routing protocol, the first-order radio model as Figure 5 is typically used to calculate the energy consumption during transmission and reception.

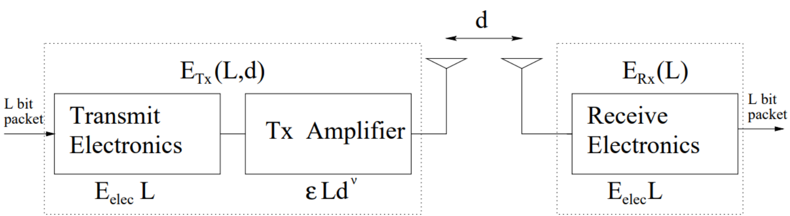

Figure 5. First-order radio energy dissipation model

- **For Intra-Cluster Communication**
  - The energy consumed by a sensor node (non-CH node) during transmission:
    If (d_t <= d_0)

$$E_{Tx} = (E_{elec} \times L) + (\varepsilon_{fs} \times L \times {d_t}^2)$$

    If (d_t > d_0)

$$E_{Tx} = (E_{elec} \times L) + (\varepsilon_{mp} \times L \times {d_t}^4)$$

  - The energy consumed by a Cluster Head during receiving packets and performing data aggregation:

$$E_{Rx} = \{(n-1) \times E_{elec} \times L\} + \{n \times E_{DA}\}$$

- **For Inter-Cluster Communication**
  - The energy consumed by a CH during transmission:
    If (d_t <= d_0)

$$E_{Tx} = (E_{elec} \times L) + (\varepsilon_{fs} \times L \times {d_t}^2)$$

    If (d_t > d_0)

$$E_{Tx} = (E_{elec} \times L) + (\varepsilon_{mp} \times L \times {d_t}^4)$$

  - The energy consumed by a CH during reception:

$$E_{Rx} = E_{elec} \times L$$

where,

$$E_{Tx} = \text{Energy consumed for transmitting a data paccket}$$

$$E_{Rx} = \text{ Energy consumed for receiving data}$$

$$E_{elec} = \text{Energydissipated in receiving or transmitting circuit}$$

$$\varepsilon_{fs} = \text{Amplification coefficient of Free Space Signal}$$

$$\varepsilon_{mp} = \text{Amplification Coefficient of MultiPath Fading Signal}$$

$$E_{DA} = \text{energy spent by CH to perform Data Aggregation}$$

$$L = \text{Length of Data Packet in Bits}$$

$$d_t \ = \ \text{Distance between sender node and receiver node}$$

$$n = \text{no. of nodes in the cluster including CH}$$

$$d_0 = \text{Distance Threshold}$$

$$d_0 \ = \ \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$$

7. Simulation

100 node positions are generated randomly in a (100 m × 100 m) area and a BS is placed at (90,90) position.

We implemented the proposed protocol on the network shown in Figure 6. To evaluate its performance, we compared it with the energy-efficient LEACH protocol, a widely used clustering method in WSNs.

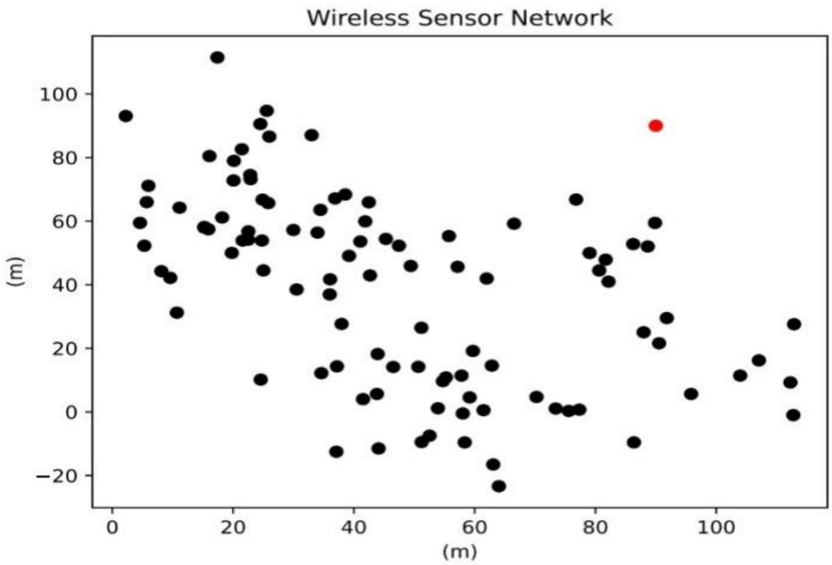

Figure 6. Wireless sensor network consisting of 100 nodes

7.1 *Simulation results*

In these Graphs (Figure 7) the Ratio of alive nodes in each round in the network is plotted. From these graphs, it can be noticed that the no. of alive nodes at a particular instance of time for the suggested method is higher than other existing methods. Nodes in LEACH (Low Energy Adaptive Clustering Hierarchical routing protocol), ERP (Evolutionary routing protocol), and HCR (hierarchical cluster-based routing protocol die quickly as compared to the suggested method. The suggested method extends the lifespan of the network keeping the maximum no. of nodes alive for a longer duration of time than LEACH.

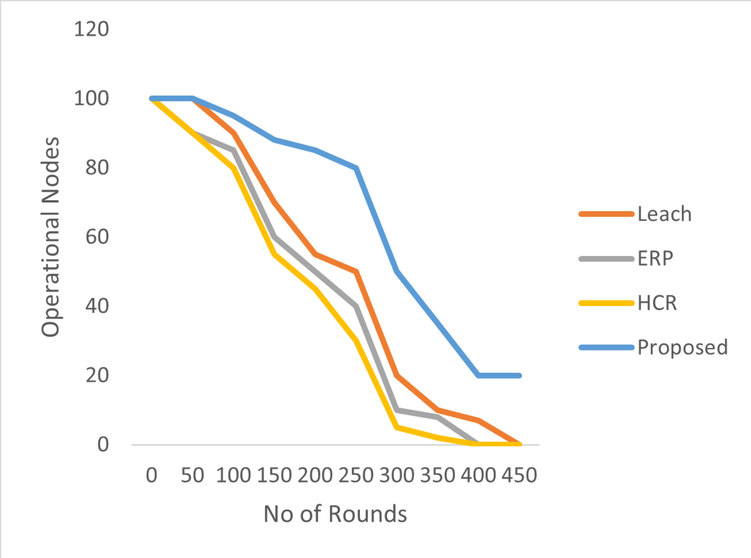

Figure 7. Ration of nodes still alive in the Proposed model with different existing methods per round

From Table 2, it is concluded that in the LEACH, after 88 rounds, the first node becomes dead as all its energy is consumed during data collection, aggregation, and transmission, half of the nodes die in 139 rounds and after 459 rounds no live node is present in the sensor field. Also, another two methods ERP and HCR show less performance in comparison to LEACH and the proposed method In the proposed method of modifying SMO, the first node becomes dead after 268 rounds, half of the nodes die in 321 rounds and after 678 rounds no live node is present in the sensor field. The network lives longer when SMO is used in the network than when LEACH is used in the network. Network lifetime increases and the energy consumption of the nodes is reduced when SMO is used.

Table 2. Lifetime of network

Parameter	Round Number			
	Proposed Method	LEACH	ERP	HCR
1^{st} node dead	268	88	55	53
50% nodes dead	321	139	110	95
100% nodes dead	678	459	450	400

In this Graph (Figure 8), the Ratio of the remaining energy in each round in the network is plotted. The proposed protocol has higher remaining energy for a longer duration of time for 678 rounds. The total energy consumed per round by the network is shown. LEACH, ERP, and HCR consume more energy than the proposed method. SMO extends the network's lifespan by using less energy and maintaining a better balance than other protocols. The average energy consumed per round by all nodes. This graph illustrates that the suggested SMO approach surpasses LEACH, ERP, and HCR regarding energy consumption and network longevity.

From the simulations, it is evident that the proposed method effectively balances energy consumption, reduces overall energy usage, and features fewer hops, resulting in an extended network lifetime compared to the widely utilized energy-efficient routing protocol LEACH, ERP and HCR.

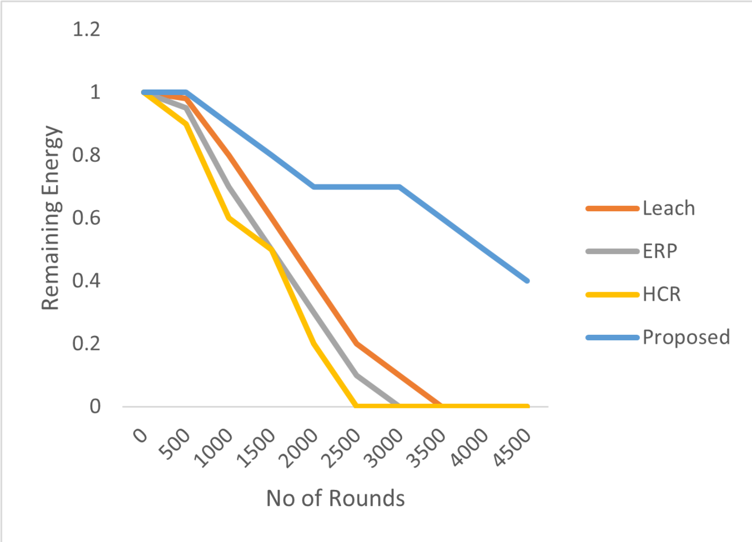

Figure 8. Comparison of energy consumed per transmission

8. Conclusions

Energy efficiency is a significant concern in Wireless Sensor Networks (WSNs). In this paper, we introduced a clustering-based hierarchical routing protocol that utilizes the Spider Monkey Optimization method to improve energy efficiency. This protocol selects the optimal cluster head (CH) within each cluster for intra-cluster routing and determines the best subsequent forwarder CH node for inter-cluster routing to transmit data from the source node to the base station. This method outperforms LEACH by extending network lifespan, enhancing CH selection, balancing energy dissipation, and improving overall network quality. Future improvements could involve integrating both intra-cluster and inter-cluster communications when selecting CHs and forwarder nodes, rather than evaluating them separately. Additionally, enhancing the clustering method with density-based clustering (such as DBSCAN) could optimize coverage area, energy density, or node density.

Confilict of Interest

The authors declare no confilict of interest.

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